Reconfigurable Manufacturing Process Monitoring Systems

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of the requirements for the degree of Ph.D.

Supervisor

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Declaration

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Summary

Performance measurement is indispensable to manufacturing, due to the fact that if the efficiency of an activity cannot be measured it could not be effectively controlled. Recent trends in process monitoring systems point towards a transformation from static centralisation to dynamic decentralisation. This change has been motivated by the need to enable reconfigurable systems that are internally flexible to production requirements, and externally adaptive to multiple processes. The convergence of industrial systems with advanced computing, low-cost sensing, and new levels of connectivity permitted by network technology has been the catalyst for this transformation. Furthermore, these decentralised cloud manufacturing systems are being combined with advanced analytics and artificial intelligence, to form cyber-physical production systems.

This research work explores the dynamics of decentralised software architecture within field-level manufacturing process monitoring systems. The need for this understanding has been driven by the prediction that these cyber-physical systems will create the next generation of innovative intelligent machines. This research investigates the capability of decentralisation design to provide the core fundamental functionality of process monitoring systems in a new reconfigurable format. The embodiment of this investigation is the design and development of a decentralised architecture for the creation of a reconfigurable process monitoring system within field-level manufacturing.

An investigation into available data interoperability systems and field-level manufacturing process monitoring system requirements, resulted in the identification of a research opportunity. Evidently, current academic and commercial mediums could not provide for the high communication speed, high data capacity, and heterogeneous data requirements present in field-level manufacturing systems.

Through a combination of decentralised modelling, and state-of-the-art technologies and techniques, a new data interoperability architecture was developed. The resultant architecture, namely the ARC, is tested in respect to speed, capacity, and correlation accuracy. The results showed a; <= 1 ms communication speed, 1 Hz to 1MHz data capacity, and 99.95% correlation accuracy. Evidently, the ARC is an effective data interoperability medium for utilisation in field-level manufacturing systems, beyond the capability of all previously reviewed systems.

Furthermore, the ARC was adapted to monitor multiple process variables from a CNC turning machine tool, such as: tool force, spindle and axis motor current, spindle and turret vibration. The ARC provided a platform to evaluate the migration of signal process techniques, and time and frequency domain analytics, within a decentralised architecture. The results from this work represent a first case migration of fundamental manufacturing process monitoring steps within a cyber-physical system. Furthermore, an advanced cyber-physical system was created for autonomous process performance characterisation.

In order to investigate the industrial application of the ARC, a study was undertaken into the variation in dry CNC turning machining, thereby evaluating the capability of the ARC signal processing techniques and analytics to achieve process insight. The result of which, was the successfully implementation of the ARC to achieve multi-scalable data acquisition, signal processing, and process performance analysis of a CNC turning machine tool. The generic building blocks present within the ARC were configured to produce unique signal feature extraction across multiple process variables. Process insight was evident in the multi-perspective view of machine actions, via the time and frequency domain analysis, of tool force, spindle and axis motor current, and spindle and turret vibration.

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Abbreviations

AC	Alternating Current
AE	Acoustic Emission
AESOP	ArchitecturE for Service-Oriented Process-Monitoring and-Control
APA	Asynchronous Programming Agents
API	Application Programming Interfaces
ASCII	American Standard Code for Information Interchange
BMM	Binary Message Model
CBM	Cloud-Based Monitoring
CC	Continuous Control
CCEB	Current Condition Evaluation-Based
CEP	Complex Event Processing
CIM	Computer Integrated Manufacturing
CM	Corrective Maintenance
CNC	Computer Numerically Controller
CoAP	Constrained Application Protocol
COM	OLE Component Object Model
CPPS	Cyber Physical Production Systems
CPS	Cyber Physical Systems
CT	Current Transformer
DC	Discrete Control
DC	Direct Current
DCOM	Distributed Component Object Model
DFT	Discrete Fourier transform
DMS	Dedicated Manufacturing System
DPWS	Device Profile for Web services
DSC	Data logging and Supervisory Control
EMF	Electro-Magentic Force
ERP	Enterprise Resource Planning
ESD	Energy Spectrum Density
EXI	Efficient XML Interchange
FCPB	Future Condition Prediction-Based
FFT	Fast Fourier Transforms
FIFO	First In First Out
FMS	Flexible Manufacturing System
FPGA	Field-Programmable Gate Arrays
HMS	Holonic Manufacturing System
IEPE	Integrated Electronics PiezoElectric
IoT	Internet of Things

KPI	Key Process Indicator
LAN	Local Area Network
MEMO	Multiple In Multiple Out
MES	Manufacturing Execution Systems
MPMS	Manufacturing Process Monitoring Systems
MRP	Material Requirements Planning
NC	Numerical Controllers
NI-PSP	NI-Publish Subscribe Protocol
NIST	National Institute of Standards and Technology U.S. Department of commerce
OLE	Object Linking and Embedding
ORC	ORChestrator
OPC	OLE for Process Control
OPC-UA	OPC Unified Architecture
PHB	Prognostic and Health Management
PID	Proportional Integral Derivativ
PM	Preventative Maintenance
PPS	Packages Per Second
PSD	Power Spectrum Density
REST	REpresentational-State-Transfer interface
RMS	Reconfigurable Manufacturing System
RMS	Root Mean Square
RT	Reat Time
RTT	Round Trip Time
SANS	Sequence-oriented ANalySis
SCADA	Supervisory Control And Data Acquisition
SCM	Supply Chain Management
SCM	Supply Chain Management
SD	Standard Deviation
SIRENA	Service Infrastructure for Real-time Embedded Networked Applications
SOA	Service Oriented Architecture
SOCRADES	Service-Oriented Cross-layer Infrastructure for Distributed smart Embedded devices
SODA	Service Oriented Devices Architecture
SPK	Signal Processing Kernel
STEP	STandard for Exchange of Product
SVE	Shared Variable Engine
TCP	Transfer Control Protocol
UNEP	United Nations Environmental Programme
WAN	Wide Area Network
XML	eXtensible Markup Language

Chapter 1

Introduction

1.1 Sustainable manufacturing through process monitoring

Manufacturing has contributed to shaping the development of human race from the start of the industrial revolution, and through progressive world industrialisation. Subsequently leading to various socio-economic influences, including the enabling and distribution of global information communication technology. In 2011 the United Nations Environmental Programme (UNEP) stated that manufacturing accounted for 23% of global employment, 35% of global electricity use, over 25% of primary resource extraction consumption, 20% of world CO2 emissions and 10% of global water demand [1]. Manufacturing's significant global impression identifies manufacturing as a leading influence in global economics, politics, technology, sociology, and ecology. Today manufacturing faces multiple challenges within its influent domains, such as its effect on: climate change, public health, poverty and social exclusion, loss of bio-diversity, increasing waste volume, soil-loss and transport congestion [2]. Manufacturing sustainability is being sought after to meet the needs of the present without compromising the ability of future generations to meet their own needs [3]. Fundamentally manufacturing sustainability is identified as the creation of manufactured products that use processes that minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers and are economically sound [4]. Engineering challenges to meet sustainable manufacturing goals, follow objectives to reduce the consumption of resources in the transformation process from input to output. Evidently performance measurement is vital to sustainable manufacturing goals, because if the effective efficiency of an activity cannot be measured, it cannot be properly controlled [5]. These metrics are achieved through process monitoring systems that provide performance measures. These performance measures enable manufacturers to achieve high accuracy manufacturing systems, sustainable production capabilities, and enable resource efficiency.

1.2 Manufacturing process monitoring evolution

1.2.1 Fundamental manufacturing process monitoring

In order to achieve performance measurement engineers utilise sensors to obtain process variables and subject these variables to analogue and digital signal conditioning and processing, with the aim to generate functional signal features that are potentially correlated to process conditions [6]. Fundamentally the systematic implementation of such system within manufacturing can be referred to as a Manufacturing Process Monitoring Systems (MPMS).

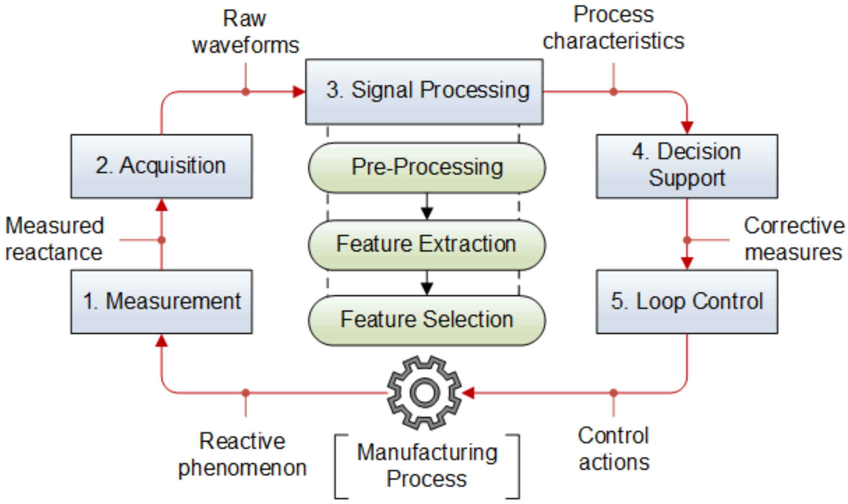


Figure 1.1 Process monitoring control loop, adapted from [6]

The types of process variables typically utilised with manufacturing process monitoring systems include; cutting force, vibration, acoustic emission, sound, temperature, power, etc. [7]. Selection of process variable for a manufacturing process monitoring systems is subjective and varies between manufacturing processes, due to the required output of the system, and the capability to extract the required variable from its environment [8]. Once the process data sources have been identified and variables are being actively measured and acquired, signal processing can be undertaken. Signal processing can be subdivided into pre-processing, feature extraction and feature selection [6], as illustrated in Figure 1.1. Signal pre-processing focuses a signal for increased resolution through filtering, amplification, conversion, and/or segmentation. Signal feature extraction aims at extracting different signal features or signal transform features that change with the process. While signal feature selection aims at selecting the most relevant features that best describe the machining process. These features enable the process performance to be characterised, and enable the input measures for decision support systems to initiate corrective measures if required [9].

The process monitoring control loop, as seen in Figure 1.1, is designed to meet a multitude of manufacturing management criteria, i.e. production performance, maintenance, and resource efficiency. Examples of production performance improvements that manufacturing process monitoring systems provide are; machining chatter detection [10], automatic ideal machine parameter selection [11], tool wear detection [12], and automated process planning [13]. Maintenance manufacturing process monitoring systems are motivated by the fact that 99% of equipment failures are preceded by certain signs, conditions, or indications [14]. Examples of manufacturing process monitoring systems within maintenance include; automated neural network predictive maintenance [15], mass remote monitoring of machine tools [16], and intelligent condition based maintenance prognostics tools [17]. Resource efficiency corresponds to the opportunities that exist across the manufacturing enterprise for more efficient usage of energy and resources [14]. Manufacturers are actively aiming to provide visibility of energy within the organisation to enable resource management. Examples of resource efficiency driven manufacturing process monitoring systems can be seen in; electrical metering and monitoring of manufacturing systems [18], energy efficient decision making for production management and scheduling [19], and identification of energy efficient machining parameters for part manufacture [20].

1.2.2 Cloud-based monitoring

Cloud-Based Monitoring (CBM) can be defined, as a model for enabling ubiquitous, on-demand network access to a shared pool of configurable manufacturing resources that can be rapidly provisioned and released [21]. Examples of manufacturing resources can be seen in the diverse manufacturing data sources present throughout a manufacturing enterprise, e.g. sensors, meters, machines, production lines, databases, etc. These data sources can be utilised by multiple enterprise level management and controls systems; e.g. Supply Chain Management (SCM), Enterprise Resource Planning (ERP) [22], Manufacturing Execution Systems (MES), machine Continuous Control (CC) and Discrete Control (DC) systems [23]. Through cloud technology these systems can all gain access to the same data sources, via a cloud service that enables dynamic data acquisition and distribution, as illustrated in Figure 1.2. This creates a decentralisation of systematic components, free from peer-to-peer relationships, with the extensibility and re-configurability to expand and meet the monitoring requirements of multiple manufacturing process.

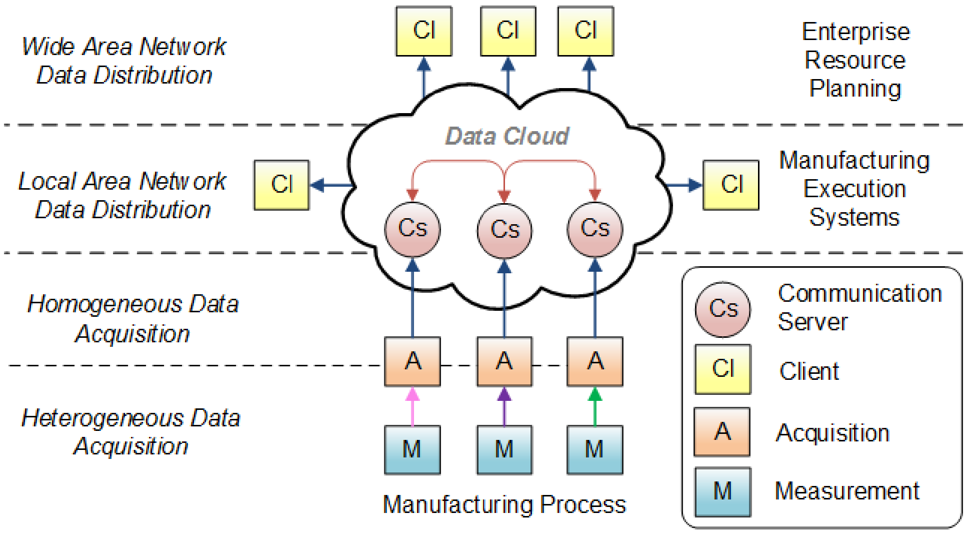


Figure 1.2 Cloud-based dynamic manufacturing data acquisition and distribution

Cloud-based monitoring is the consolidation of multiple decentralised technologies and methodologies, i.e. Ubiquitous and Cloud Computing, Internet-of-Things (IoT), and Service Oriented Architecture (SOA) [1]. Cloud-based monitoring data interoperability has been at the forefront of manufacturing production Supervisory Control And Data Acquisition (SCADA) research and development [24]. This has resulted in multiple architectures to-data; the industrial standard OPC-Unified Architecture [25], the emergent open factory floor communication protocol MTConnect [26], and the ArchitecturE for Service-Oriented Process-Monitoring and-Control (AESOP) initiative [27]. Each system varies in functionality and capacity and there is no one solution to meet the requirements of every manufacturing system or enterprise level. The adoption of any data interoperability architecture is dependent on the required desired attributes of the system as a whole, i.e. speed, capacity, openness, network range, security, etc.

1.2.3 Cyber physical production system

Within manufacturing, the incorporation of decentralised interoperable cloud solutions in combination with advanced analytics and artificial intelligences, is aimed at creating innovative intelligent machines, that will represent the Cyber Physical Systems (CPS) of the future [28], as illustrated in Figure 1.3. It has been envisioned that the future enhancement of manufacturing machining systems and their operation performance will depend upon the development and implementation of these innovative sensor monitoring systems [6].

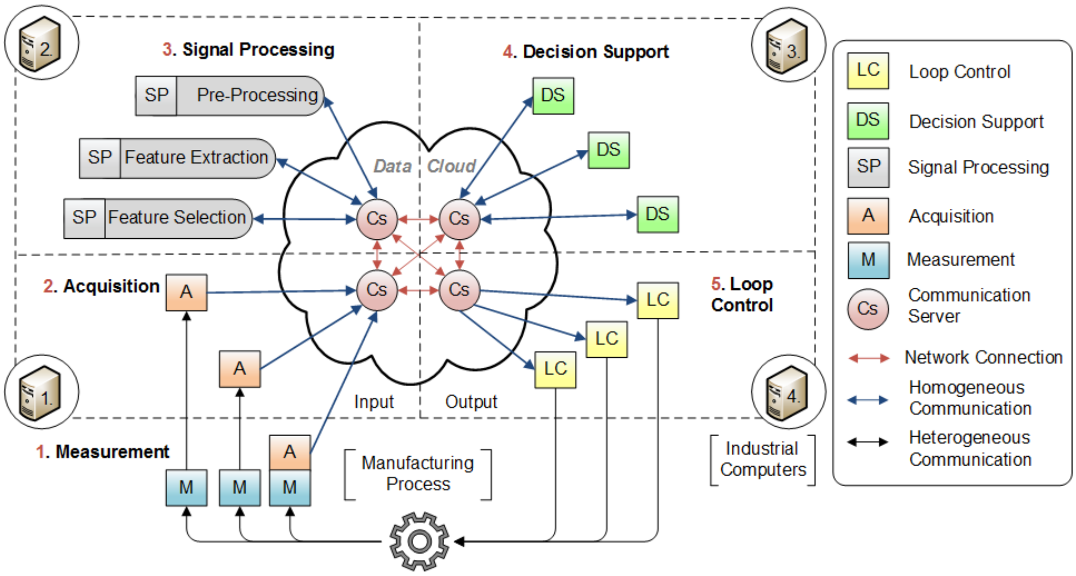


Figure 1.3 Cloud-based process monitoring control loop; cyber physical production system

Cyber-physical systems are open, interconnecting systems that operate flexibly, cooperatively (system and system) and interactively (human and system) [29]. Cyber-physical systems are expected to exceed traditional embedded systems in various aspects, such as efficiency, safety, reliability, robustness, adaptability, and more [30]. These systems provide the link between the physical world and virtual world, with the seamless integration of information technology and software through various types of digital communication services. Cyber-physical system research covers multiple domains, which are associated with decentralised networked systems; e.g. Healthcare, Automotive, Smart power grid, Aerospace [31], etc.

Cyber-physical system development in manufacturing specifically, has been categorised by Cyber Physical Production Systems (CPPS). Cyber-physical production systems consist of autonomous, cooperative elements and sub-systems from processes, machines, and up to production and logistics networks [32].

This early stage of cloud-based monitoring adoption and cyber-physical production systems development has identified various research and development challenges; context-adaptive and autonomous systems, cooperative production systems, identification and prediction of dynamical systems, robust scheduling, fusion of real and virtual systems, human-machine symbiosis [32]. In particular it has been recognised that improvements are needed in terms of custom algorithms and techniques that provide effective summaries, filtering and correlating information coming from different sources [33]. To-date Cloud-based technology and design paradigms have enabled the loose coupling of both cyber and physical manufacturing systems. However the desired artificial intelligence, dynamic analysis, and systematic cooperation are in their infancy stage of development.

A wealth of knowledge has already been generated to achieve intelligent manufacturing systems through development of manufacturing process monitoring system methods and techniques in a centralised way. The adoption of a new decentralised architecture via cloud-based technology provides the potential to incorporate these methods and techniques more easily, and enable reconfigurability and extensibility within the system. Subsequently, manufacturing process monitoring systems can now be viewed as colonies of interactive cyber-physical systems, similar to decentralised design paradigms of Agent-based design and Holonic systems [34]. Systematic functionalities can now be added or removed freely, and collaboration between components is provided via services. A multitude of processes can now utilise the same monitoring tools, that are customised through plug-and-play components and reconfigurable software attributes. Additionally the decentralised environment promotes sensor fusion analysis, which possesses the potential to generate new process characterisation insights previously unexplored.

1.3 Research focus

The goal of the present research is to explore the dynamics of decentralised software architectures within field-level manufacturing process monitoring systems. The hypothesis of this research is that decentralised reconfigurable monitoring systems can enable multi-scalable analysis and process performance characterisation.

The research objectives are:

(1) Define and develop a manufacturing reconfigurable process monitoring architecture. The key to achieving this objective is the adoption/creation of a data/entity interoperability medium to meet the requirements of field-level manufacturing systems. Requirements include high data acquisition rates, high communication speeds, and effective/high accuracy data correlation.

(2) Develop interoperable decentralised reconfigurable process monitoring system entities. This objective focuses on the integration of the previously defined data interoperable architecture with fundamental signal processing and analysis techniques, to form entities of a cyber-physical production systems. The collaboration and reconfiguration of these entities will form multi-scalable process analytic capabilities.

(3) Achieve multi-scalable analysis and process performance characterisation in a manufacturing process through utilisation of the reconfigurable process monitoring architecture. This objective investigates the effectiveness of the previously defined cyber-physical production systems framework to be assimilated into a real manufacturing process.

The current manufacturing application of this research will be focused around the monitoring and analysis of a CNC turning machine. This process was selected due to its wide industrial utilisation, variety of process kinematics, and multitude of reactive process variables for analysis. This research will indirectly provide a multiphase investigation into CNC turning machining process characterisation and analysis.

Chapter 2

Literature survey

2.1 Manufacturing process monitoring systems

2.1.1 Monitoring system fundamentals

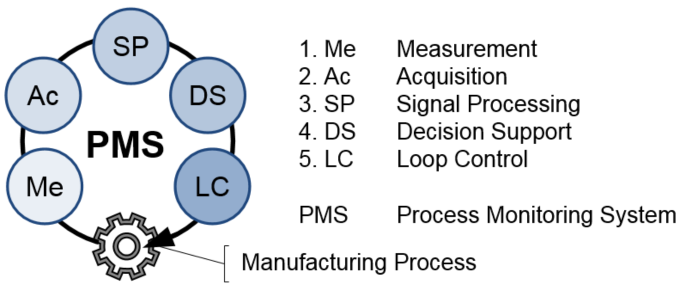


Figure 2.1 Process Monitoring System

Since 1976 machining process monitoring has been an interesting topic for engineers trying to understand machine actions and subsequent reactions [6]. Since then more than a thousand academic publications have been produced to further investigate and understand how to optimise machining operations. Predominantly process monitoring incorporates indirect measurement, which utilises auxiliary measurements from other process variables to correlate reactive effects to scaled measurement parameter deviation. A CIRP keynote paper by Teti et al [6] provided a comprehensive study on machine process monitoring, illustrating core fundamentals and state-of-the-art developments. Through this work a Manufacturing Process Monitoring System (MPMS) is able to be characterised into the multiple steps, which is visualised Figure 2.1:

(1) Measurement: physical hardware, e.g. sensors, for measuring the physical process parameter

(2) Acquisition: interconnecting hardware and software elements for providing high speed data acquisition from the sensor to a computational device

(3) Signal Processing: methods, techniques and algorithms for the manipulation of data for specific process feature extraction and selection
(4) Decision Support: subsequent methods, techniques and algorithms appertaining to identifying the required corresponding process action from analysed results
(5) Loop control: hardware and software elements associated with facilitating corrective action from decision support functions.

2.1.2 Enterprise integration

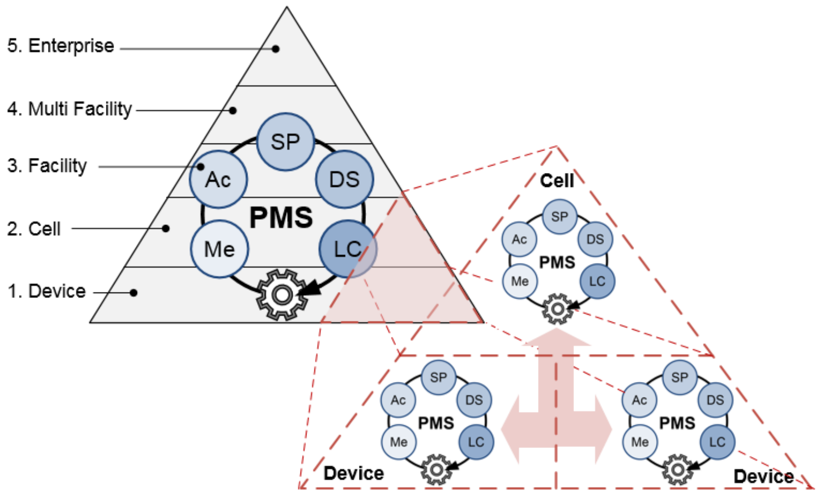


Figure 2.2 Process monitoring manufacturing distribution structure

A manufacturing process monitoring system is distributed throughout a enterprises structure. In 2010 Reich-Weiser et al [35] identified four levels of complexity in manufacturing to assist in understanding an organisation for accurate environmental analysis. The levels are; product feature, machine device, facility/line/cell, supply chain. In 2012 Duflou et al [36] expanded on these levels to identify energy and resource efficient methods and techniques. There are five levels in total, as seen in Figure 2.2:

(1) Device/unit process: individual devices or machine tools that are performing a unit process
(2) Line/cell/multi-machine system: logical organisation of devices in the system that are acting in series or parallel to execute a specific activity
(3) Facility: distinct physical entity, housing multiple devices, which may or may not be logically organised into lines or cells

(4) Multi-factory system: different facilities within close proximity to one another making use of possible synergies in terms of reuse of waste and lost energy streams

(5) Enterprise/global supply chain: the entire manufacturing system, consisting of all the individual facilities, the infrastructure required to support the facilities, as well as the transportation and supply chain externalities

Each manufacturing level utilises the fundamental process monitoring steps of measurement, acquisition, filtering, analysis, decision support, and closed loop control.

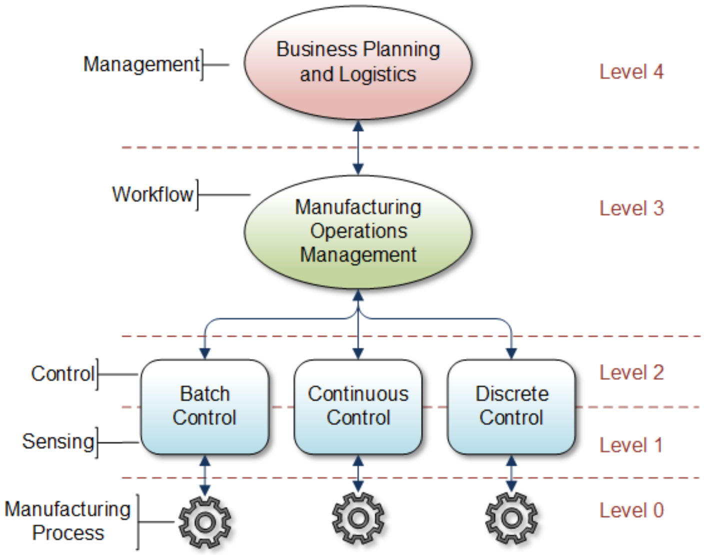


Figure 2.3 ISA-95 architecture of automation system, functional hierarchy according to (IEC 62264-3) , adapted from [37]

Similarly from a production monitoring and control system perspective a 5 level architecture is specified within the ISA 95 enterprise architecture [38]. ISA 95 is an international standard that was created to define models and terminology to determine which information has to be exchanged between systems for sales, finance and logistics and systems for production, maintenance and quality. There are five levels in this standard, as seen in Figure 2.3:

- Level 0 is the production process itself
- Level 1 is associated with all sensing and manipulating elements within the production process
- Level 2 addresses monitoring, supervisory control and automatic control of the production process

- Level 3 incorporates the management of the workflow to produce the desired end-products, maintaining records and optimising the production process
- Level 4 aims at establishing the basic plant production schedule, material use, delivery and shipping, and inventory

Each layer contains different analysis criteria, a separation in functional requirements is observed as data is abstracted up the hierarchy. Vijayaraghavan and Dornfeld [39] identified different temporal analysis layers within a manufacturing structure, as seen in Figure 2.4. This demonstrates the varying data acquisition rates at different enterprise layers.

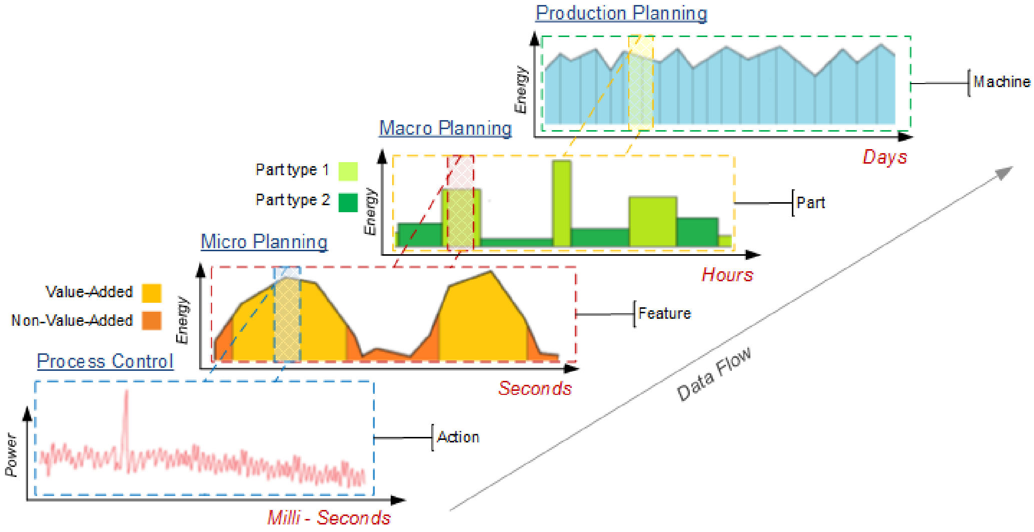


Figure 2.4 Examples of process monitoring analysis across temporal scales, adapted from [39]

Higher data acquisition rates are observed at lower levels due to the high speed reaction control requirements, i.e. position control systems. However the lower level heterogeneous manufacturing environment presents many challenges in regards to computer integrated manufacturing. This is due to the diversity of communication mediums and protocols present within machine tools and automation equipment [40]. Protocols include; PROFIBUS, Modbus, TCP/IP, USB, etc. These protocols are comparable in regards to bandwidth, transmission speed, and peer relationships, and have been implemented across a diverse range of manufacturing machinery. Enabling data acquisition from a single source requires conformance to its communication medium and protocol. However, manufacturing process monitoring systems have an increased challenge in enabling interoperability from multiple sources [8]. More standardisation of programming and communication interfaces are sought after to enable more implementable solutions [41].

Lower data acquisition rates are observed at higher levels, as data is abstracted throughout the hierarchy to meet more global factory responsibilities, i.e. Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP). Challenges at the enterprise level include the identification of robust methods for interoperability between manufacturing levels, to enable orchestration by manufacturing execution systems and enterprise resource planning systems [42]. The need for data sharing amongst system entities has yielded web-based-concepts such as E-manufacturing. E-manufacturing was envisaged to meet the needs of business strategies, and meet the requirements for the complete integration of all business elements; suppliers, customer service networks and manufacturing unit, through the effective use of web-enabled computational tools and tether-free technologies [22].

2.1.3 Domains of influence

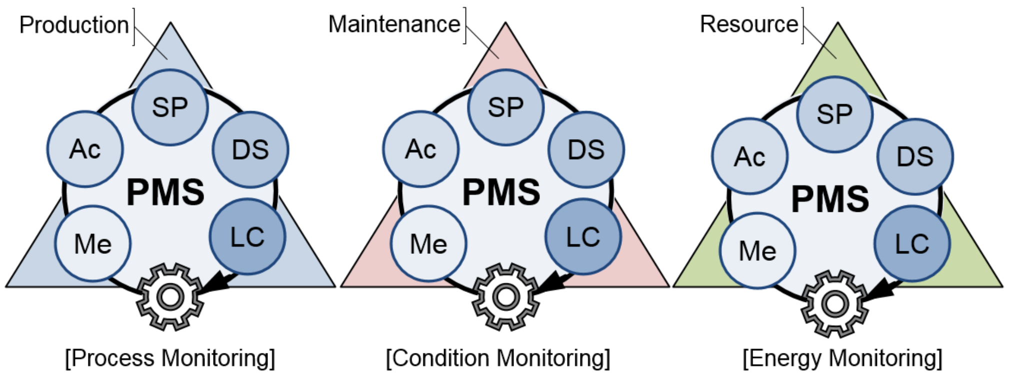


Figure 2.5 Process monitoring domains

Domains of recent study for manufacturing process monitoring system over the past decade have included production, maintenance and resource efficiency, which is visualised in Figure 2.5. Each domain has its own goals yet implements the same process monitoring steps, to enable assisted and even automatic decision support.

Production monitoring

The future enhancement of machining systems and their operation performance will vitally depend upon the development and implementation of innovative sensor monitoring systems [6]. Production monitoring enables a production process to achieve manufacturing product specifications accurately and repeatedly. In machining processes internal production monitoring systems are focused to achieve adaptive control in response to monitoring tool conditions [43], chip formation conditions [44], surface integrity [45], machine tool state [46], and chatter detection [47]. Examples of external machining production monitoring can be seen in automated scheduling of production machines [48], and automated machining parameters selection [49]. Other areas of production research includes, new data manipulation algorithms and paradigms have been a topic of extensive research to show how data can be filtered and used to identify Key Process Indicators (KPI) for decision making support [50] [51] [39]. Additionally ongoing and recent technology advancements have and will continue to improve the availability of process data, and its capacity to be fused together [52] [53] [54] [55].

Maintenance Monitoring

Maintenance is defined as a set of activities or tasks used to restore an item to a state in which it can perform its designated functions [56]. Maintenance strategies can be broadly classified into Corrective Maintenance (CM) and Preventative Maintenance (PM). Corrective maintenance is a strategy to restore equipment to its required function after it has failed. This strategy leads to high levels of machine downtime and maintenance costs due to sudden failure. Preventative maintenance involves the performance of maintenance activities prior to failure of equipment. One main objective of preventative maintenance is to reduce the failure rate or failure frequency of the equipment. This strategy contributes to minimising failure costs and machine downtime and increasing product quality. Preventative maintenance deploys process monitoring over the lifetime of the equipment. The motivations of process monitoring for preventative maintenance are that 99% of equipment failures are preceded by certain signs, conditions, or indications [14]. Maintenance activities are performed when needed or just before failure. The main goal of process monitoring or condition monitoring, is to perform a real-time assessment of equipment conditions in order to make maintenance decisions. Example parameters for measurement within the machinery or process include vibration monitoring, sound or acoustic monitoring, oil-analysis or lubricant monitoring, electrical consumption analysis and, temperature monitoring. Maintenance decision making can be carried out based on Current Condition Evaluation-Based (CCEB) and

Future Condition Prediction-Based (FCPB). Additionally a new trend emerging is the concept of Prognostic and Health Management (PHM) [57]. Prognostic and health management consists of monitoring parameters and analysing data using prognostic models, to assess the reliability of a product in its actual life cycle conditions, to determine the occurrence of failure.

Resource Monitoring

Opportunities exist across the manufacturing enterprise for more efficient usage of energy and resources [36]. Environmentally organisations face a moral responsibility to seek out environmental sustainability through sustainable resource consumption. Economically organisations are looking to reduce production costs to stay competitive in the market place. Resource Monitoring has been an investment for manufacturers since the 1970, beginning with the introduction of Material Requirements Planning (MRP) systems to optimise and control inventory levels within plants [58]. Material requirements planning has developed to incorporate not only manufacturing resource requirements but enterprise resource planning requirements; such as product design, information warehousing, materials planning, capacity planning, communication systems, human resources, finance, and project management. An area in recent focus for enterprise resource planning is energy measurement, monitoring, and management. In the last decade, the manufacturing industry has witnessed a dramatic increase in electricity costs, which can no longer be treated as an overhead, but a valuable resource to be managed strategically [18]. Manufacturers are actively aiming to provide visibility of energy within the organisation to enable resource management. Manufacturers are implementing various industrial electricity metering and monitoring equipment spanning multiple manufacturing structural layers. Additional to energy management manufacturers are implementing various strategies to optimize resource efficiency and effectiveness of their manufacturing systems.

These strategies include;

- The launch of self-regulatory initiative for supporting the identification of measures to improve the energy and resource efficiency of the machine tools by the European Association of the Machine Tool Industries [59]
- The introduction of automated energy monitoring systems for continuous quantitative and qualitative analysis [18]

- The introduction of proximity waste energy recovery systems for cross patterned production lines [60]
- The application of advanced process sequencing algorithms for process scheduling [61].

2.1.4 Manufacturing production system topologies

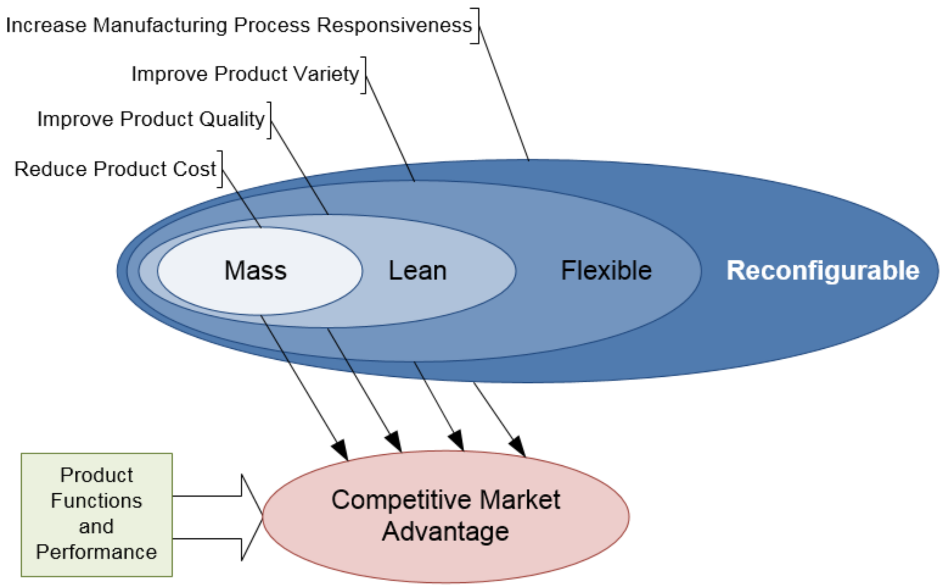


Figure 2.6 Economic goals for various manufacturing paradigms, adapted from [62]

There are three types of production system, Dedicated Manufacturing System (DMS), Flexible Manufacturing System (FMS), and Reconfigurable Manufacturing System (RMS) [63], as seen in Figure 2.6.

Dedicated systems are fixed automation which produce parts or products at high volume. Each dedicated line is typically designed to produce a single part at a high production rate through the operation of several tools at once. Dedicated systems are cost effective as long as demand exceeds supply and is operating at full capacity.

Flexible manufacturing systems consist of general purpose Computer Numerically Controller (CNC) machines, which can produce a variety of products with changeable volume and mix, on the same system. However CNC machines only allow part programs to be changed, not the software architecture or control algorithms, therefore the system is semi-static, with a degree of flexibility. Flexible systems possess a lower throughput than dedicated systems and have a higher initial cost due to increased functionality.

A reconfigurable manufacturing system is designed at the outset for rapid change in structure, as well as in hardware and software components. Reconfigurable systems can swiftly adjust production capacity and functionality within a part family in response to sudden changes in market or in regulatory requirements [63]. Reconfigurable systems focus on enabling reconfiguration through system design combined with the simultaneous design of open-architecture controllers with modular machines. Key characteristics of reconfigurable systems include; modularity, integrate-ability, customization, convertibility, and diagnose-ability. Reconfigurable systems can be less expensive than flexible and dedicated systems when the entire life-cycle cost of a production system in an uncertain marketplace is taken into account. The main factor that makes a reconfigurable systems less expensive is the initial precision of production capacity and functionality on instalment, with the availability/capability to upgrade in the future.

Traditional production control and monitoring systems are fully hierarchical and based on Computer Integrated Manufacturing (CIM) paradigm [64]. These systems divide a global control problem into hierarchical dependant subsystems. These subsystems consisted of strategic, tactical and operational entities, such as planning scheduling and supervising applications, enabling sufficient long-term optimisation to be maintained. The computer integrated based approach is known to provide near optimal solutions where long term availability and reliability of supply and demand are met, where there is a low product diversity, and where all the possible internal variables are observable and controllable. However, today's turbulent market place has a movement towards a higher product mixture and a low product volume production [65]. Manufacturers need to have the ability to be cooperative, have quick responses to changes and disturbances to stay competitive in the market place [66]. Similarly to the production system components, production control and monitoring systems have moved away from central operational structures and towards decentralised [67]. This shift in manufacturing technology paradigm is aimed at enabling the manufacturing plant of the future, through the introduction of intelligent and reconfigurable, or adaptable manufacturing systems, with a modular architecture which can be restructured without a loss in efficiency [68]. Decentralised operational structures are more flexible and reconfigurable solutions through a semi heterarchical and full heterarchical control structure [67], as seen in Figure 2.7. A hierarchy can be seen as a vertical distribution of control or function, while a heterachy can be seen as a horizontal distribution [64]. Advantages of a heterarchical structure include; full local autonomy at a level of peer-to-peer relationships, implicit fault tolerance as a single component failure should not affect total system operation, reconfigurable and adaptable ability due to interconnecting and disconnecting element functionality, and a faster diffusion of information due to parallel element communication [69].

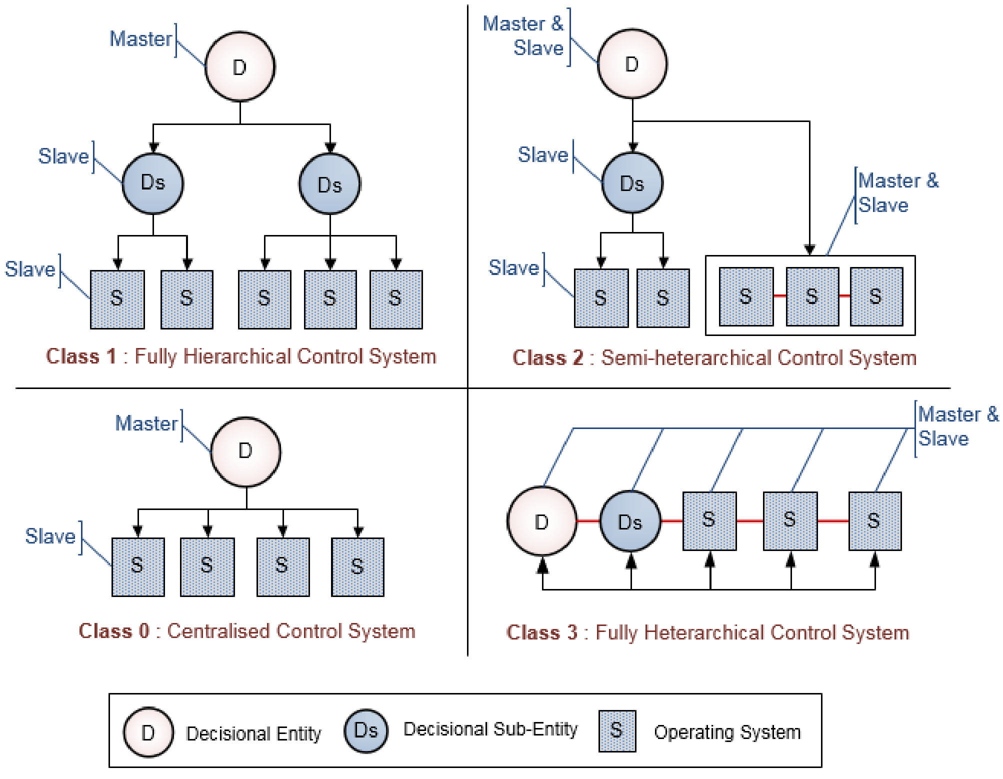


Figure 2.7 Distribution of decisional capabilities from centralised control systems to decentralised control systems, adapted from [13]

2.1.5 Decentralised design paradigms

It has been previously shown how a manufacturing process monitoring system has multiple dimensions due to the diversity of process monitoring steps, the distribution throughout a manufacturing organisation, and the separation of end goals via different domains of influence, which is visualised in Figure 2.8. Similar to production systems, manufacturing process monitoring system are seeing a shift in architecture design from centralised to decentralised, from hierarchal to heterarchical. Two conceptual paradigms have emerged over the past two decades that enable a collaborative representation of complex distributed multi-functional systems, Holonic manufacturing systems, and Agent-based design.

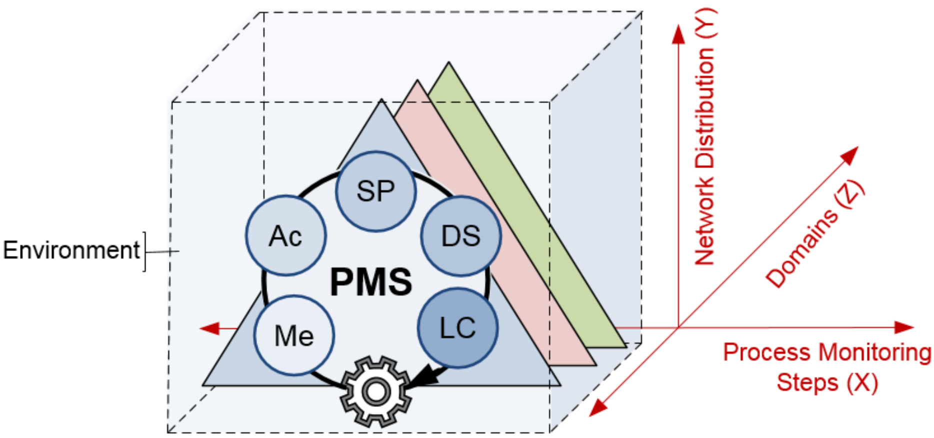


Figure 2.8 Process monitoring system dimensions

Holonic Manufacturing Systems

The concept of Holonic systems was proposed by Koestler in 1967 [70] in order to explain the evolution of biological and social systems. Koestler identified how in living and organisational systems it is generally difficult to distinguish between 'wholes': an autonomous body, and 'parts': an integrated section of a larger, more capable body [71]. Subsequently the word Holon was defined, which is a combination of the Greek word 'holos', meaning whole, and the Greek suffix 'on', meaning particle or part. A Holonic system can be considered to be scalar chains of Holonic entities, where at each level the reference entity can be considered to consist of part of a higher level system and to contain lower level subsystems of their own [72], as seen in Figure 2.9. A system of Holons cooperating with one another is called a Holarchy. Features of Holonic systems include:

- Semi-Autonomy: Holons need to be self-sufficient
- System Dependence: Holons are required to function within constraints and are subject to the direction of higher level systems
- Entity Concatenation: system integration or interoperability across the same level plain, or across multiple levels requires a recursive communication to be established.

The adoption of Holonic systems to meet manufacturing requirements was observed by the need to break down rigidity to decompose exponentially expanding systems into smaller more manageable sub-systems [72]. The Holonic Manufacturing System (HMS) approach was first envisaged as a means of providing a building block or plug-and-play capability for developing and operating a manufacturing system in the factory of the future [73]. The Holonic concept combines the best features of hierarchical and heterarchical organisation, as it preserves the stability of hierarchy while providing the dynamic flexibility of a heterachy [69]. The ultimate aim of the Holonic manufacturing systems is to enable decentralised manufacturing systems built from a modular mix of standardised, autonomous, co-operative and intelligent components, in order to cope with rapidly changing environments.

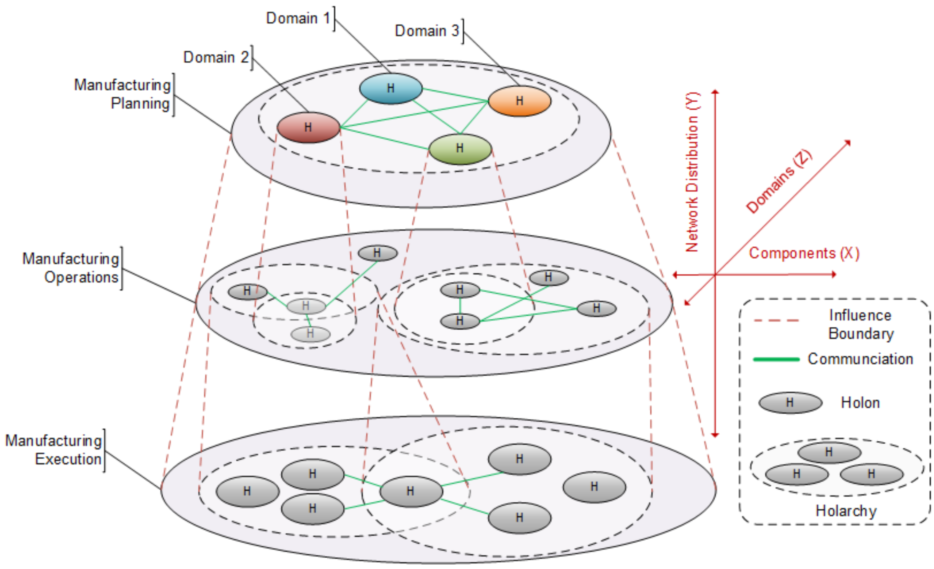


Figure 2.9 Holonic manufacturing systems

Some key characteristics of Holonic systems include [71]:

- Autonomy: the capability of a manufacturing unit to create and control the execution of its own plans and/or strategies
- Co-operation: the process whereby a set of manufacturing units develop and execute mutually acceptable plans
- Self-Organisation: the ability of manufacturing units to collect and arrange themselves in order to achieve a production goal
- Reconfigurability: the ability of a function of a manufacturing unit to be simply altered in a timely and cost effective manner

Agent Based Design

Agent-based-design is a paradigm of information communication technology [74]. Agents aim to address autonomy and complexity through adaptive capabilities allowing agents to be resilient to changes and disruptions, exhibit intelligence and are distributed in nature. An abstract visualisation of agent-based design is represented in Figure 2.10. This visualisation identifies how Agents vary in functionality, are dispersed within an environment, act in different domains, and expand throughout an enterprise. Individually, agents are problem solvers with some capacity of sensing and acting upon their environment, to deciding their own course of action, as well as communicating with other agents. Depending on the problem and available resources/technology, agents can apply various faculties of problem solving, including searching, reasoning, planning and learning [74].

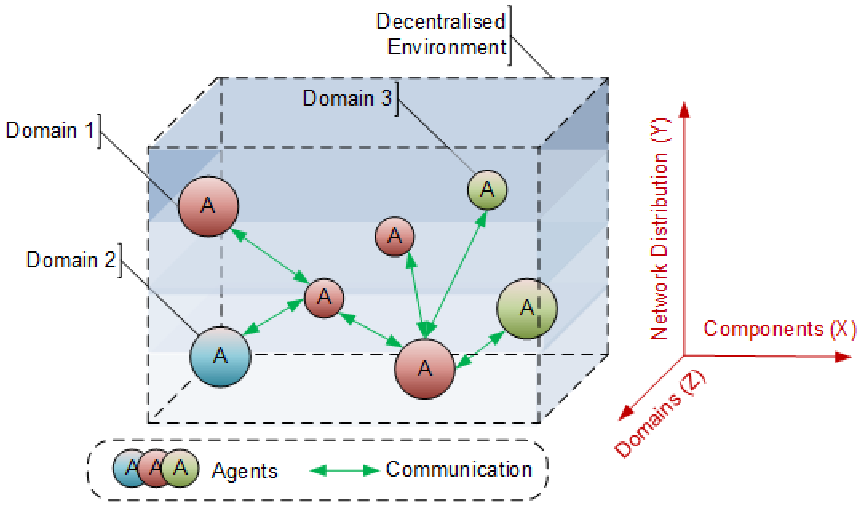


Figure 2.10   Agent based design systems

Holonic and Agent Comparative Discussion

When comparing Holonic and Agent based architectures many factors need to be evaluated, due to the fact that both systems are very similar. In 1998 Bussmann [75] reviewed and compared Holonic and Agent systems. Within this work, a clear division between the concepts was made through referencing how Agents are general software technology that was motivated by fundamental research questions concerning aspects such as autonomy, cooperation, and team foundation. While Holonic manufacturing systems deals with the overall structure of the manufacturing process, in particular with the integration of equipment, control, and workers. Bussmann concluded by outlining how Holonic manufacturing systems should be used to design the overall manufacturing process and derive requirements for the information processing from the intended interactions. While Agents should provide a basic reasoning and incorporate cooperation techniques necessary to meet manufacturing control requirements.

In 2004 Giret and Botti [34] identify Agent and Holonic systems as two paradigms to meet the future manufacturing challenges of the 21st Century. Within this work Giret and Botti take a similar position to Bussmann in outlining how a Holonic system is tailored for meeting flexible manufacturing tasks, through distributed intelligent control, while Agent is a broad software approach that can be used for distributed intelligent control. In summary, Giret and Botti define a Holon as a special case of an agent, due to its similarities but defined operation sector.

Similar to Giret and Botti, Fischer et al [76] outlined a framework for Holonic multi-agent systems, which combines both paradigms of Holonic and Agent systems. Within this work the idea of interconnecting agents representing Holonic entities is prevalent. The definition of a new framework, namely "Holonic multi-agent systems", demonstrates how Fischer identifies the benefits of combining both paradigms, but makes the clear separation of doing so through the creation of a newly defined structure. This separation aims at removing stringent requirements, present mainly in Holonic systems, due to Holonic origins being firmly present within the manufacturing sector. The result identifies a Holon as a concept that is realised by the commitments between agents, to maintain a specific relationship concerning goals. This point is re-enforced when considering the origins of both paradigms. As a Holonic system is a representative of a decentralised system with multiple levels of influence and association. While an Agent system came from AI co-operation in order to achieve collaborative goals. The aggregate of Agent Based Design and Holonic systems results in the visualisation of a complex system through the Holonic identification of hierarchical and heterarchical structures and substructures, and the incorporation of interactive decentralised Agent elements who accomplish localised goals and network wide goals through collaboration.

2.2 Cloud process monitoring and service oriented architecture

2.2.1 Prologue

Cloud manufacturing systems are set to overcome today's limitations in rigid system structure, standalone software usage, centralised resource utilisation, unidirectional information flow and off-line decision making [77]. Similarly Ubiquitous information systems are supporting a global compatibility of digital services over ubiquitous computing technologies anywhere and anytime [78]. In order to meet future manufacturing support and sustainability requirements a combination of both Cloud and Ubiquitous Manufacturing Systems have been identified as the perfect setting [79]. The origins of Cloud and Ubiquitous manufacturing can attributed to various ideologies of decentralised design, such as holonic and agent-based paradigms [75], and the enabling technologies of Ubiquitous computing, Cloud computing, social media, the Internet of Things (IoT), and Service-Oriented Architecture (SOA) [80]. Traditionally Cloud manufacturing at an enterprise level has been addressed by E-manufacturing, which was designed to meet the needs of business strategies, and business elements; suppliers, customer service networks and manufacturing unit, through the effective use of web-enabled computational tools and tether-free technologies [22]. However Cloud manufacturing addresses a global mode of organisation through non-linear structuring, to enable dynamic transformative capabilities. The incorporation of cloud manufacturing technologies from management to execution is present on every level of a manufacturing enterprise [42]. Specifically field-level cloud systems has been an expanding research area, characterised by SOA development.

2.2.2 Service Oriented Architecture

A Service-Oriented Architecture (SOA) is a set of architectural tenets for building autonomous yet interoperable systems [81]. SOA specifies that distributed resources and organisations should provide their functionalities in the form of services that requesters can have access to [82]. An entity or service can be discovered dynamically through asynchronous messaging by exposing its interface [83]. In doing so SOA systems enable multiple client oriented entities to utilise the resources embedded within the service, making the way for more reconfigurable and flexible decentralised systems. These core SOA principles can be modelled in different ways to address application requirements, providing a different architecture perspective. Within the field of manufacturing SOA offers the potential to provide the necessary system-wide visibility and device interoperability for complex collaborative automation systems [84]. Designed around standard web-technologies, such as Transfer Control Protocol (TCP), SOA is aimed at being technology-neutral, enabling system extensibility and distribution throughout an organisation [85].

In 2005 Jammes and Smit [86] reviewed the service-oriented paradigms for industrial automation adoption. This work highlights the benefits of; interoperability, scalability, Plug-and-Play connectivity, seamless enterprise network integration, legacy technology integration, simplicity of application development, and manageability. In 2008 Mendes et al. [82] provided a survey on the engineering of service-oriented automation systems. This work provides insight into main SOA engineering fields of; semantic web-services and ontology, modelling, orchestration and choreography, service composition, analysis and simulation, and collaboration. In 2009 Cândido et al. [87] provided a research roadmap to SOA in reconfigurable supply chains. This work provides a brief overview of public and private initiatives; SIRENA 2006, STREP CobIs 2006, ITEA SODA 2007, STREP InLife 2007, IST SOCRADES 2008, OPC-UA 2008. In 2010 Cˆandido et al. [88] provided a technical assessment of the OPC-UA and Device Profile for Web services (DPWS) for device level SOA in the industrial domain. In 2012 Jammes et al. [89] reviewed technologies for SOA-based Distributed Large Scale Process Monitoring and Control Systems. Technology reviewed included the Efficient XML Interchange (EXI) structuring, Constrained Application Protocol (CoAP), OPC-UA, Distributed Service Bus, and Complex Event Processing (CEP).

Modelling

<u>Abstract model</u>

A SOA data model can be abstracted into a common structure that can be described by four technical layers; Meta Model, Data Model, Generic Services, and Mapping on Protocols [90], as seen in Figure 2.11;

- Meta Model: defines the basic components that the data model can be built from, which includes concepts and rules

- Data Model: is a semantic or abstract description of the data owned by a subsystem which can be accessed by other systems within a specific domain.
- Generic Services: defines an abstract common way for exchanging data between subsystems, which are technologically independent. Mapping on
- Protocols: defines how abstract services are mapped for physical implementation

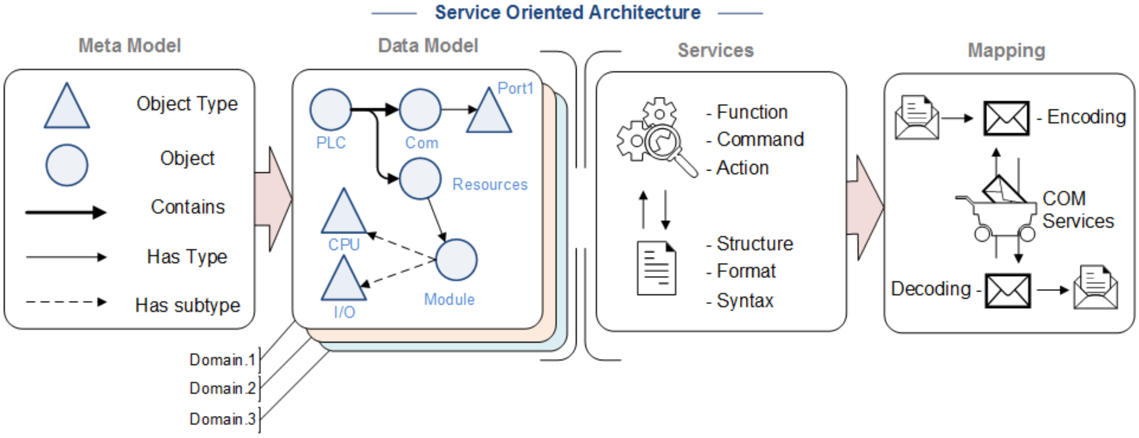


Figure 2.11 Service-oriented architecture common structure, adapted from [90]

<u>Engineering model</u>

In 2013 Nagorny et al. [91] outlined an engineering approach to assist in the development and visualisation of a SOA based system. This approach incorporated the use of the ISA-95 enterprise architecture to define the different component types and their location within a hierarchical manufacturing enterprise. The approach incorporated a five step method:

(1) Legend, identifies the symbols for different architecture elements across multiple domains. These symbols include inputs, outputs, boundary layers, and events. These components define the different objects present within the SOA.

(2) Domain and system categorisation, incorporates the assembly of domain specific components and categorisation within specific layers defined in the ISA 95 standard. System categorisation corresponds to the identification of system boundaries, and embedded subsystem boundaries. An abstract visualisation of his step is presented in Figure 2.21. Specific manufacturing

domains are identified, the architecture components are identified on each level of the ISA-95 standard, and communication streams are defined.

(3) Interface definition, incorporates the definition of what services will be provided by what system, and what the interfaces will be, e.g. inputs and outputs.

(4) Service and orchestrator integration, requires the specification of orchestrator systems, which are services capable of orchestrating two or more services/orchestrators.

(5) Topology generation, connects all components within domains and between domains using the previously defined interfaces, creating a topology of the SOA system.

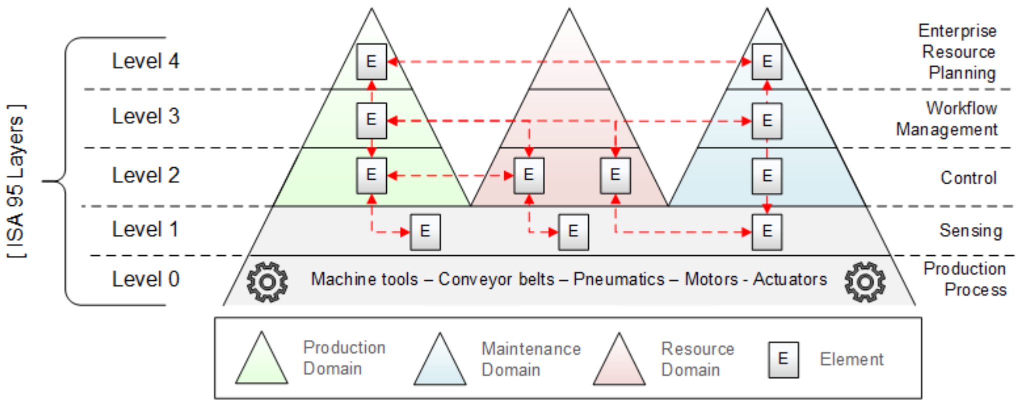


Figure 2.12 Service Oriented Architecture Domain Characterisation, adapted from [91]

<u>Holonic model</u>

Another perspective of SOA modelling is defined by the National Institute of Standards and Technology (NIST) U.S. Department of Commerce, which provides a reference architecture for cloud computing [92]. This architecture resembles the principles of Holonic systems. These systems are considered to be scalar chains of Holonic entities, where at each level the reference entity can be considered a subsystem of part of a higher level system and to contain lower level subsystems of their own [72]. NIST defines a Cloud Provider as a person, or organisation that is responsible for making a service available to interested parties; And a Cloud Consumer as a person or organisation that maintains a business relationship with, and uses the service from a cloud provider. The Cloud Provider and Consumer share control of resources in a cloud system that are structured within a classical software stack design, as seen in Figure 2.13; Application layer, Middleware layer, and Operating system layer. The application layer includes software applications targeted at end users or programs. The middleware layer provides software building blocks for developing application software in the cloud, e.g., libraries, databases, etc. The operating system layer includes operating systems and drivers.

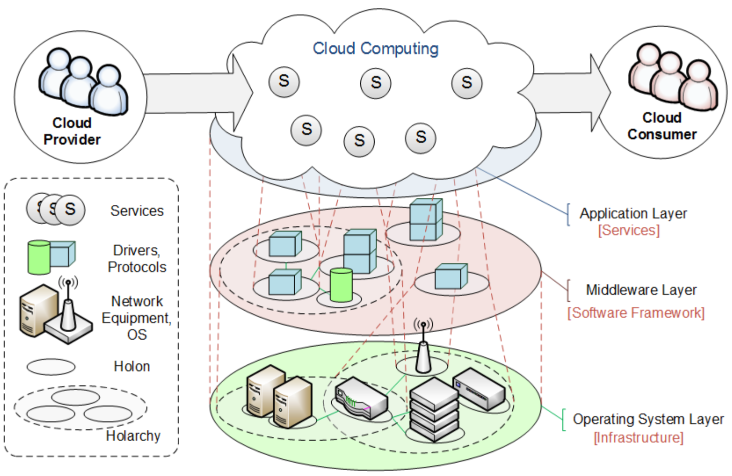


Figure 2.13 Holonic Cloud Computing

Enterprise integration

Enterprise integration research has been ongoing since the 1990s addressing both enterprise modelling and information technology, which was characterised by Panetto and Molina [93]. Key issues addressed in this work was the high level of communication heterogeneity within dynamic enterprises, and the need for collaborative networked environments where integration and interoperability enhance the competitive advantages. Heterogeneity within a manufacturing enterprise starts at the lowest hardware levels and transverse throughout.

At low enterprise levels, within the shop-floor, communication standards are domain specific, as they utilise proprietary codes, protocols and data representations [94]. With diversity comes incompatibility with the inability to support collaboration between hardware and software throughout a manufacturing organisation. This incompatibility is due to the lack of standardisation amongst technology suppliers and the difference of resource capabilities amongst embedded devices. In order to overcome this communication barrier SOA identifies the utilisation of mediator software entities to enable the conversion of proprietary or legacy technology into the SOA standard, to enable free data distribution throughout the networks [95]. Alternatively devices can be service enabled by embedding the SOA communication service within them, allowing the device to be a direct data/service source. This solution enables a ubiquitous data collection, and furthermore offers the potential to support sensor fusion capabilities within process monitoring and control systems [6].

At high enterprise levels Manufacturers have utilised manufacturing suites and platforms, to assist in multiple decentralised organisation aspects; design of manufacturing, business strategy, sales and marketing, shop-floor operation, supply chain collaboration, collaboration engineering, etc [96]. These systems utilise Web technology to enable manufactures to be become more agile, and flexible in the areas of Supply Chain Management (SCM), enterprise resource planning, and manufacturing execution systems [22]. However the individualistic manner in which these systems are implemented makes it difficult for coordinated interactions to exist [97]. These systems have been identified to not enable seamlessly cross layer enterprise collaboration, as they are islands of automation with no obvious integration points [98]. Next generation SOA ubiquitous cloud manufacturing platforms are aiming to remove these bottlenecks of incomparability, through the standardisation of data interoperability, while facilitating the hosting of unique application functions via services [42]. Industrial applications will be rapidly composed by selecting and combining the information and capabilities offered via services in the manufacturing cloud.

Considerable research has been achieved to-date to incorporate the STandard for Exchange of Product (STEP) standard as the manufacturing data model [99]. The STEP standard is a neutral data format within the heterogeneous CAD systems which has been extended to meet the requirements of a product over its whole life cycle [98]. The extent of STEP standard research in distributed manufacturing systems was achieved by Zhao, Habeeb, and Xu [100]. This standard would act as a standard meta and data modal for manufacturing SOA enterprise solutions.

Technology integration

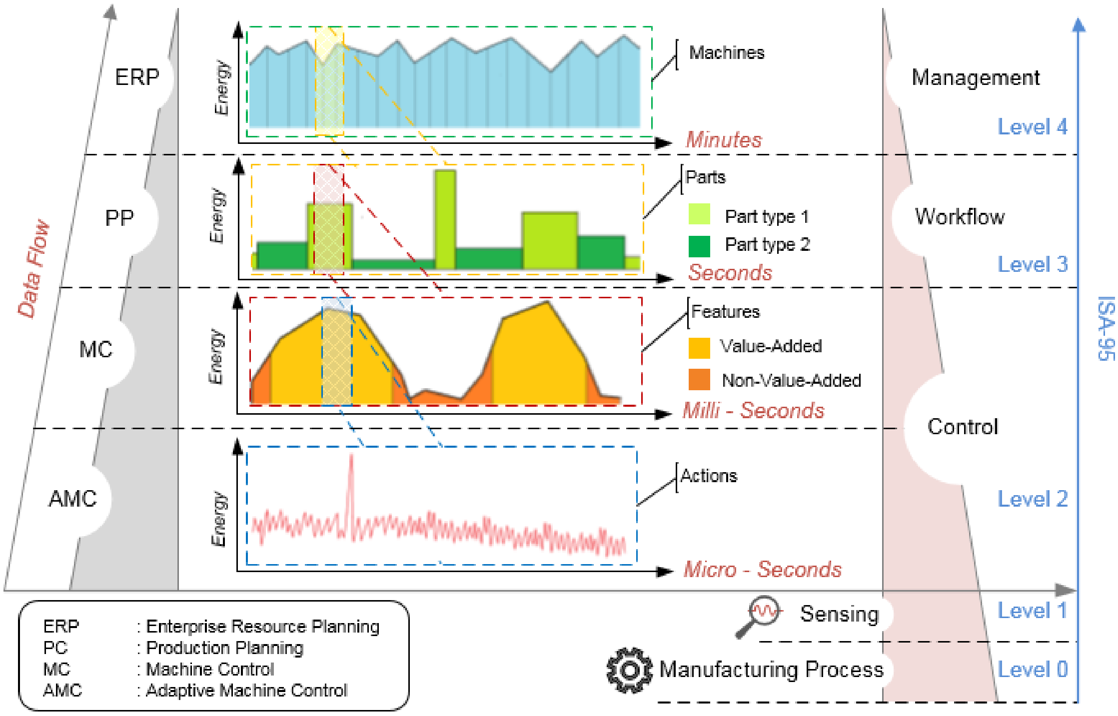


Figure 2.14 Temporal scales of analysis and manufacturing execution systems

As engineers lean towards more standardised data structuring for enterprise through the STEP standard, a divergence in data modelling can be observed between product and process. Product data viewed from the STEP standard recognises a multitude of data types and relationships, as a product is identified throughout its lifecycle. While process data is associated with the multitudes of control and management systems that enable the creation of a product from raw materials. Product data is more easily structured due to the common abstracted attributes shared amongst manufacturing products; material, dimensions, CAD files, part numbers, etc. However process data various largely due to the complexity and diversity of production processes and machines. This diversity increases further when state-of-the-art process and condition monitoring systems are involved. The varying data sources, data manipulation techniques, and transition of transient state information to process characterisation or corrective action data, lead to highly complex and unique data structures.

As defined previously, the ISA-95 model helps define boundaries between the different industrial enterprise levels. However the ISA-95 structure has been seen as rigidly hierarchical by limiting the capacity of cross layer interoperability due to highly integrated vendor-locked communication standards [37]. These standards exist due to the different functional control requirements present at each enterprise level. When data is acquired from a source the information is abstracted the further it is passed up the enterprise hierarchy, to meet different management requirements, as seen in Figure 2.14. Each temporal level requires different computation and communication capabilities to provide for the control operating characteristics and data analysis. Subsequently a question is how can SOA be implemented across a manufacturing enterprise to enable more interoperable systems while maintaining the critical functional requirements at each level?

In 2012 Delsing et al. [37] proposed a migration procedure for ISA-95 decentralised control systems into enabled SOA systems. This work identified the presence of supporting service driven informatic systems at level 4 for enterprise resource planning and level 3 for production management. A key challenge identified in this work was for SOA to be adopted Real-Time (RT) control system execution must be preserved. This challenges the capability of SOA to meet the requirements of level 2 of a manufacturing enterprise which is associated with monitoring, supervisory control and autonomous control of the production process. In order to understand what role SOA can play to either meet the requirements of or coexist with machine control systems, a computational review of manufacturing control must be achieved to identify the functional requirements at this level.

Machine control and computation

Traditionally Manufacturing control systems utilise either closed or open loop control to regulate the operating characteristics of a system. Closed loop control utilises the feeding back of the measured system output to the system controller input allowing a control error to be determined and corrective action to be applied to reach the desired output [101]. Open loop control uses desired system output and potentially other measured disturbance inputs to reach the desired system output. A manufacturing enterprise utilises a mix of these methods as closed loop control cannot always be implemented due to the incapacity to measure system output on a continuous bases or in real-time.

Additional to these control models different control methods are utilised; continuous and discrete-control. Continuous-control maintains continuous response relationships between input and output, e.g. adaptive motion control of a CNC axis through a Proportional Integral Derivative (PID) controller [102]. Alternatively discrete-control can exhibit multiple modes of operation and maintain discrete relationships within the system through discrete transitions between feedback measurements, or control adaption, e.g. the multifunctional control of machine events or scheduling of a production process [66]. Traditionally continuous-control operate on a micro perspective of control systems relying on analogue controllers. However the speed, flexibility, accuracy, and reliability of digital controllers has exponentially increased over the past 20 years, uniquely offering greater advantages over analogue controllers, allowing for discrete controllers to achieve continuous-control operations [103].

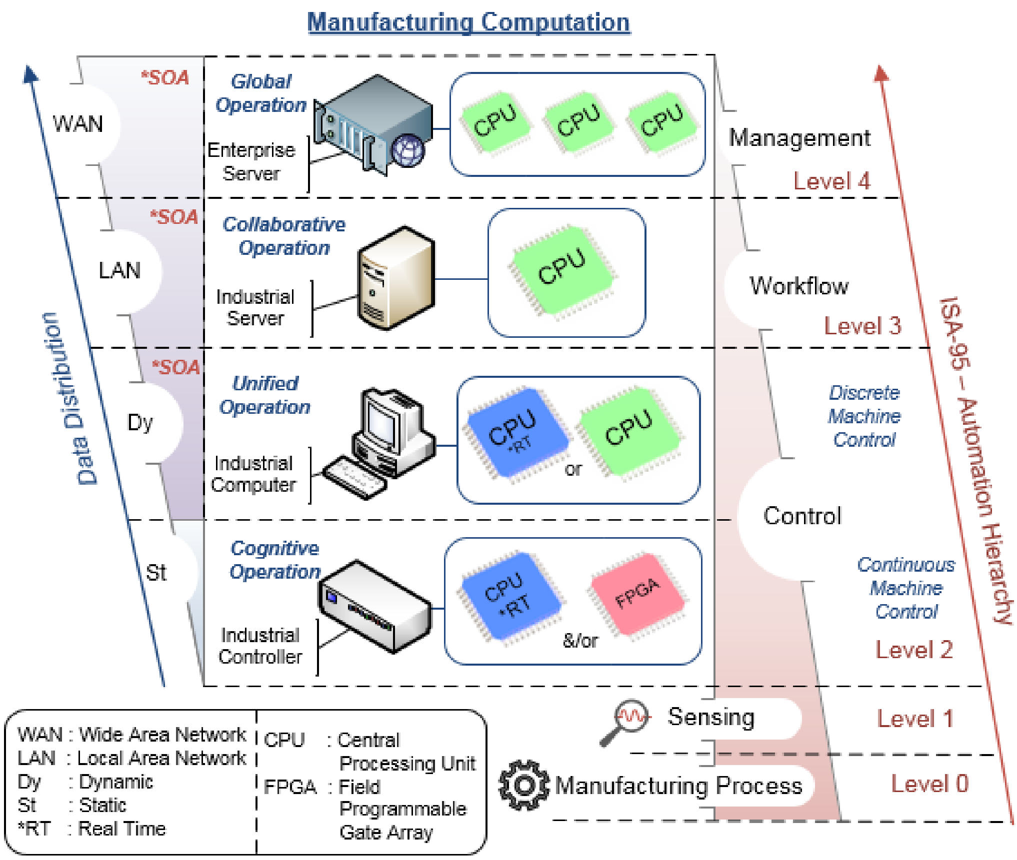


Figure 2.15 Manufacturing execution control computation

Continuous-control can be achieved by digital controllers through real-time operating characteristics. real-time systems can be characterised by achieving operation within defined jitter limits [104], and control latency as close to zero as possible to achieve just-in-time execution to minimise the disturbance input and control error which could lead to the degradation of system stability [101]. A divergence in real-time definition can be identified through systems operating at real-time speeds deterministically, namely hard real-time and through systems operating at real-time speeds non-deterministically, namely soft real-time [104]. Real-time systems aim to achieve operational actions as close to Real-time as possible. In high performance motion control systems real-time is obtained under 1 millisecond [105]. Real-time systems are designed to optimise computation through streamlining programming for high speed execution. Multiple operation states can be achieved with real-time programming, as tasks are queued for computation via the CPU.

Other real-time systems utilised within high performance computation control are Field-Programmable Gate Arrays (FPGA). FPGA’s are reprogrammable silicon chips that consist of prebuilt logic blocks and programmable routing resources. FPGA’s exceed the computing power of digital signal processors by breaking the paradigm of sequential execution and accomplish execution per clock cycle by hard coding operation directly to the processor [106].

Both real-time CPU’s and FPGA’s are dedicated processing units that enable the creation of highly optimal systems, for both continuous and discrete control systems, through reconfigurable programming means. However the function environment of these high performance units is static. When achieving deterministic execution all programming code needs to be specified and compiled together, to enable the optimal performance and execution time limits to be determined. Dynamic execution environments can only be achieved through undedicated processing units, where computation tasks are queued for execution by the CPU. These systems can operate at high computation speeds of under 1 millisecond in soft real-time. However this flexibility comes at a price as the undedicated systems are not deterministic, and cannot achieve hard real-time operation due to their ambiguity of execution from sharing of resources in a dynamic execution environment.

A topological view of manufacturing control computation systems identifies a separation in technology from real-time deterministic static systems, to dynamic interoperable open systems, as seen in Figure 2.15. This separation can be identified by the divergence in systematic requirements from deterministic high speed performance, to multifunctional flexible network capable features. A system requires a greater flexibility when dealing with a dynamic environment. However to achieve guaranteed hard real-time control systems must be optimised for reaction speed.

SOA implementation and communication

SOA specifies that distributed resources and organisations should provide their functionalities in the form of services that requesters can have access to [107]. An entity or service can be discovered dynamically through asynchronous messaging by exposing its interface [83]. These characteristics meet the criteria of dynamic execution systems and require a dynamic communication medium for support. SOA originated from Web technology of Ethernet TCP/UPD, which enable the loose connectivity of hundreds or thousands of devices. However ultimately the use of asynchronous time-division multiplexed networking introduces time varying delays which are sources of potential instability for real-time targets [108]. Subsequently this incapacity to utilise deterministic communication mediums has identified a incapability of SOA to meet the requirements of deterministic continuous and discrete control present in level 2 of the ISA-95. Other solutions to meet these requirements can be seen with Profibus DP [109] and EtherNet/IP [105]. SOA may not be a primary interoperability member at the lowest point of computation in a manufacturing execution system. However these systems should be enabled to either provide their data for higher levels systems directly or indirectly from communicating their data to a mediator or orchestrator.

Traditional implementation of SOA within manufacturing systems identified the use of WS for communication protocol, e.g. HTTP in MTConnect [110] and DPWS in AESOP [89]. However these medium utilise a eXtensible Markup Language (XML) base message structure. XML was identified to not meet the high speed requirements of a for industrial machinery applications due to its verbose syntax and the need for parsing which can slow down processing speed and cause real-time constraints [111]. Limitations with traditional XML structuring can be overcome through adoption of the Efficient XML Interchange (EXI), which utilises binary representation of data and is designed for compactness and high performance parsing and serialisation [112]. Subsequently the introduction of binary messaging has identified a means for nondeterministic discrete-control present in level 2 of the ISA-95 [111].

The time restrictions present within level 2 of the ISA-95 are not present in the above levels due to the abstracting of data in the higher temporal scales of analysis in manufacturing execution systems. These systems favour flexibility and open connectivity rather than high speed deterministic behaviour. Due to the fact that latency within the millisecond range will not destabilise systems operating within a >1sec scale of temporal operation, e.g. scheduling, resource management, production planning. Subsequently traditional or high speed WS technology can be utilised to achieve SOA at levels 3 and 4 in the ISA-95.

2.2.3 Field level service oriented architecture platforms

An acumination of diversity in field level data structures and enterprise integration requirements has resulted in the creation of SOA's within manufacturing. Four Key SOA are; the industrial standard OPC-UA, the data sharing platform, the open standard MTConnect, commercial National Instrument Shared Variable Engine (SVE), and the data protocol DPWS through the EU initiatives SERINA, SODA, SOCRADES, and AESOP. These systems provided different SOA capabilities, to meet different requirements of a manufacturing enterprise.

OPC-UA

OPC originated from a collaboration of world leading automation suppliers, aimed at achieving interoperability for process control and manufacturing automation applications. The OPC specification defines a set of standards of objects, interfaces and methods for dynamic data acquisition and distribution via a central server [113]. The OPC server would allow a user to define what communication medium, ex. RS485, to communicate across to the machine tool, and what protocol, ex. Modbus, was required to interact with the machine tool. Originally OPC utilised Microsoft's OLE Component Object Model (COM) and Distributed Component Object Model (DCOM) to achieve interoperability, namely OLE for Process Control (OPC). This allowed client applications, i.e. SCADA systems, to acquire data dynamically from the server. Client applications can utilise the COM communication interface for local access to a server, or the DCOM interface to access data across a local area network.

Current trends towards web services have led to a new generation of OPC technology, namely OPC Unified Architecture (OPC-UA). OPC-UA is a platform-independent standard through which various kinds of systems and devices can communicate by sending Messages between Clients and Servers over various types of networks [114], as seen in Figure 2.16. OPC-UA provides an integrated service model that allows a single server to integrate data, alarms, and events, and provide access to them using an integrated set of Services. Uniquely OPC-UA utilises XML/text and or UA binary encodings, and can incorporate OPC-UA TCP, SOAP/HTTP, and HTTPS transport protocols. The integration between OPC-UA Clients and Servers is defined by a set of Services. These services are organised in groupings called Service Sets. Clients can issue requests to servers and receive responses, as well as subscribing for notifications. Uniquely Servers can also act as clients to enable the interlinking of OPC servers throughout different networks. This enables the OPC-UA information model topology to no longer be limited to a tree formation, as it now allows for full mesh topology, through the interconnection of multiple OPC servers [115].

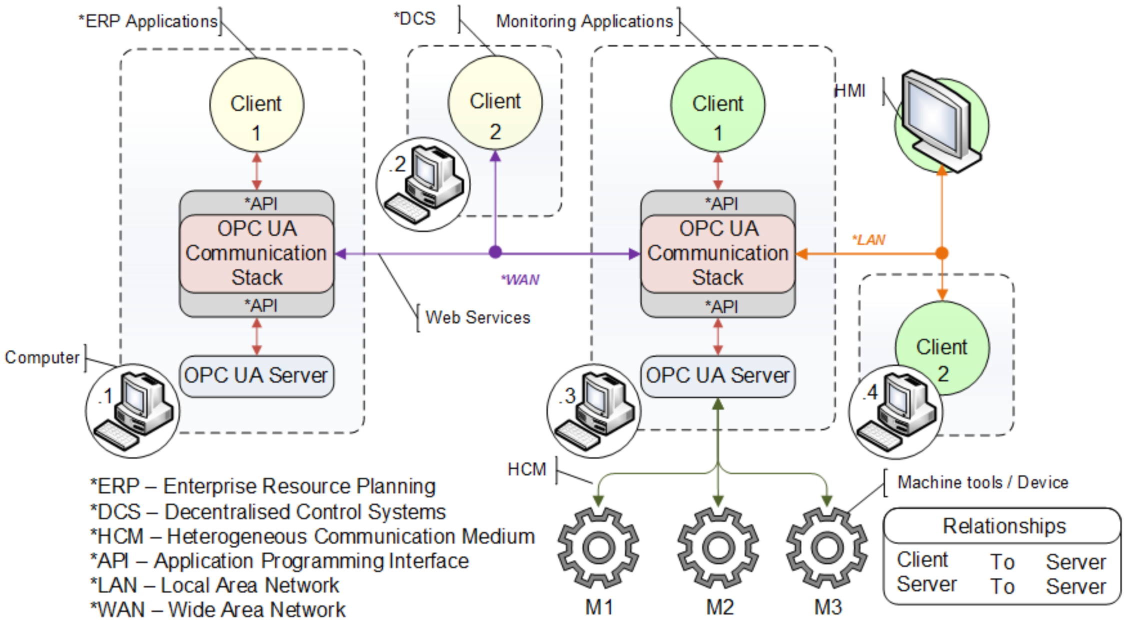


Figure 2.16 OPC UA Topology, adapted from [114]

The industrial adoption of OPC and OPC-UA is widespread in manufacturing and industrial systems, with OPC technology currently installed in over 17 million machines and factories worldwide [116]. Examples of industrial adoption can be seen in; the Texas oil and gas company's adoption of OPC enabled software-toolbox [117], and chemical manufacturer Saudi Arabian Fertilizer Company's adoption of OPC enabled Owl Perimeter Defence Solution [118]. OPC also has a presence in academic research. An example of which can be seen in Eckstein and Mankova's work [52], that utilised an OPC to achieve sensor fusion analysis through a Siemens Sinumerik 840D CNC controller. OPC-UA is ultimately a total cloud solution for manufacturing enterprise.

MTConnect

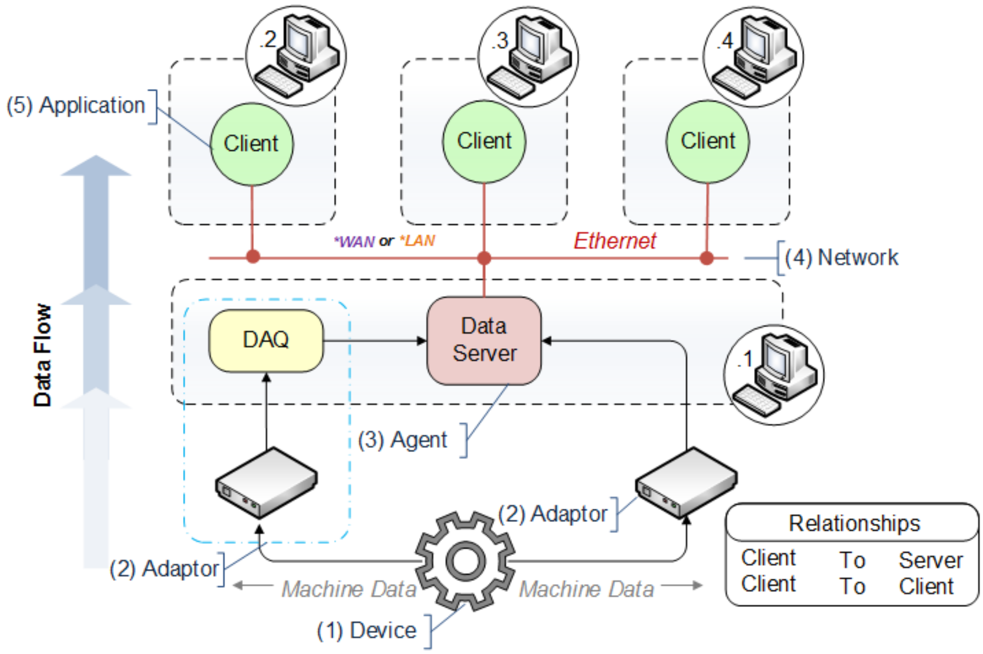


Figure 2.17 MTConnect topology, adapted from [110]

MTConnect is an open, extensible, and royalty free standard, that outlines a universal factory floor communication protocol for the shop floor environment [110]. This standard enables users to link data from shop floor machines to software applications used to run their businesses. The MTConnect protocol is based on standard internet technologies, such as: HTTP and XML. The standard sets out a structure of five fundamental components that interact with one another, as seen in Figure 2.17; Device, Adapter, Agent, Network, and Application. (1) Device: represents a piece of equipment, commonly a machine tool or a data source. (2) Adapter: an optional piece of software/hardware that provides a link or conversion from the data source and proprietary data definition in the device to the MTConnect data definition standards. (3) Agent: a piece of software that collects, arranges, and stores data from the device or adaptor, while also receiving requests for the data from external applications, and processes the requests to further transmit the required data. (4) Network: the physical connection between a data source and the external data application. (5) Application: the actual requestor and consumer of MTConnect data.

The operational functionality of an MTConnect system can be summarised with the following definition; MTConnect organises information and data from a data source, typically a machine, into an information model that defines the relationship between each piece of data and the source of that data [119]. Furthermore, this information model allows an application to interpret the data received from a data source and correlate that data to the original definition, value, and context. MTConnect was the solution proposed by the committee known as the Shop Floor Connectivity Working Group, to solve the problem of how to concurrently connect to existing machine tools and new machine tools. The distinctive difference of MTConnect compared to the numerous other communication solutions available, is that MTConnect is the first standard to define a dictionary for manufacturing data, meaning that data from multiple machines will have common definitions, e.g. name, units, values, context, etc. MTConnect can be seen to provide an array of different functional problem solving abilities for addressing machine tool process monitoring requirements, such as; production dashboard or monitoring, alerts, equipment availability and usage, machine downtime analysis, OEE, production reporting/tracking, maintenance tracking/planning [120].

MTConnect has been gaining significant momentum in manufacturing with multiple leading technology companies, e.g. Mitutoyo, OKUMA, Boeing, etc [121], enabling their systems with MTConnect data access. MTConnect also has a presence in academic research. An example of which can be seen in Vijayaraghavan, Fox, Dornfeld, and Warndof [26] work that utilised a MTConnect system to gain access to machine tool path data for planning verification. MTConnect is ultimately a field level cloud solution for manufacturing data acquisition and distribution.

National Instruments - Shared Variable Engine

The Shared Variable Engine (SVE) is a software framework that enables variables to exist on a network and be communicated between applications, remote computers, and hardware [122]. The SVE is a generic SOA for distributing data, as it enables dynamic service discovery, data acquisition, data replication, and data distribution inside a local computer and across a network. The SVE enables applications to expose their data as services, by publishing the data to a SVE. The SVE hosts the data, buffers the data, and distributes the data to multiple applications which subscribe to it.

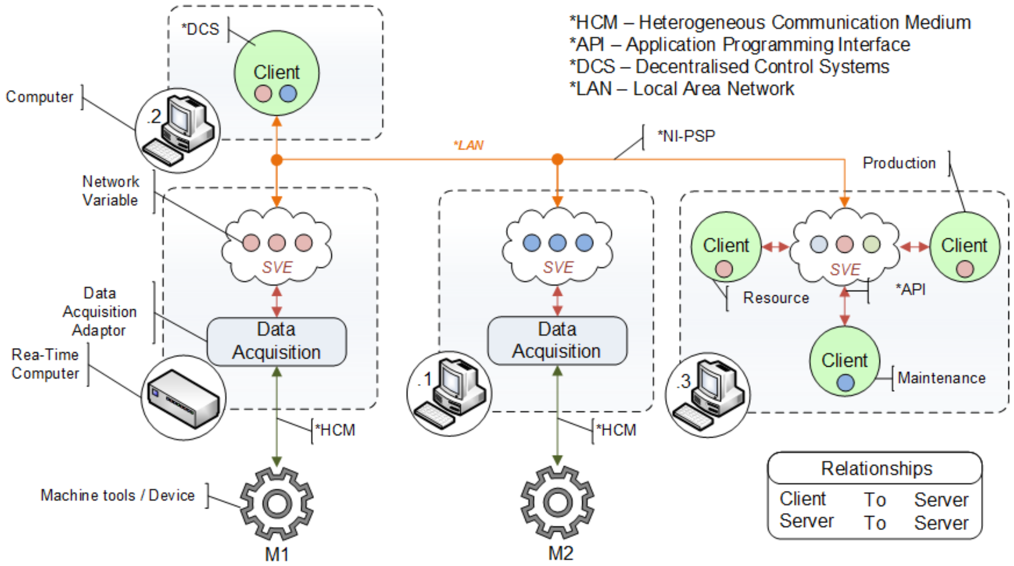


Figure 2.18 Shared Varibale Engine topology, adapted from [123]

The network variable is made up of three parts; network variable nodes, the NI-Publish Subscribe Protocol (NI-PSP), and the SVE [124], as seen in Figure 2.18. Network variable nodes consist of the readers and writers Application Programming Interfaces (API), for interacting with the SVE [125]; static shared variable node, programmatic shared variable API, DataSocket API, Data logging and Supervisory Control (DSC) API, and DSC event structure API. The NI-PSP is a proprietary networking protocol that optimises the transport of network shared variables, and operates above TCP/IP, with a LogosXT transmission algorithm [123]. The SVE hosts the published data, enabling dynamic data acquisition through data buffering. Other functions provided include data integration of multiple streams into a singular output, data event notification, and dynamic data discovery of networked shared variables across a network. Additionally SVE can be hosted on PC's and real-time targets. One SVE is required to enable interoperability within a system, as applications can connect to SVE on computers that they are not hosted on. This allows applications to publish their data to other computational devices that will handle the data management requirement and reduce their own computation resource requirements. The SVE is ultimately an open field level cloud solution for local area decentralised data interoperability.

Device Profile for Web Service

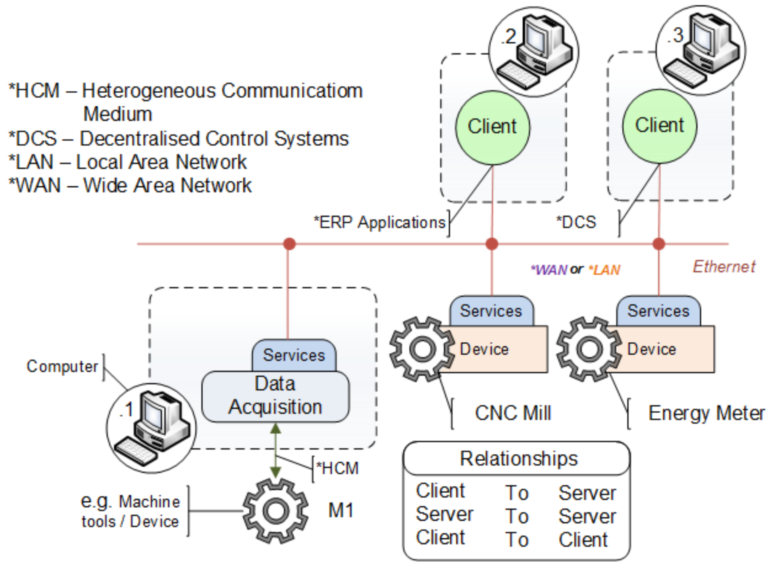


Figure 2.19 Shared Varibale Engine topology, adapted from [126] [127]

Device Profile for Web Services (DPWS) is a profile developed by Microsoft to promote both interoperability between resource-constrained WS implementations and interoperability with more flexible client implementations [126]. DPWS is based on existing WS standards XML, WSDL, XML Schema, SOAP, MTOM, and HTTP. The profile identifies a core set of WS to; send secure messages to and from a WS, dynamically discover a WS, describing a WS, and receiving events from a WS. DPWS specifies a structured format for which users can define services and map them for standardised interoperability on a network. A DPWS topology consists of devices and software adaptors that have their services encapsulated by DPWS, enabling them to be dynamically discovered and via clients on a network, as seen in Figure 2.19. In manufacturing, devices would consist of measurement devices; sensors, meters, controllers, etc., and machines tools; CNC lathes, CNC Mills, etc.

For the last decade DPWS has been at the centre point of SOA EU research through the initiatives SERINA, SODA, SOCRADES, and AESOP. These projects have enabled the development of an IT driven interoperability standard for utilisation with manufacturing enterprise.

SIRENA (2003-2005)

The Service Infrastructure for Real-time Embedded Networked Applications (SIRENA) project started in the framework of the European premier cooperative R&D program ITEA in 2003, to leverage SOA to interconnected devices inside the domains of; industrial telecommunication, automotive, and automation [128]. SIRENA aimed to utilise DPWS to address system wide interoperability, scalability of service composability and aggregation, plug-and-play connectivity, integration with enterprise networks, and integration with legacy technology [129].

SODA (2006-2008)

Continuing on from SIRENA, the Service Oriented Devices Architecture (SODA) projects main goal was to implement a complete ecosystem for designing, building, deploying and running device-based applications within different domains of application including industrial automation [87]. SODA provides an abstract service model of a device by providing an interface to proprietary and standard device interfaces, and presents device services as SOA services over a network through a bus adaptor [130].

SOCRADES (2008-2009)

The Service-Oriented Cross-layer Infrastructure for Distributed smart Embedded devices (SOCRADES) primary objective was to design and develop, an execution and management platform for next-generation industrial automation systems, exploiting SOA both at the device and at the application level [131]. Key research areas in SOCRADES included:

- Gateway entities for direct incorporation of legacy equipment not capable of WS-technology [95]
- Mediator entities that poses the capability of data manipulation prior to service access [95]
- Orchestration control methods consisting of a central control unit that facilitates interoperability between decentralised entities [87]
- Choreography control methods that define how distributed entities use collaboration without a centralised controlling entity [87]
- SOA enabled e-maintenance [132]

- Timing properties and network determinism associated with network message communication [133]
- SOA for wireless sensor networks [134][135][136]
- Dynamic optimisation of production planning [137]

AESOP (2010-2013)

The ArchitecturE for Service-Oriented Process-monitoring-and-Control (AESOP) project is targeted at optimisation within architectural and functional levels of logical and physical network architectures behind process automation systems [27]. AESOP maps out the industrial environment into 'Cloud Services', comprising of devices and applications distributed across the different layers of enterprise, which are exposing their characteristics and functionalities as 'Services'[89]. Key research areas in AESOP included:

- Complex Event Processing (CEP) tools and techniques for real-time analysing and handling series of events that circulate at fast speed in distributed information systems [138]
- Binary representation for reduced transmission overhead via the Efficient XML Interchange (EXI) to replace traditional XML [112]
- Strategies and approaches for migration of legacy process monitoring and control systems to SOA [139] [37]
- Expansion of network technology and integration strategies to increase system flexibility and enable real time operation of integrated SOA elements [111] [140] [141]
- Optimisation of network loads present within SOA communication [142] [112]

A successful implementation of DPWS was demonstrated in the AESOP project with the creation of an energy management system called EcoStruxure by Schneider Electric [143]. EcoStruxure is a systematic solution-based approach that creates intelligent energy management systems and allows people to view, measure, and manage energy across different domains. EcoStruxure combines the domains of Power Management, Process & Machine Management, IT Room Management, Building and Security Management, with a common platform SOA. DPWS is ultimately a total SOA modelling solution for manufacturing enterprise.

Hybrid service-oriented architecture solutions

The comparative view of manufacturing SOA has identified a separation in functionality from architecture to architecture, due to the multifaceted requirements of manufacturing enterprise. Ultimately there is no single solution to cloud manufacturing implementation, which has led to the incorporation of hybrid architectures. Hybrid architectures enable the integration of other architectures within their own networks. This collaboration enables an architecture to gain access to specific beneficial functionalities not currently support, and also enable further data interoperability through manufacturing systems. Examples of hybrid SOA can be seen in;

The incorporation DPWS with OPC-UA and SAP xAPP through the SOCRADES project [144]. In this hybrid solution OPC-UA enables dynamic data acquisition of production data sources within the SOCRADES SOA. The interconnection of SAP xAPP ensures a wider network interoperability, as SOCRADES data can now be utilised in SAP enabled enterprise applications. Cross platform integration of the SVE with MTConnect [145]. In this test-case the SVE was utilised to provide ad hoc dynamic data acquisition. The data was then buffered in MTConnects RESTful mechanism and formated to enable the distribution to MTConnect analysis client applications.

Cross platform integration of the SVE and OPC [146]. Systematically the creator of the SVE, National Instruments, has developed the SVE to connect with OPC. The SVE incorporates an OPC client to enable the acquisition of OPC data from OPC servers. Additionally the SVE contains an OPC server plugin to enable OPC clients to gain access to SVE data. This seamless integration enables the comprehensive OPC data communication library to be utilised in any SVE architectures.

Cross platform integration of DPWS with OPC-UA through the AESOP project [90]. In this hybrid solution the integration of both architectures serves a multitude of mutual benefits; enabling the linking of the industrial world with IT enterprise, improved dynamic service discovery, improved event notification, establishing a data model for DPWS, etc.

2.2.4 Field-level service oriented architecture comparative

Introduction

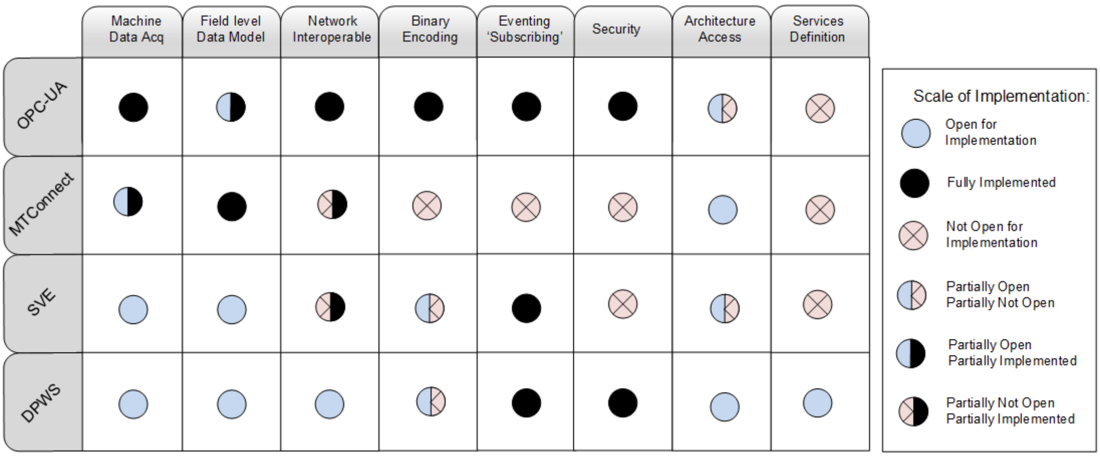


Figure 2.20 Service Oriented Architecture Comparative

The reviewed field level SOA technology provides a unique look into key composed solutions to-date to meet the diverse interoperability requirements of the desentralised nature of manufacturing systems. The SOA's for comparison are OPC-UA, MTConnect, SVE, and DPWS. All architectures utilise WS to achieve dynamic data acquisition and data distribution. However they all have aspects that separate them from one another; Machine data acquisition, Client data model, Network interoperability, Binary encoding, Event 'Subscription', Security, Architecture access, and Service definition. The architectures are compared in Figure 2.20, which identifies the scale of implementation of each aspect with an icon. These icons identify if the specific aspect of the architecture is; open for implementation, fully implemented, not implemented, or a variety of all three.

Comparative aspects

Machine data acquisition

Machine data acquisition defines how a SOA can gain access to data from a manufacturing machine or device. OPC-UA is an industrial standardised technology, designed to meet the diverse nature of communication protocols on the manufacturing floor. The standard enables interoperability of process data from multiple sources. Uniquely OPC-UA consists of a vast library of communication mediums and protocols to achieve M2M communication. MTConnect similarly to

OPC-UA, was created for data acquisition and distribution within a heterogeneous industrial environment. MTConnect is working to provide the required drivers and protocols to communicate with various machines. DPWS and the SVE both identify the capability to provide homogenous manufacturing floor data interoperability. However they are open client data model architectures and would require the development of drivers for specific machine data acquisition. Alternatively DPWS and the SVE could utilise a hybrid solution through the integration of OPC-UA and/or MTConnect to acquire data into their network.

Client data model

Client data model characterises the data types and relationships within a manufacturing system. MTConnect contains a defined library of manufacturing machine data variables. Meaning MTConnect provides a specific data model for the variables acquired by its agents. This data model is separate from the service data model internally incorporated within each standard. MTConnects client data model specifically defines the types of data and their relationships in machines and devices. This enables engineers to easily identify the data they need from a machine tool. OPC-UA has an abstract yet defined client data model that allows data to be seen in its simplest form; data types, values, meta relationship data, etc. DPWS and SVE do not specify specific client data models, enabling messages to be sent in any format. An advantage to not having a data model is that the technology is not tied down to a specific standard and can be adopted as needed. A disadvantage of this operation is that the data acquired does not provide metadata to identify itself. This identification is required to be carried out initially by the engineer installing the system through manual reference of the technology being communicated with. An exception to this disadvantage can be seen in DPWS who’s data service can be created with a data model and include metadata description through an identification service.

Network interoperability

Network interoperability identifies how a system transfers data amongst its components and throughout its network. Within manufacturing this addresses how information can be communicated from machine to machine, application to application, and network to network. DPWS incorporates a multitude of communication mechanisms for service access. A machine or device can be created with a multiple DPWS enabled services for data acquisition, control, and monitoring. Furthermore other architecture components can actively achieve their own data integration through custom built services created through the DPWS service meta-model. MTConnect is open to allow for broad connectivity through the creation of data acquisition adapters for machine and device data sourcing. However it is unclear how the client data model would handle the broader range of manipulated data being integrated back into the system. Furthermore MTConnect does not utilise orchestration for data sharing, meaning client applications may need to connect to multiple MTConnect agents to gain access to the data they need. Subsequently MTConnect is a specifically defined data interoperability medium for field level data acquisition and distribution. All data is accessed throughout a network through TCP/HTTP. Similar to DPWS, OPC-UA offers a multitude of communication mechanisms for service access. A machine or device can integrate OPC-UA services or be accessed by OPC-UA plugin service adapters. Further network applications can integrate their data through adherence to OPC-UA's abstract client data model. OPC-UA has been developed for enterprise integration, through tiered server to server data linking. However it is still uncertain how the defined standard would be integrated with STEP standard. The SVE is similar to MTConnect, as it defines a data distribution WS for network interoperability. The SVE does not however specify a client data model, allowing architecture to be utilised for a range of different application requirements. Additionally the SVE allows for sever to server connectivity, enabling data interoperability through single source client connectivity. However the range of the SVE is restricted to local area networks, meaning data in not freely available throughout a larger network.

Binary encoding

OPC-UA utilises two different message encoding; XML/text and UA binary. Traditional WS utilise XML/text messages, however the data volume footprint of this method can be large, as it utilises character code representation, i.e. ASCII, which corresponds to 1 byte of data per character. Subsequently it has been identified that XML accounts for a 50% increase in latency for small single variable messages and up to 1800% for large messages with thousands of variables [112]. Binary encoding offers the potential for more efficient data transmission, due to its lower message data volumes. Binary encoding does not use a character code representation format, meaning the data in a binary format would be illegible in a text based referencing system. However this format can be easily serialised for transmission and deserialised for application utilisation with minimal time overhead. Text based message structuring may not affect lower data communication, but at high data acquisition speeds and high data trafficking in CPS, text-based XML WS were identified to not meet real-time requirements and resource constraints for industrial machinery applications [142]. DPWS utilises XML for message structuring, however the AESOP project has identified the potential present within the EXI standard to overtake traditional XML structuring within DPWS [112]. EXI a binary representation of the XML information set that is designed for compactness and high performance parsing and serialisation. The introduction of EXI into DPWS would require a fundamental change in the standard, however the standard is open to utilise it in the client data model since it is defined by the architect developer. The SVE's communication medium is the NI-PSP protocol which is proprietary to NI, meaning it is not open for binary encoding for service level data modelling. However the client data model is open for interpretation enabling the utilisation of binary messages. MTConnects standard only facilitates HTTP with XML message structuring. The introduction of EXI would require a fundamental change in the standard on both the server and client data model.

Eventing 'subscription'

Eventing is a subscriptions service that enables a system to provide client applications with the data they need autonomously. Subscription are a 'pushing' data mechanism which provides data when available. The alternative to pushing is the pulling or polling of data, where clients are given data on their request. DPWS fully implements both event subscription and data polling. The SVE fully implements both event subscription and data polling. OPC-UA also implements both event subscription and data polling through data, event, and alarm services. However MTConnect utilises a REpresentational-State-Transfer (RESTful) interface which defines how the MTConnect server will interpret the interactions of Client Applications. RESTful systems specify that the server within a system is unaware of a client's state, and can only process their specific requests. Subsequently

MTConnect cannot provide for eventing message services, and client applications will have to continuously pull data from the server through requests.

Security

Security in network technology is imperative due to the ever evolving and increasing cyber-attacks on manufacturing systems [30]. The increasing connectivity of our networks, and integration of our CPS increases the availability and severity of potential attacks. In order to overcome this, SOA has turned to enabling security mechanisms within their standards to ensure more reliable control. However in SOA there is a trade-off between security and performance [147]. At the top level security is more important than performance since the corporate network is connected to the Internet. At the bottom level performance is more important than security as data has to be acquired in a fast and efficient way in order to control a production process. Both OPC-UA and DPWS incorporate a security model that governs the authentication of clients and servers to ensure data integrity. Both MTConnect and the SVE do not support security services. There are other ways to protect a network from a cyber-attack without integrating security within every element of a SOA. However if a networks access was breached there would be no other mechanisms available to detect or stop the intruder.

Architecture access

Architecture access defines the capability level for a user to gain access to the SOA and their defined standard schematics. MTConnects standard is an open source standard that enables any engineer to gain access online. DPWS consists of a collection of standards that are freely available online; SOAP 1.2, WSDL 1.1, XML, etc. By enabling the free distribution of web standards a multitude of end users can incorporate them within their own systems, further expanding the interoperability capabilities between venders. OPC-UA's standard is available for incorporation, however a subscription fee would be required. The SVE's NI-PSP is proprietary and cannot be acquired for person development. However the SVE itself is freely available to anyone programming with the NI programming language LabVIEW.

Service definition

Service definition identifies the capability of a SOA to generate user driver services within the cloud architecture. Fundamentally the only SOA capable of doing so is

DPWS due to service generating model. MTConnect is an open standard, however to create a custom service would deviate from the standard. However developers can choose to do so if they wish to create hybrid solutions. OPC-UA is a comprehensive standard, and to deviate from the standard would not be possible, as the OPC user group would not validate it. The SVE is proprietary, there are no ways of altering it to create custom services or gain access to current software infrastructure. End users can only utilise the SVE data distribution service, where they can provide customisation through the open client data model.

2.2.5 Cyber-physical production systems

The unification of cloud-based data interoperability and manufacturing intelligence research in manufacturing process monitoring systems is aimed at creating the innovative intelligent machines of the future. These Cyber-Physical Production Systems (CPPS) has to potential to enable an open access interaction platform for limitless virtual collaborative elements to interact with and expand the capabilities of the physical production equipment [148].

The foundation to these system is the utilisation of SOA to enable data to become interoperable via a data hosting communication server. Cloud computing has identified the need for multiple communication servers to cooperate together across multiple computers seamlessly. This generates an interoperable data cloud for process data to be accessed by any networked client. The internet-of-things encourages the dynamic data collection of process data sources, and Ubiquitous computing enables data representation on multiple mediums. The resultant cloud-based manufacturing process monitoring system overcomes the traditional centralised design paradigms limitations of incompatible proprietary communication, incompatible side-ways software integration, lack of scalability, lack of potential extensibility, limited computation resources and customised singular process solutions [87].

Examples of CPPS development can be seen in; Savio et al. development of a dynamic optimisation system for production planning through an interconnected vendor enterprise resource planning application [137], Pinto et al. [149] development of decision support system for automation control via path planning, production scheduling, and preventative maintenance, Riedl et al. [150]

development of a service oriented distributed automation monitoring and control system, Izaguirre et al. [138] development of a automation signal processing feature selection system via complex event generation for process monitoring, and Colombo et al. deveopment of a service oriented automation SCADA system for manufacturing execution systems orchestration [151].

2.3 CNC machine tool monitoring

2.3.1 Sensing and measurement

CNC Turning, along with all other core machining systems, use a variety of auxiliary measurements; power/current, vibration, acoustic emission, cutting force, etc., to identify a range of different production deviations; dimension accuracy, surface quality, cutting tool health, etc. [152]. The selection of these process variables is dependent on the required output of the system.

Force, acoustic emission, and vibration have been utilised for tool wear estimation, chatter prediction, chip form categorisation, surface roughness prediction, and monitoring of tool condition [6]. Similarly sound measurement is reactive to independent sources and can be utilised for identification machining failures, tool breakage, and chatter detection [7]. Uniquely temperature measurement can be utilised to identify tool wear, degree of plastic deformation, degree of diffusion and corrosion, fatigue properties, and compositional changes in the work-piece material [7].

Power

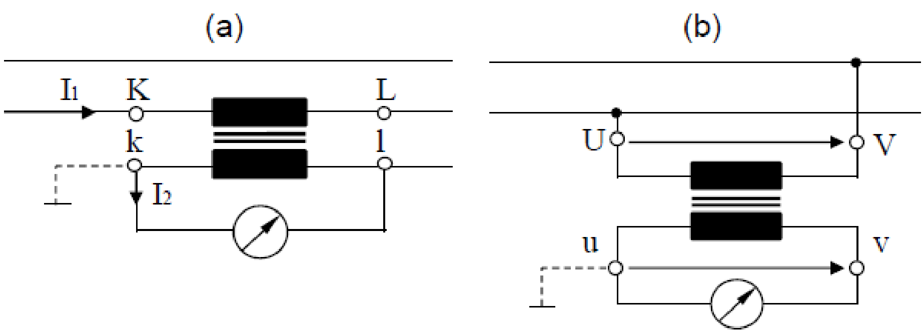


Figure 2.21 Current (a) and voltage (b) transformer circuits [18]

The electric drive/s and spindle/s provide the mechanical force necessary to remove material from a part. By measuring the motor power or current, measures of the machine tool and drive condition can be realised [6]. Power measurement is a non-invasive measurement medium, as power readings already exist in the drives controller, and additionally, other measurement devices do not interfere with machining actions. Modern CNC machining systems can provide internal operating signals to external applications via standardised communication mediums. Other methods include the instalment of current and/or voltage transformers [18], as seen in Figure 2.21. Transformers transfer energy between two or more circuits through electromagnet induction. The measurement of both current and voltage enables for a processes power to be analysed.

Motor power and current are both reactive to the cutting process, through a linear relationship with cutting force, and independent sources, through operating actions [153]. However obstacles to achieving force measurement include; the small power response to material removal, the influence of motor temperature on power consumption, the variable motor power response to varying acceleration/deceleration, and the adequacy of axis lubrication. Other motor phenomenon include the increase in spindle current due to inrush current, and back Electro-Magentic Force (EMF). Inrush current causes an immediate high current flow in the circuit due to the initial lack of resistance in the circuit [154]. Back EMF is created across an inductor from the changing magnetic flux produced by a change in current. The rapid reduction of current during motor switch off causes high back EMF, which can leading to sparking across connectors as stored energy is released from the motors magnetic field [155].

Vibration

Mechanical vibration denote oscillations in a mechanical system. Fundamentally vibration is characterised by its frequency/frequencies, amplitude, and phase. Vibration analysis involves the identification of deterministic and random vibrations, forced and free vibration, linear and no linear vibration [156]. Using vibration analysis, the condition of a machine can be constantly monitored [157]. Detailed analysis can be made to determine the health of a machine and identify any faults that may be arising or that already exist. Faults include; unbalance, a bent shaft, eccentricity, misalignment, looseness, bent drive problems, gear defects, bearing defects, electric faults, oil whip/whirl, cavitation, shaft cracks, rotor rubs, resonance, hydraulic and aerodynamic forces, etc. However in machining, vibration is reactive to independent sources, and not just dependent on the cutting process. The most fundamental analysis in vibration is the determination of amplitude characteristics in the time domain, and spectral distribution of the signal in the frequency domain [158].

Piezoelectric transduction is the most common type of vibration sensing in machining operations [6]. Fundamentally accelerometers rely on the piezoelectric effect of quartz or ceramic crystals to generate an electrical output that is proportional to applied acceleration [159], as seen in Figure 2.22. Force is applied to the crystals from the seismic mass located inside the sensor. Wires connected to a signal conditioner to excite and condition the circuit. Sensor containing inbuilt signal conditioners are classified as Integrated Electronics PiezoElectric (IEPE). These sensors can be mounted in different ways, which has an effect on the accuracy of the signal. Direct coupling stud mounting generally yields the highest mechanical resonant frequency and, therefore, the broadest usable frequency range. The addition of any mass to the accelerometer, such as an adhesive or magnetic mounting base, lowers the resonant frequency of the sensing system and may affect the accuracy and limits of the accelerometer's usable frequency range.

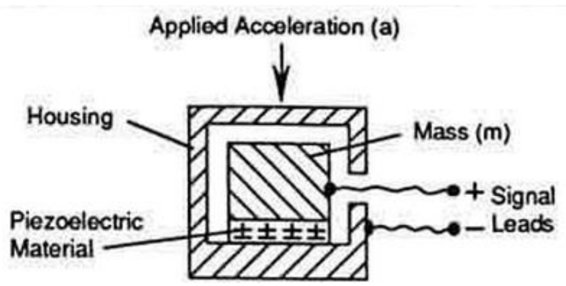


Figure 2.22 Piezoelectric accelerometers [159]

Any object has a natural frequency which is determined by its characteristics of mass, stiffness and damping [157]. A free vibration (not forced) at a natural frequency is called the resonance. In order to find the natural frequency of any object a bump test is undertaken. A bump test involves using an impact hammer to strike an area where a vibration sensor is positioned. The period after the forced vibration occurs is the natural frequency of the area. When forced vibration meets natural vibration, it is called critical speed. Critical speed yields significantly higher vibration amplitudes than unbalanced effects. High vibration amplitudes at critical speeds can be catastrophic for any system, and must be avoided at all costs.

Acoustic Emission

Acoustic Emission (AE) is defined as the phenomena whereby transient elastic waves are generated by the rapid release of energy from localized sources in a material [7]. Sources of this energy release in machining are; primarily due to chip formation, secondarily due to friction between the cutting tool and chip, and thirdly due to the friction between the cutting tool flank and workpiece, as seen in Figure 2.23. Acoustic emission occurs over a wide frequency range but typically from 100 kHz to 1 MHz [160]. Acoustic emission sensors utilises the direct connection of piezoelectric transducers to the measurement surface. The output signal from the sensor is fed through a preamplifier, and further filtered to remove noise.

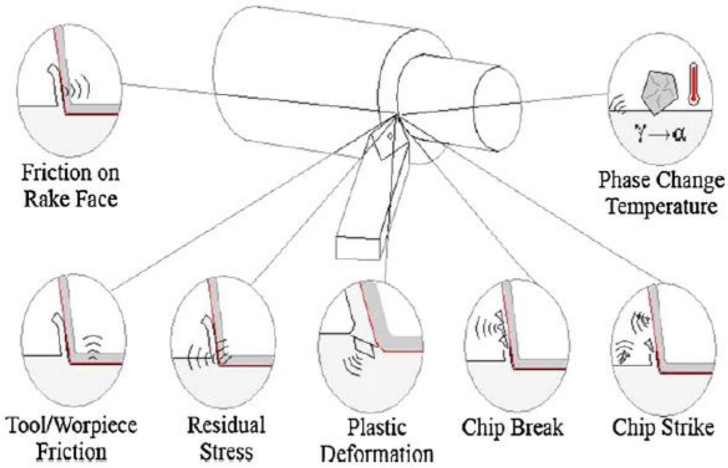


Figure 2.23 Sources of acoustic emission in machining [6]

Force

Any cutting operation requires a certain force to separate and remove the material [6]. Cutting force measurement enables thermal analysis, tool wear estimation, chatter prediction, chip form categorization, surface roughness prediction, monitoring of tool condition [7]. There are two types of force sensors; piezoelectric based, and strain based. Typically direct force measurement using piezoelectric sensors is possible when the force transducer is mounted in line with the force path. However Rotating cutting force dynamometers are also available that contain the force sensing elements capable to measure 3 components of force and torque. Strain gauge force transducers consists of a structure that deforms under a force. The usage of these sensing methods is most popularly represented by a dynamometer. These devices can be IEPE enabled, or require outside excitation.

2.3.2 Signal processing

Signal processing is performed in order to extract the various forms of information carried in the signals, which have been found to relate to the properties of the measured system [158]. Signal processing can be subdivided into pre-processing, feature extraction and feature selection [6]. Signal pre-processing focuses a signal for increased resolution through filtering, amplification, conversion, and or segmentation. Signal feature extraction aims at extracting different signal features or signal transform features that change with the process. While signal feature selection aims at selecting the most relevant features that best describe the machining process. Different processing techniques are applied to different types of signals.

$\mu = \frac{1}{n}\sum_{i=0}^{n-1} x_i$ 1. Mean	$\Psi_x = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1} \lvert x_i \rvert^2}$ 2. Root Mean Square (RMS)
$\text{median} = \begin{cases} s_i & \text{if } n \text{ is odd} \\ 0.5(s_{k-1} + s_k) & \text{if } n \text{ is even} \end{cases}$ 3. Median	$\sigma^2 = \sum_{i=0}^{n-1} \frac{(x_i - \mu)^2}{w}$ 4. Variance
$kurtosis = \frac{\frac{1}{n}\sum_{i=0}^{n-1}(X_t(i) - \mu)^4}{\sigma^4}$ 5. Kurtosis	$skewness = \frac{\frac{1}{n}\sum_{i=0}^{n-1}(X_t(i) - \mu)^3}{\sigma^3}$ 6. Skewness
$X(f) = \mathcal{F}\{x(t)\} = \int_{-\infty}^{\infty} x(t)\, e^{-j2\pi ft}\, dt$ 7. Fast Fourier Transform (FFT)	$S_{xx}(f) = X(f)\, X^{*}(f) = \lvert X(f) \rvert^2$ 8. Power Spectrum

Figure 2.24 LabVIEW formulas; 1. Mean, 2. Root Mean Square, 3. Median, 4. Variance, 5. Kurtosis, 6. Skewness, 7. Fast Fourier Transform, 8. Power Spectrum

A signal can be categorised by being stationary, and non-stationary, and can be sub-categorised as being deterministic, random, continuous and transient, as seen in Figure 2.25. Stationary deterministic signals are made up of a combination of sinusoidal signals with different amplitudes and frequencies. Stationary random signals as described by their statistical properties, such as the mean value, standard deviation, amplitude probability, etc. Transient signals have a finite short duration, and are characterised by total energy. Nonstationary continuous signals consist of one or more of; sine components with varying frequencies and changing amplitudes, random signals with statistical properties changing with time, and transients that appear with varying intervals and characteristics in time and frequency.

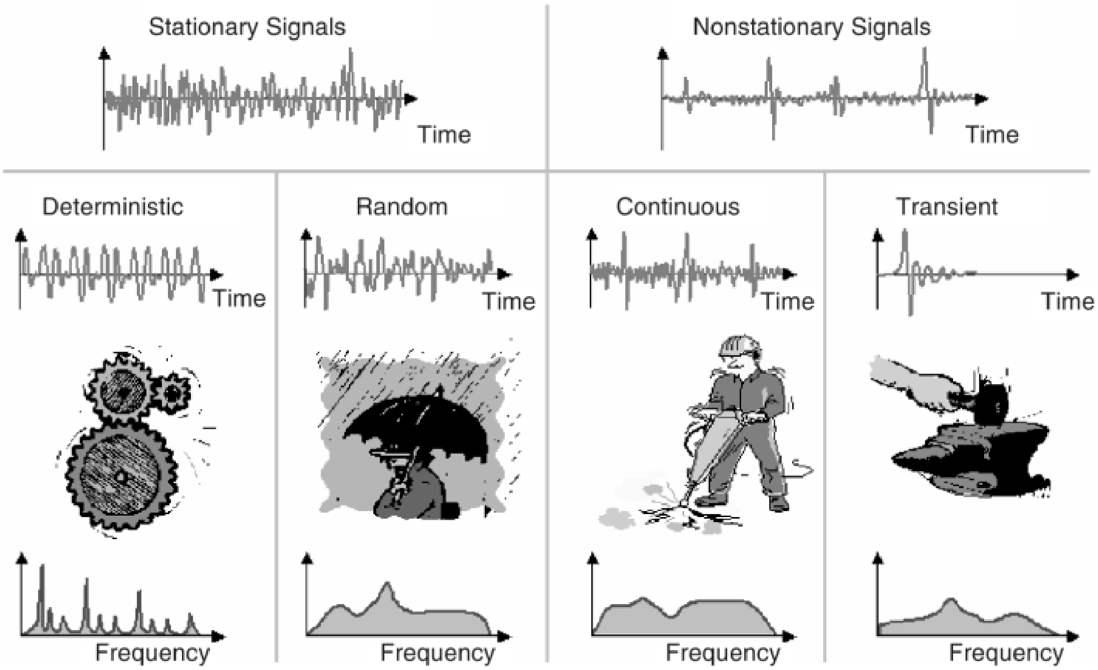


Figure 2.25 Examples of different types of signals and their spectral content [158]

Time domain –techniques

Mean, Median, and Mode [6]

The mean is the average value of a sum of numbers, the median is the middle value in a sum of numbers, and the mode is the number that appears the most in a sum of numbers.

Variance and Standard Deviation [6]

The variance measures the average squared difference from the mean of a set of numbers. Similarly the standard-deviation measures the average difference from the mean of a set a numbers, subsequently the standard deviation = √Variance.

Root Mean Square [158]

The Root Mean Square (RMS) gives information about the power in a signal in value of units in the measured quantity. It is a value characteristic of a continuously varying quantity, obtained by taking the mean of the squares of the instantaneous value during a cycle.

Skewness and Kurtosis [6]

Skewness quantifies how symmetrical the distribution is in a set of numbers. Kurtosis quantifies whether the shape of data matches the Gaussian, or normal distribution.

Frequency domain -techniques

Fourier transform [161]

Discrete Fourier transform (DFT) maps a discrete–time sequence of N samples into a discrete–frequency representation [6]. This enables a signal to be represented by the various frequencies present in signal, with the varying influence magnitude or power represented per frequency. A more widely used algorithm for computing DFTs are Fast Fourier Transforms (FFT). FFTs reduce large amounts of computational complexity in computing the coefficients of DFTs. Other factors to include when utilising FFTs is weighting. Weighting is concerned with the jointing of the discrete signals from digital signal processors, to enables smoothening between the transitions [158]. Weighting mediums include; Hanning, Kaiser-Bessel, Flat-top, and rectangular. Rectangular weighting refers to when no weighting medium is utilised.

Spectrum analysis [158]

(1) Power Spectrum

Power spectrum is characterised by power readings at discrete frequencies. This means that each frequency contains a specific RMS/MS value, of which the sum of is equal to the total RMS/MS of the signal.

(2) Amplitude Spectrum

In some vibration applications, the spectra are sometimes rescaled to the amplitude of the sine components, which represents an amplitude spectrum, √2*RMS. Applicable to deterministic signals.

(3) Power Spectral Density (PSD)

Due to the continuous distribution and disturbances in spectral content, an effective way to scale the spectra is in terms PSD. The power in each frequency band in a PSD spectrum is represented by the integral over the frequency band's width, U^2/Hz. Subsequently decreasing the bandwidth in the spectrum will lower the noise RMS. Applicable to random signals.

(4) Energy Spectral Density (ESD)

ESD represents the total energy present in each spectra over a time period, U^2s/Hz. Applicable to transient signals.

<u>Digital filtering</u>

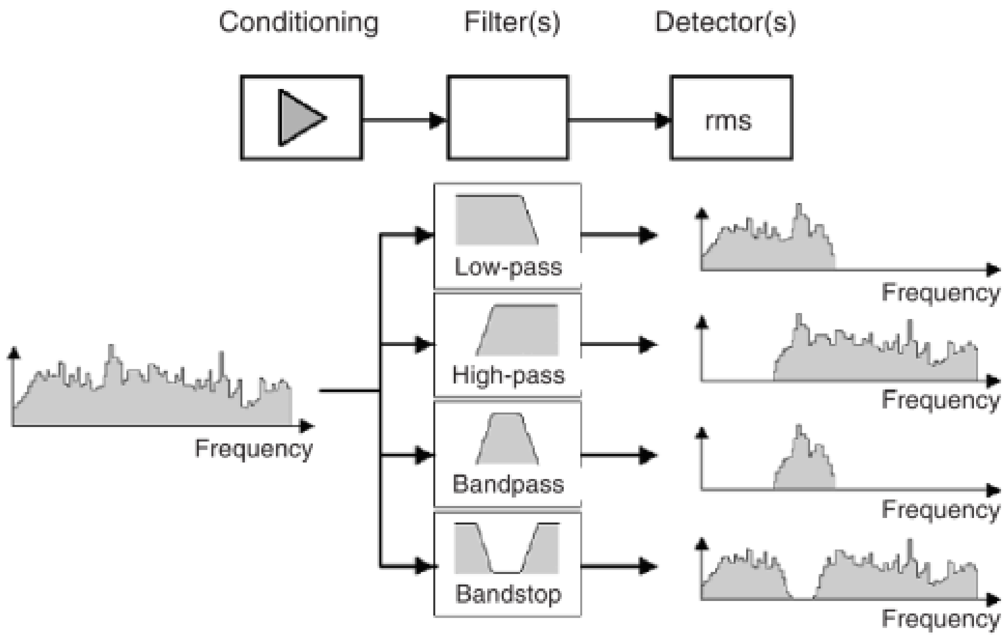


Figure 2.26 Filter types [158]

Filtering is a common form of signal processing, which is utilised to remove specific frequencies from a signal, or to amplify the signal or desired feature in the signal. Filter types include, lowpass, highpass, bandpass, and bandstop filters [162]. Each filter identifies an area of frequency on a spectrum to either allow pass through, or be stopped by the filter, as seen in Figure 2.26. Additional to types there are multiple design methods for implementing these filters, each of which with different advantages and disadvantages. These designs include; Butterworth, Chebyshev, Elliptic, and Bessel [162]. Butterworth is the most widely utilised filter due to its all-around performance.

2.3.3 Process characterisation

In order to achieve high accuracy part dimensions, engineers have sought to control the factors influencing these process variables. Influencing factors can be characterised by the cutting tool state, and the material removal process conditions [6]. The cutting tool state corresponds to the ability of the mechanism to maintain its operation effectively, i.e. cutting motions, and feeding motion [163]. The material removal process conditions corresponds to the fundamental cutting parameters of machining; i.e. cutting speed, feed-rate, depth of cut, tool geometry, work-piece material, etc. [163]. In order to meet the control criteria, engineers have utilised a variety of sensor fusion monitoring systems to identify; optimal operating parameters [164], tool wear [165], tool breakage [166], machining chatter detection [167], and work-piece surface roughness [45]. However both influencing factors affect the same variables. Root cause analysis of the process can only be achieved through an understanding of the influences of both the cutting tool state, and the material removal process conditions, in real-time, across the monitored variables in the system. For example, tool wear is a normal phenomenon occurring in any metal-cutting process, due to the abrasive interaction between the tool and the work-piece [168]. Tool wear dulls the tools cutting edge, and increases the friction between the tool and the work-piece. Increased friction causes increased vibration and requires increased energy to perform the operation at the expense of the surface finish of the part [169] [20]. However tool wear is not the only cause of vibration and increased energy consumption in the machine tool. Vibration and energy are influenced by; multiple cutting conditions [170], motion paths [171], and machine operations [172]. Additionally the degradation of the machine tool can result in the irregularities of operation resulting in a higher energy demands [173], and the generation of higher vibrations [174], which reversely enhances the tool wear and surface roughness of the work-piece [168].

2.3.4 Sensor fusion

Machine tool monitoring systems favour the utilisation of multiple process variable measurements, with multiple sensors, to achieve data fusion analysis. This is due to the fact that sensor fusion provides multiple perspectives of processes operation [175], ultimately enabling a wider scope of process prognostics and diagnostics, to be achieved. These systems achieve context specific analysis through data stream clustering via windows of analysis [176]. Windows of analysis are identified through process characterisation, i.e. the identification of machine operations, states, and events. Research undertaken by Vijayaraghavan and Dornfeld [39] proposed an framework for cloud-based signal characterisation of manufacturing machine tools. This work proposed the dynamic generation of process events from a multitude of process data types, e.g. machine controller data, and measured phenomenon. These events would then enable the characterisation of a process into machining operations via a Complex Event Processing (CEP) application. Identification of process states facilitates the correlation of process data to machining operations, allowing for context specific analysis to be achieved.

Examples of context specific analysis in other processes monitoring systems can be found in:

- Eckstein and Mankova [52] utilised a Numerical Controllers (NC) state data to identify machine movements in CNC drilling to examine multiple process variables, e.g. torque, power and feed force.
- Brazel et al [177] correlated machining tool path position with cutting power data in grinding to identify magnitude of feature specific power consumption over a parts machining cycle time.
- Liao and Lee [178] utilised a controllers state data to analysis vibration for machining operation prognostics of a CNC mill.
- Other simulated examples of context specific analysis through process state acquisition and cross reference has been visualised in [39] [179] [180].

These examples demonstrate the benefits of monitoring complementary variables to achieve collaborative decision support goals. These complementary variables came in form of CNC controller data; axial position, G-code execution, and digital outputs. This data is fixed and is not subject to change, unless machine failure occurs. However not all processes can avail of this option, due to the lack of data sharing capabilities present in the control technology. In these cases other complementary process variables are required to enable process characterisation. These variables need to be reactive to specific process oriented sources, to provide stable windows of analysis.

Sensor fusion is very challenging as it requires the homogeneous data acquisition of heterogeneous data sources. Through cloud-based monitoring the challenges of sensor fusion are overcome, as data is made available on request, standardised for correlation, and distributed freely on a network as needed [145].

2.4 Literature Summary

The evolution of manufacturing process monitoring systems has resulted in the combination of decentralised collaborative technology and advanced analytics. The drive for decentralisation aims to achieve a multi-dimensional cyber-physical system, capable of traversing different process monitoring steps, domains of influence, and enterprise levels. Ideologically these systems are the materialisation of the design paradigms known as Agent-based design and Holonic systems. The resultant cyber-physical production systems are predicted to create the next generation of innovative intelligent machines. The research has identified a key requirement for these systems, which is the identification/development of a dynamic or multi-purpose interoperability medium, to ensure the integration and collaboration of multiple Holonic/Agent entities within its multi-dimensional environment.

Decentralisation has been encapsulated with cloud-based technology, namely service-oriented architecture. The utilisation of these mediums within manufacturing creates a new open access data environment. The reviewed interoperability mediums vary in functionality and capacity. Ultimately there is no one solution to meet the requirements of every manufacturing system or enterprise level. The adoption of any data interoperability architecture is dependent on the required desired attributes of the system as a whole, i.e. speed, capacity, openness, network range, security, etc. A research opportunity is present within the creation of a cloud-based interoperability medium to meet the requirements of field-level manufacturing process monitoring systems. Requirements include; high communication speeds, high data throughput, high correlation accuracy.

The previous examples of cyber-physical production systems, have implemented some form of manufacturing process monitoring intelligence. However a multitude of development potential is available due to the advantageous open access data environment. Evidently, research and development into the migration of proven methods to achieve the fundamental process monitoring steps is imperative. A research opportunity is available in the realisation of dynamic multi-scalable signal processing. This incorporates the migration of fundamental signal processing techniques to a cloud-based architecture, to form a manufacturing monitoring specific cyber-physical production system.

Chapter 3

Design and development of a reconfigurable field-level manufacturing process monitoring architecture

3.1 Introduction

The adoption of any data interoperability architecture is dependent on the required desired attributes of the system as a whole, i.e. speed, capacity, openness, network range, security, etc. This work is aimed at field-level manufacturing process monitoring systems, i.e. level 2 and level 3 of the ISA-95 standard, which addresses non-deterministic discrete control systems. Performance requirements in these systems include; (1) High data rates, > 10 kHz, (2) High communication speed, <= 1ms, (3) High accuracy correlation, <= 1ms. Evidently, no current field-level SOA could provide for these requirements, and subsequently a new custom architecture is required for development. However development creates more requirements, as the architecture needs to be; (a) open source to allow for data structuring that meet the needs of the dynamic manufacturing environment, and (b) incorporate, or be open to the integration, of state-of the art technologies and techniques. These are the design requirements for a new manufacturing field-level reconfigurable process monitoring system.

The developed architecture is named after its fundamental data interoperability operation of Acquisition Recognition and Clustering (ARC). The ARC is; programmed through the Labview graphical programming language, modelled after SOA modelling techniques, and utilises state-of-the-art technologies, to provide a shared pool of data amongst decentralised manufacturing process monitoring system software applications. The performance of the architecture is quantified through an experimental investigation, to identifying the speed, capacity, reliability, and correlation accuracy.

3.2 Architecture modelling and development

In order to model the ARC a cross-over modelling approach is applied, combining the SOA abstract model and the SOA engineering model. This cross over aims at addressing the requirements of a process monitoring system. The model steps are; legend definition, domain specification, meta and data modelling, service and mapping, and topology generation.

3.2.1 Legend definition

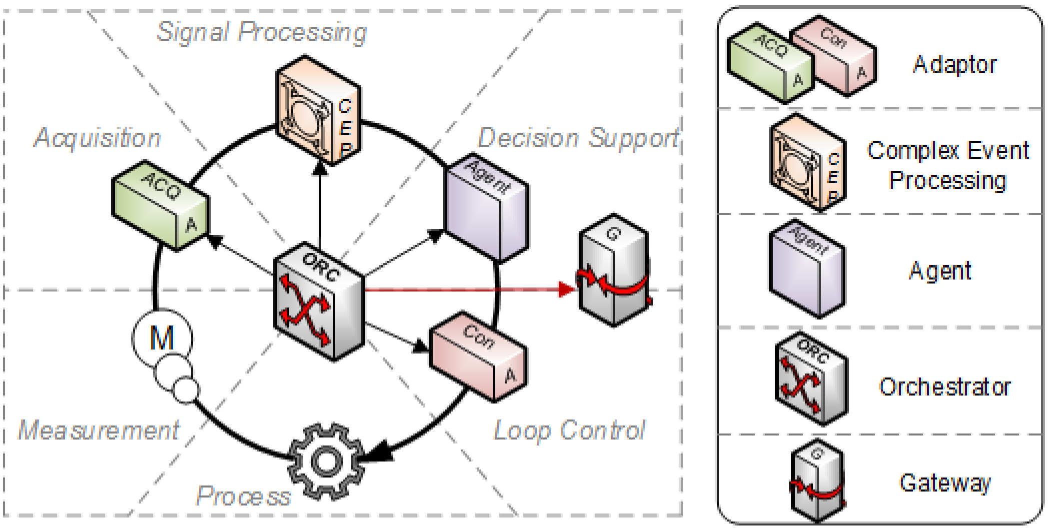


Figure 3.1 Acquire Recognise Cluster legend

A legend identifies the symbols for different SOA elements across multiple domains. These symbols include inputs, outputs, boundary layers, and events [1]. These components define the different objects present within the SOA.

The ARC's elements illustrated in Figure 3.1, consist of;

- Adaptor, the physical connection points of cyber-physical-systems [2], which can acquire data from a physical or virtual source and release the data within the SOA as a service, or oppositely transfer system commands or data to a physical controlled body. Adaptors would represent data acquisition and loop control steps within a process monitoring system. Adaptors are either acquisition-Adaptors: inputs, or control-Adaptors: outputs.
- Complex Event Processing (CEP), entities that derive and analyse higher level information out of low-level or atomic events [3]. The scope of event processing is limitless due to its open definition, any data manipulation services can be

represented as an event processing engine. A defining characteristic of an event processing element is its ability to acquire data from a source, process it, and then re-release it as a new service to the network. Event processing can represent the signal processing and decision support steps within a process monitoring system. Complex event processing is an open-representation of a computational service, and can be distinguished by their primary functions, e.g. CEP-Filter, CEP-Analysis, etc.

- Agents, active consumers of service data for individual utilisation. The scope of Agent entities is limitless due to its open definition. This is because any data consumer can be represented as an Agent. A defining characteristic of an Agent is its localised individual use of data, as it does not release data back into the system as a service. Agents, if required, can utilise multiple services that are available within the network, communicate with entities to achieve goals, and perform system control actions through the available services. Agents can represent the signal processing, and decision support within a process monitoring system. Agent is an open representation of a system component, and can be distinguished by their primary functions, e.g. database-Agent, filter-Agent, management-Agent, etc.
- Gateway/Mediator, elements that enable the connection of different network types within the architecture, or provide a means of transportation of data to different network areas for distribution [4].
- Orchestrator, central control applications which can dictate operation to organise decentralised entities, or enable interoperability between two or more entities [5].

3.2.2 Domain specification

Domain and system categorisation incorporates the assembly of domain specific components and categorisation within layers defined in the ISA 95 standard.

The focus of this work incorporates level 1 measurement and sensing, for level 2 and 3 monitoring and control. The capability of a SOA discrete control system to achieve enterprise wide integration throughout higher levels is evident in the AESOP initiative, and OPC-UA. However, this work aims at providing a specific model starting with a bottom up approach to reconfigurable manufacturing process monitoring systems, consisting of the measurement, acquisition, signal processing, and decision support steps. An example of which can be seen in the merging of infrastructure layers across domains, as seen in Figure 3.2. Level 0 and 1 represent a common platform for the higher level domain specific levels to share. Each domain requires monitoring of the manufacturing process, this data can be subsequently shared by providing its action as a service to applications inside and outside the specific domain of initial implementation. The Adaptor element can enable this goal by utilising custom data acquisition functions to take unique inputs from a sensor to produce a common output that is hosted as a service and transmitted to multiple sources.

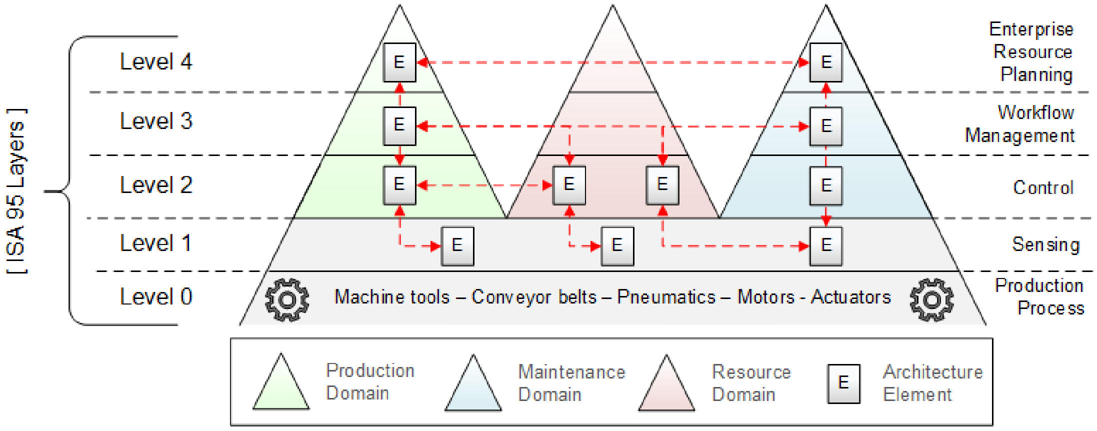


Figure 3.2 ISA-95 layers, adapted from [1]

3.2.3 Meta and data modelling

A meta-model defines the basic components that the data-model can be built from, which includes concepts and rules. A data-model is a semantic or abstract description of the data owned by a subsystem which can be accessed by other systems within a specific domain [6].

Within the Adaptor element, the data model can be seen to represent different types of data that is able to be acquired by data acquisition functions present within the application, as seen in Figure 3.3. This data has sub-type-data corresponding to different variable parameters, i.e. its data type, sample rate, unit representation, and time of occurrence. Timing within a process monitoring system is crucial as it enables the correlation of different data streams through an instance of occurrence reference. This requires the data that is being acquired to share a timing element, e.g. a clock reference. Traditional SCADA systems are less concerned with correlation given that their requirements are specific to the most recent data reading. However, sample rate requirements within manufacturing process monitoring systems can range between 1Hz-to-1MHz and beyond. Computational-units or networks have an incapability to sustain such a large amount of traffic, especially for single value references at high frequency. In order to overcome this challenge data is clustered into packets, with meta-data specifying time of occurrence with a reference clock reading. Within the data model, specified in Figure 3.3, a data packet is a collection of raw data points with timing-meta-data, namely;

- Clock: specifies a reference point from the acquisition clock appertaining to when data was first acquired
- Time-Line: the total time that has passed since the initial clock reading was taken
- T-Delta: the common time increment between samples which is dictated by the sample rate.

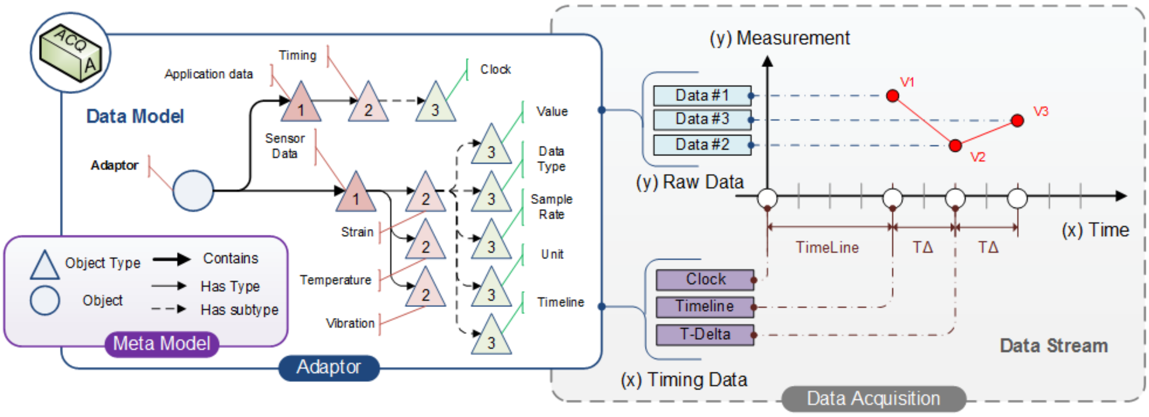


Figure 3.3 Adaptor modelling

The combination of raw-data and timing-meta-data enables a data stream to be packed by a sourcing application and then subsequently assembled and consumed by a seeking application.

3.2.4 Services and mapping

Generic Services are an abstract common way for exchanging data between subsystems that are technologically independent, and Mapping defines how abstract services are mapped for physical implementation [6].

Shared Variable Engine

The SOA interoperability system selected to achieve the goals of the reconfigurable manufacturing process monitoring system is the Shared Variable Engine (SVE). The SVE was selected due to its available services, network integration, and open source meta and data models. In order to summarise, the SVE is a software framework that enables variables to exist on a network and be communicated between applications, remote computers, and hardware [7], as seen in Figure 3.4. The SVE utilises the NI-Publish Subscribe Protocol (NI-PSP), which consists of the Ethernet TCP/IP and a LogosXT transmission algorithm [8]. The SVE enables applications to expose their data as services, by 'publishing' the data to a SVE. The SVE hosts the data, buffers the data, and distributes the data to multiple applications which 'subscribe' to it. Furthermore, the open-source meta and data model ensured that advanced SOA attributes could be integrated, such as binary messaging for efficient communication.

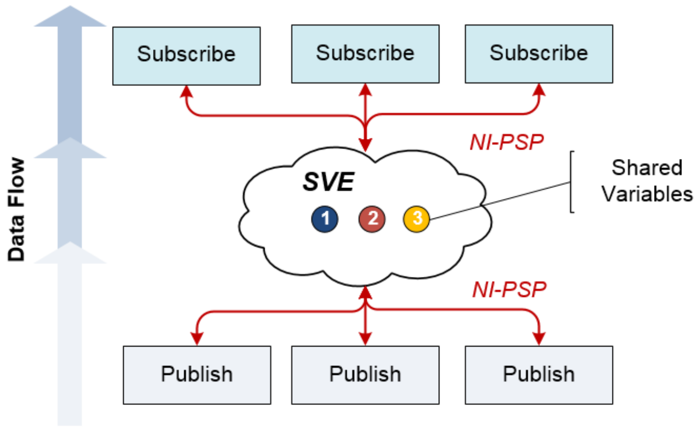


Figure 3.4 National Instruments – Shared Variables Engine

Binary Message Model

Binary conversion enables the conversion of any data type or cluster to a binary string format which can be represented as byte string. The binary conversion specifics are presented in the Appendix A.3: Binary Conversion. In order to distribute data within a network via the SVE a message structure needs to be defined. The design requirements for the message structure includes;

- Multi-sample, the message must be capable of containing a single variable value as well as multiple values

- Meta-data, the message requires the incorporation of timing-meta-data and variable characterisation data
- Data-types, the message must be able to incorporate multiple data types, e.g. Boolean, Double, Integer, etc.
- Binary-compression, the raw data and message must be compressed into a binary representation.

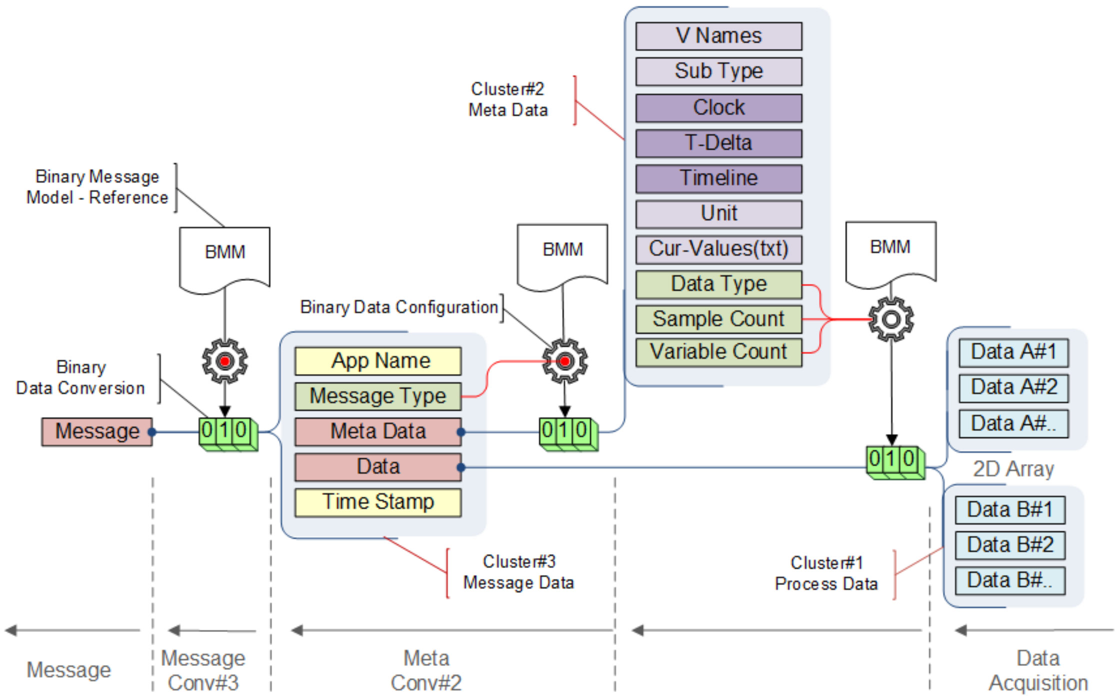


Figure 3.5 Binary message model conversion

A three step Binary Message Model (BMM) was utilised to meet the previous stated requirements. A visualisation of the BMM is shown in Figure 3.5, and the data descriptor is presented in Table 3.1. Both the process-data and metadata could be converted into byte strings and structured in a generic message model, which identifies what type of message it is, the owner of the message, and the time at which the message was created.

Binary conversion enables flexibility within the message as different data types and quantities can be assembled without the need for changing the message structure. In order to decode the message the receiving application needs a data structure reference in which to transpose the binary data into. The initial message data model acts as a base reference model to achieve this, enabling the message type to be exposed and enabling the application to determine what structure the metadata is in. Subsequently, the metadata will provide details in how to transpose the process data binary string, e.g. data-type, sample count, variable count. The BMM can be expanded to incorporate multiple types of messages, including request and response messages between applications. The only change will be present within the message type specified and the corresponding data structure of the metadata and data binary strings.

ARC Message

Name	Data Type: (String 1D Array)	Example
Application Name	String (ASCII)	adapter178
Message Type	String (ASCII)	wave
Meta Data	String (Binary)	N/A
Data	String (Binary)	N/A
Timestamp	String (ASCII)	19/12/1987 12:12:12

Meta: Wave

Name	Data Type: (Data Cluster)	Example
Variable Names	String	V1/V2/V3...
Current Values	String	1.23/1.23/1.23...
Clock	Double (msec)	123456.1235
T-Delta	Double (msec)	0.5
Timeline	Double (sec)	123.123
Unit	String	volt
Variable Count	Integer	3
Total Samples	Integer	3
Data Type	String	double
REF	String	. . .

Data: Wave

Name	Data Type: (String 2D Array)	Example
Rawdata	Bool or Double or Integer	1,2,3... (Varibale 1)
		1,2,3... (Varibale 2)
		1,2,3... (Varibale 3)

Table 3.1 Binary message model data descriptor

Data interoperability

The ARC data interoperability operation can be reviewed in 7 steps, as data flows from source to service and finally to consumer. These steps are characterised by name of the architecture; Acquire, Recognise, and Cluster (ARC), as illustrated in Figure 3.6. The software elements in this example include an acquisition-Adaptor for data sourcing, the SVE for data interoperability, and a data client-Agent for data consumption.

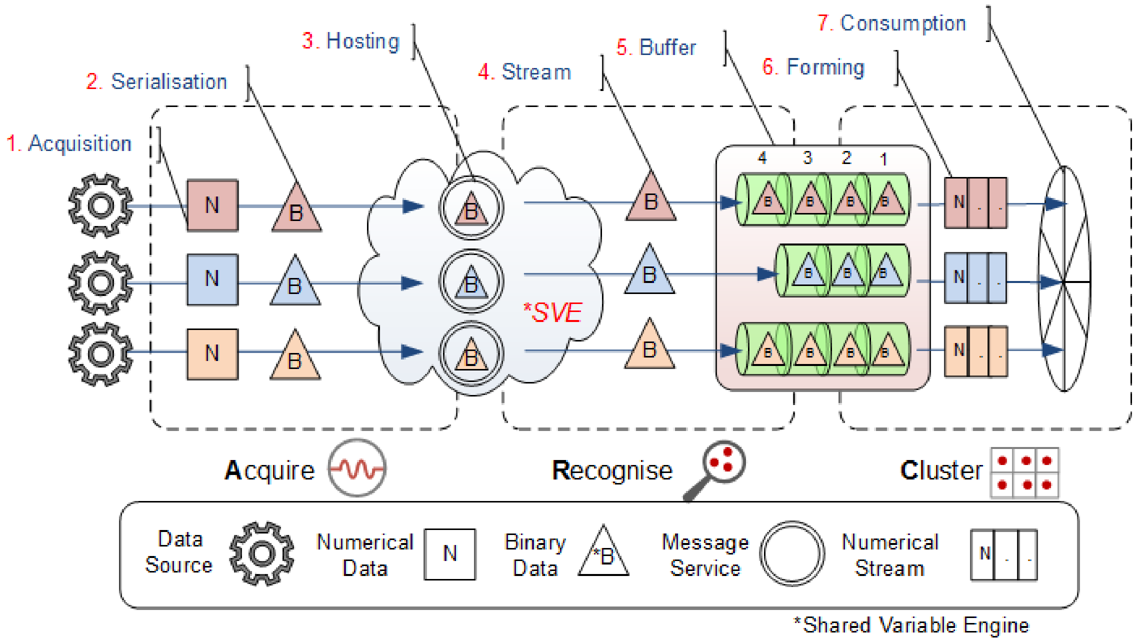


Figure 3.6 Acquire recognise cluster, sequential data flow

(1) Acquisition: data is collected via an Adaptor and time-stamped with a CPU timing mechanism.

(2) Serialisation: data is serialised to a Binary Message Model (BMM) format, data can range from single values to thousands of values in an array which is bundled into a singular message packet

(3) Hosting: packets are published to and hosted by the SVE for internal and network wide data distribution

(4) Stream: data is acquired and streamed dynamically from the SVE by the data client-Agent which can be present locally on the same computer or remotely across a network

(5) Buffer: data is acquired from multiple sources that arrive at different times and are then loaded into a designated buffers for processing

(6) Forming: data buffers are emptied cyclically where message packages are deserialised, data streams are correlated, and further buffered for consumption

(7) Consumption: processed data streams are consumed depending on the functionality of the application.

3.2.5 Topology generation

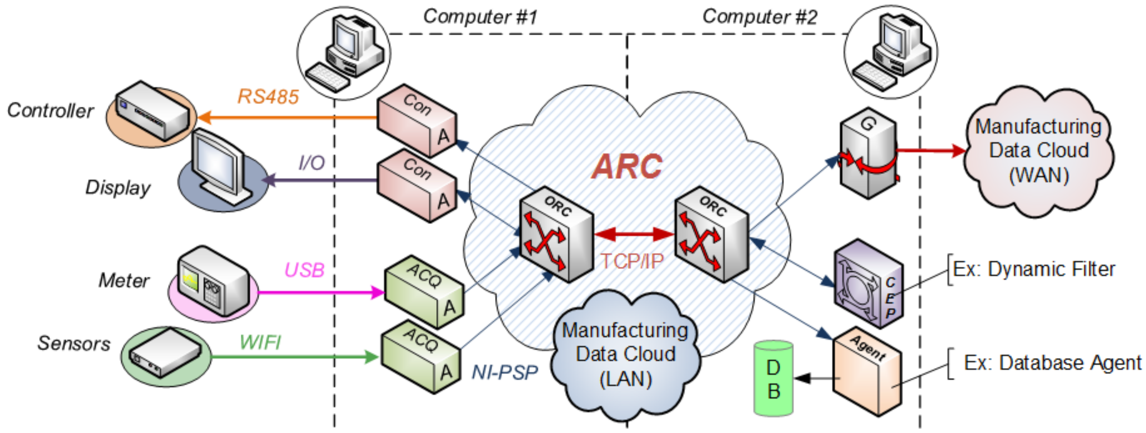


Figure 3.7 Example ARC service oriented architecture topology

Topology generation connects all components within domains, and between domains, using the previously defined interfaces. A simple reconfigurable manufacturing process monitoring system topology example for data acquisition, signal processing, and decision support can be seen in Figure 3.7. Adaptors acquire data, format it to the BMM, and publish it to the orchestrator, i.e. the SVE. Connected computers can gain access to the data via local SVE's that provide for network interoperability. Complex event processing elements subscribe to data streams, manipulate the data (signal processing) and publish it back to the SVE. Agent elements subscribe to data within the network and provide data management and decision support capabilities. The modular structure of the SOA manufacturing process monitoring system enables the expansion, retraction, and reconfiguration capabilities to adapt to any analytical requirement. The dynamic data acquisition elements allow the system to adapt to environmental changes, e.g. changes in sensors types, data sources, etc. The network distribution capabilities enable collaboration of computation, allowing multiple analysis functions to be achieved through dedicated processing units. The resultant manufacturing reconfigurable process monitoring system is decentralised in nature, yet cooperatively united through asynchronous services.

3.3 Performance measurement

3.3.1 Communication and message serialisation speed

Setup

Two experiments were undertaken to test the performance of the SVE and BMM. Firstly the message structure serialisation and deserialisation time frame was quantified. Secondly the Round Trip Time (RTT) was identified, and contrasted with other architectures. RTT measures the time taken to send a message to a networked application and receive the same message. Three types of message structure were tested to enable a performance comparison; the BMM, normal XML coding, and a hybrid structure which utilised binary conversion of sample data values with a XML structure. The data contained within the messages was in accordance with the BMM, consisting of metadata and raw data, which had a varying data quantity of 100, 500, and 1000 samples per message. All three methods utilised the SVE as an interoperability medium. The SVE enables data interoperability across a network and within a central computer. Both scenarios were tested for RTT capabilities.

Results

The numerical experimental results are presented in Table 3.2: serialisation and deserialisation, and Table 3.3: RTT. Furthermore, Karnouskos and Somlev [9] performed similar experiments in order to assess the performance of WS, namely; traditional web services with Axis2, DPWS, REpresentational State Transfer (REST), and Constrained Application Protocol (CoAP), as seen in Table 3.4. A comparative analysis of results from both studies is given in Figure 3.8.

From the results, as illustrated in Figure 3.8, there is an 87.2% time reduction when utilising the BMM serialisation at 100 samples compared to SVE-XML and a 95.6% reduction compared to DPWS. Data representation within the BMM produced on average a 66.2% reduction in message size compared to XML. BMM deserialisation provided a 96.7% time reduction at 100 samples compared to SVE-XML and a 98.7% reduction compared to DPWS. The SVE RTT has a linear response to data transmission size. This provided a reduced RTT of 89.1% on average at 100 samples per messages across SVE BMM, XML, and XML-B compared to DPWS. Comparatively, the SVE in combination with the BMM provides the shortest serialisation, RTT, and deserialisation time of all measured services at 0.88 ms, with a sample rate of 100 kHz at 100 samples per message, within a Local Area Network (LAN), which is within the 1 ms requirement of soft real-time systems. These results also indicate that local interoperability within a central computer can yield greater time reductions as the SVE provided a 0.23 ms RTT. The combination of SVE and BMM within a central computer can provide interoperability within 0.24 ms with a sample rate of 100 kHz at 100 samples per message, or 0.37 ms with a sample rate of 1 M Hz at 1000 samples per message.

	100 samples		500 samples		1000 samples	
	Size (B)	Time (ns)	Size (B)	Time (ns)	Size (B)	Time (ns)
	Serialisation					
BMM	923	13,033	4123	14,233	7323	16,800
XML	2626	101,900	11826	576,500	23326	1,575,600
XML B	1826	78,100	7826	435,567	15326	1,159,933
	Deserialisation					
BMM	923	3,367	4123	4,967	7323	9,233
XML	2626	101,600	11826	762,800	23326	2,054,500
XML B	1826	70,633	7826	458,567	15326	1,274,500

*All data points consisted of double precision floating point @ 8 Bytes; values = 123456789.123456
* Time values represent the mean 3 test consisting of 1000 measurements each

Table 3.2 BMM experimental results: serialisation and deserialisation

	100 samples		500 samples		1000 samples	
	Size (B)	Time (ns)	Size (B)	Time (ns)	Size (B)	Time (ns)
	Central Computer					
BMM	923	224,200	4123	244,833	7323	342,200
XML	2626	232,167	11826	241,400	23326	379,100
XML B	1826	238,333	7826	364,233	15326	274,467
	Local Area Network					
BMM	923	865,067	4123	1,118,833	7323	1,372,700
XML	2626	969,367	11826	1,188,833	23326	1,940,967
XML B	1826	838,733	7826	1,305,167	15326	1,634,200

*All data points consisted of double precision floating point @ 8 Bytes; values = 123456789.123456
*Time values represent the mean 3 test consisting of 1000 measurements each

Table 3.3 SVE experimental results: round trip time

	Serialisation (ns)	RTT (ns)	Deserialisation (ns)
Axis 2	54,340	12,221,588	167,866
DPWS	297,461	8,467,042	262,764
REST	20,019	1,064,523	60,482
CoAP	5,296	5,996,933	7,600

Table 3.4 Karnouskos and Somlev experimental results [9]

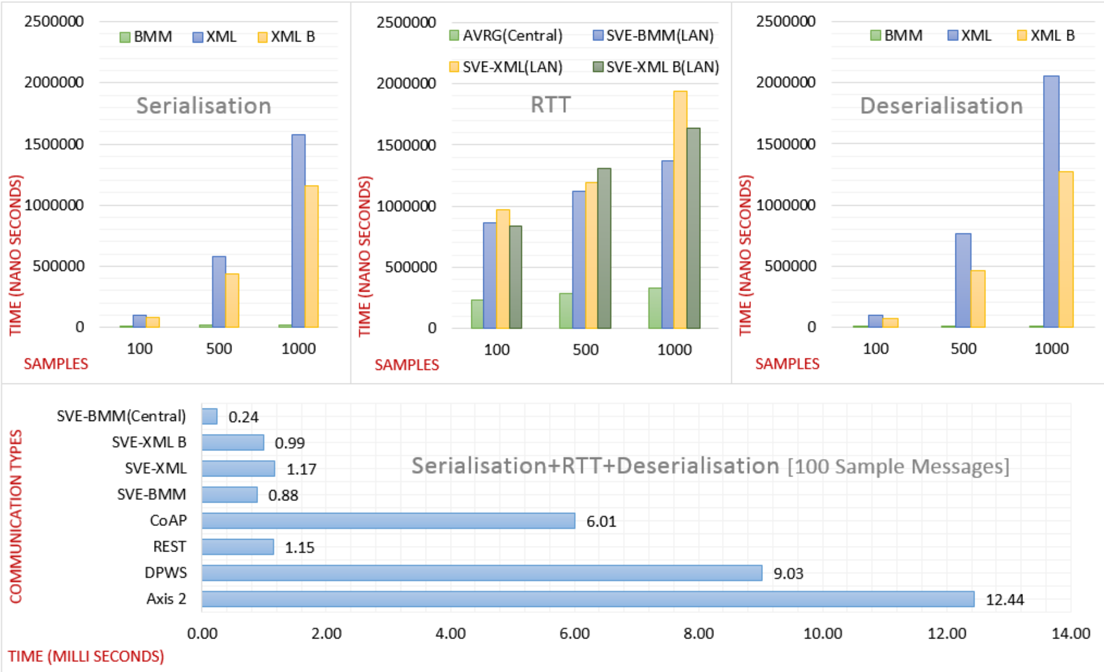


Figure 3.8 BMM and SVE experimental results

Architecture comparison

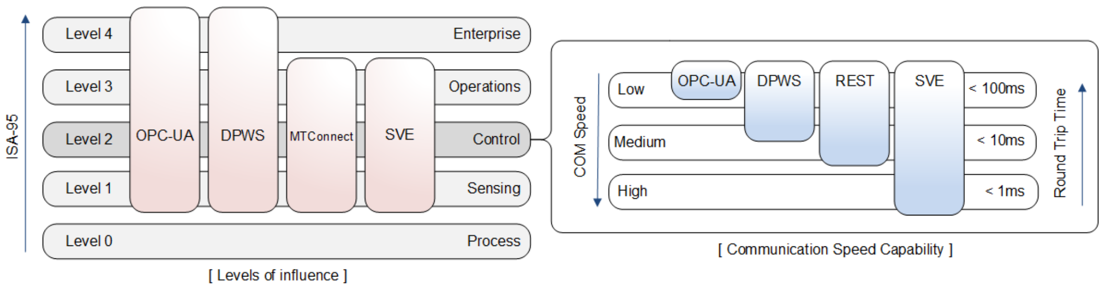


Figure 3.9 Service-oriented architecture enterprise integration and field-Level speed capability, adapted from [6]

Several studies have been undertaken by researchers to characterise the performance of the specified SOA's; OPC-UA [10], DPWS and REST [9], and the SVE [11], as illustrated in Figure 3.9. The characterisation of the MTConnect speed performance has not yet been specifically addressed. However the characterisation of similar REST interfaces has been achieved, and will represent MTConnect in this comparison. The SVE with the BMM and REST provided the fastest communication speeds of between 10 to <1 ms, with OPC-UA and DPWS providing lesser speeds of 100 to 10 ms. The causality of the communication speed difference can be identified in the simplification of communication stacks that exist within the SVE and REST. While OPC-UA and DPWS provide a greater service functionality, enterprise integration capability, and security measures.

3.3.2 Data capacity and communication reliability

Setup

Two experiments were undertaken to provide a contrasting view of how large data packages can be communicated through the ARC reliably. Data was transmitted from an acquisition-Adaptor to a data client-Agent via the SVE. The software applications were being hosted in the first test by a singular computer, and in the second test between two computers networked together via a 100 Mbps network switch. Network communication speed was identified through the measurement of message arrival times in the Agent. The Adaptor was set to communicate 1 message or “package” of set data size every 1 ms, which is 1000 Packages Per Second (PPS) per variable. The set 1 ms timeframe acted as a defining limit for capable data communication. The mean communication time was determined through 3 repeated tests. Additionally the quantity of variables being transmitted was incremented between test sets. Samples per package were varied between local and network tests, as the network tests were limited by 100 Mbps on the network. Local communication time experiments were undertaken with a 1000 samples per package with double point precision variables resulting in 8.134 kB per package. Network communication time experiments were undertaken with a 100 samples per package with double point precision variables resulting in 0.934 kB per package.

Results

Experimental results are illustrated in Figure 3.10 and Fgure 3.11. Each figure has two sets of data, the bar chart represents the total transmission of data of each test (Mbps) axis Y1, and the dot plot represents the average package communication time (ms) axis Y2. The X axis in the charts represent each test undertaken, and identifies the number of shared variables utilised and PPS sent.

From the results, as seen from Figure 3.10, it can be concluded that the ARC has a local maximum capacity to maintain 20 M Hz of data, i.e. 20000 packages, across 20 shared variables, with a standard deviation of 0.32 ms, at 1301.4 Mbps.

It can be seen from Figure 3.11 that the ARC has identified a network maximum capacity to maintain 1 M Hz of data across 10 shared variables, with a standard deviation of 0.83 ms, at 74.2 Mbps. Results beyond these two set points in both experiments, identify an increase in mean communication time above the 1 ms set time, indicating an incapacity to maintain the set throughput target.

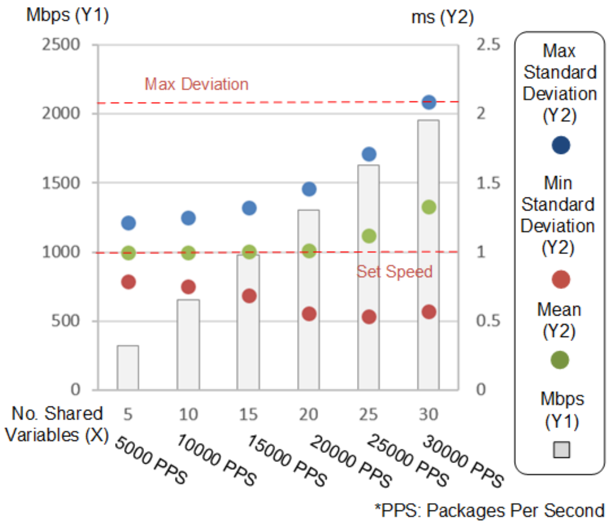


Figure 3.10 Local communication time bench marking

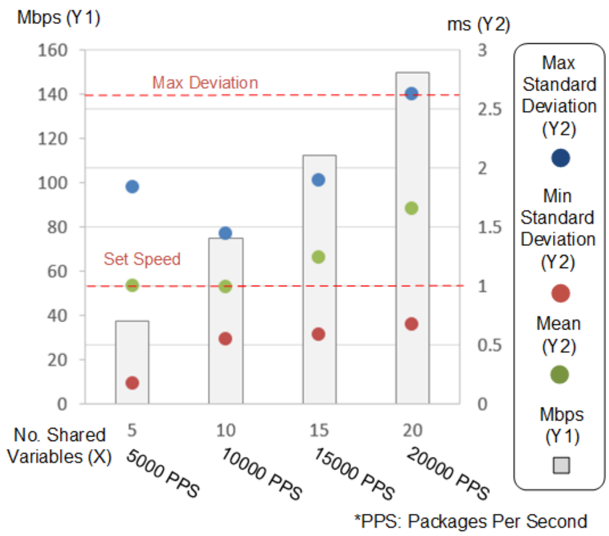


Figure 3.11 Network communication time bench marking

It is important to note that:

- A larger number of variables can be utilised depending on the systems requirements, meaning 5 to 30 variables is not the maximum limit. However message communication times will increase with increasing message sizes and communication traffic.

- Decreasing message sizes will enable a higher PPS throughput capacity, and vice versa.
- Faster and more reliable results could potentially be achieved within network tests through increasing the connection speed >100Mbps, which is a bottle neck in the system's capacity.

3.3.3 Correlation accuracy

Setup

The decentralised architecture of cloud-based interoperability systems need a common clock reference to correlated data. On a network of servers, clock synchronising is undertaken autonomously. However the accuracy of operation varies between 10-100-1000 ms. Since the ARC operates on a local area network, all data sourcing software adaptors are required to operate on a single computer, to ensure the highest correlation accuracy of data streams. However there is a variation in clock referencing mechanisms. Subsequently an experiment was undertaken to identify the accuracy of correlation between data streams, utilising different time referencing mechanisms. The clock referencing mechanisms include;

- Windows clock: references the computers operating system's clock, and sets the timestamps when data arrives
- CPU clock: references an internal CPU clock and sets the timestamps when data arrives
- Calculation: utilises a base reference from the CPU clock from when data first arrived, and then timestamps data on a calculation utilising a set distance between samples.

These three mechanisms are utilised to measure vibration from two equally distanced sources, from the impact of a force measurement hammer. Vibration was measured with two separate triaxial accelerometers, A and B, connected to 9234 analogue input modules, with separate cDAQ 9191 Ethernet data acquisition devices. Two acquisition-Adaptors acquired data from the data sources, timestamp the data using the different timing mechanisms, and published their data to the SVE. A database-Agent acquires the sources and correlates the data streams together for analysis. The force of the impact hammer was recorded in the same analogue input module and data acquisition device, as accelerometer A. This insured that the natural reaction from impact to vibration was measured on a single data acquisition rate, enabling a near perfectly correlation between the two data streams, regardless of time stamping mechanism. However accelerometer B was operating on a separate data acquisition system, with a different data acquisition clock. The only point of correlation between A & B's data streams are through the timing mechanisms in the acquisition-Adaptors. In order to identify the accuracy of the different mechanisms, the accelerometers were excited periodically over a 60 minute period. The primary vibration reaction response time, T1, was recorded between the impact force and accelerometer A. Also the secondary response time, T2, was recorded between the impact force and accelerometer B. T1 identifies the variation in the natural response to vibration from impact. T2 identifies the natural response to vibration from impact, and also the variation in timing correlation mechanisms. Subsequently, T2-T1=T3, T3 being the variation in timing correlation mechanisms.

Results

Experimental results are presented in Figure 3.12. The results show for all three timing mechanisms; the deviation of correlation over time, as seen in Figure 3.12.A, the average deviation in correlation over the testing period, as seen in Figure 3.12.B, and the standard deviation in correlation over the testing period, as seen in Figure 3.12.C.

Both the operating-system and CPU clock timing mechanisms provide a stable measurement timing correlation, with the CPU clock maintaining a standard deviation of 0.165 ms, and the operating-system maintaining a standard deviation of 0.434 ms. However the calculated mechanism identifies a continuous drift in correlation between data streams, with a standard deviation of 3.35 ms. This drift is due to the losses in the system from errors in measurement, rounding of calculations, and other disturbances. The calculation cannot provide for these irregularities as it utilises set values. Subsequently any deviation is progressive, resulting in a separation in data stream correlation.

As specified, both the operating system and CPU timing mechanisms provide a stable timing correlation. However, initial correlation with the operating-system timing identifies a large deviation in correlation, represented by an average correlation deviation of 14.578 ms. This identifies a significant inaccuracy in the operating-system timing mechanism to timestamp data.

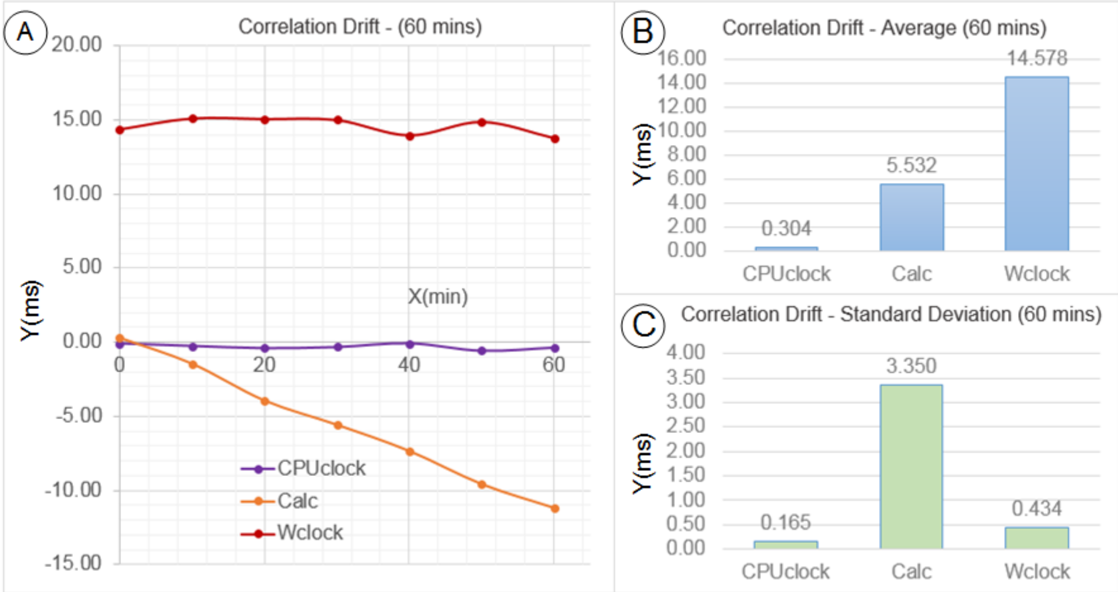


Figure 3.12 Data stream correlation timing mechanism comparison; A: correlation over time, B: average correlation drift, C: standard deviation in correlation drift

In conclusion to this experiment, the CPU timing mechanism has been identified as the best choice in data stream correlation, with an average correlation deviation of 0.304 ms, and a standard deviation of 0.165. This equates to a maximum correlation deviation of ±0.05%, e.g. a deviation of ±1 sample @ 2 kHz, or ±10 samples @ 20 kHz, ±100 samples @ 200 kHz, or ±500 samples @ 1 MHz, etc. This can be considered highly adequate for multi-system inputs in a manufacturing process monitoring system. However this is depending on the accuracy required by the analytics. Where sampling correlation is most significant, parallel data acquisition hardware devices can achieve a near 0% correlation deviation. These systems can also feed into a decentralised system, however the correlation deviation would be present among other distributed data acquisition resources. Further measures to overcome high data acquisition rates and/or higher accuracy correlations, would include the use of integrated dedicated technology such as FPGA's or real-time CPUs. The utilisation of high-spec hard-real-time technology can provide localised high speed data processing and correlation, resulting in lower sampling rates of shared data, and subsequently reduce correlation deviation.

3.4 Summary

This chapter focused on the design and development process for creating a reconfigurable manufacturing process monitoring system. Fundamental to this task was the creation of a dynamic multi-purpose interoperability medium, to ensure the integration and collaboration of decentralised software components. Key design and performance requirements included (a) open source data structuring, (b) incorporate, or be open to the integration, of state-of the art technologies and techniques, (c) meet performance criteria; (1) High data rates, > 10 kHz, (2) High communication speed, <= 1ms, (3) High accuracy correlation, <= 1ms.

The following summarises the developed reconfigurable manufacturing process monitoring system, namely the Acquire Recognise Cluster (ARC) service-oriented architecture.

The ARC utilises the National Instruments Shared Variable Engine (SVE) for dynamic data interoperability. The SVE incorporates key SOA aspects such as data interoperability, discovery, and eventing. Furthermore, the utilisation of the SVE enables the solution to both of the design requirements of (a) open source data structuring, and (b) the integration of state-of the art technologies and techniques. The solution to both of these design requirements is represented in the integration of the Binary Message Model (BMM) within the SVE. The BMM utilises state-of-the-art binary representation for efficient data exchange. The dynamic behaviour of binary conversation enables the adaption of the model to meet the variation present in manufacturing systems. The variation in data type, data size, data length, data format, can now be serialised into a common message format.

Fundamentally, SVE acts as an orchestrator unit to represent data sources as services on a network. The SVE utilises the National Instruments – Publish Subscribe Protocol (NI-PSP), which operates on Ethernet TCP/IP with use of the LogosXT transmission algorithm. The NI-PSP enables the pulling and pushing of data within the network, via event services, as data variables can be referenced on request or subscribed to for event driven data acquisition. Ultimately the ARC enables the facilitation of process data variables within a cloud that is acquirable dynamically locally and/or across a network. The functionality fundamentally meets the requirements to form the platform on which a cyber-physical production system can be built.

Multiple experiments were undertaken to test the effectiveness of the ARC to meet design requirement (c), which corresponds to performance criteria within a field-level manufacturing environment. The results of these experiments have resulted in the creation of a performance characterisation table, as seen in Table 3.5. Evidently the ARC meets the performance criteria of (1) High data rates, > 10 kHz, (2) High communication speed, <= 1ms, (3) High accuracy correlation, <= 1ms. The functionality and performance of the ARC has surpassed all previously reviewed SOA technologies within field-level manufacturing systems, or levels 1 to 3 in the ISA 95 standard.

Metric	Result	Info
Serialisation Time	0.013 ms	@100 samples, ≈1000B
DeSerialisation Time	0.003 ms	@100 samples, ≈1000B
Round Trip Time - Local	0.224 ms	@100 samples, ≈1000B
Round Trip Time - Network	0.865 ms	@100 samples, ≈1000B
Average COM Time	<= 1 ms	-
Data Capacity - Local	20 MHz – 20 Shared Variables	± 0.32 ms, 1301.4Mbps
Data Capacity - Network	1 MHz – 10 Shared Variables	± 0.83 ms, 74.2Mbps
Max Shared Variables	100	See SVE Spec
Max message size	1000 samples	≈7500B
Max variables per message	10	@ 100 samples (<≈7500B)
Correlation Accuracy	= 0.3 ms	± 0.165 ms (0.05% deviation)

Table 3.5 ARC performance characterisation

Chapter 4

Investigation and development of decentralised manufacturing data acquisition, signal processing, and process analysis entities

4.1 Introduction

A case study was required to investigate the initial application of the ARC in a manufacturing environment, and enable the development of multi-scalable signal processing and analysis elements, which form the reconfigurable manufacturing process monitoring system.

This phase 1 investigation focused on monitoring a single spindle turning operation in a CNC turning machine tool. CNC turning is a complex process of interactive variables and reactive phenomena. Challenges in monitoring these processes include; multiple process sensors/variables, large data acquisition rates, accurate correlation of data streams, parallel/high capacity data processing computation, and the utilisation of advanced analytics. Key process variables selected for acquisition, signal processing, and analysis are; tool force, single phase motor electrical current, and spindle/turret vibration.

The process data acquired provided a point of reference for the design and development of decentralised signal processing and analysis techniques. These entities formed the reconfigurable tools within the ARC process monitoring system. Key signal processing techniques and analytics for both the time and frequency domain are migrated into the architecture. A detailed review of how signals can be processed to extract specific process features is provided. Considerable focus is placed on frequency analysis through utilisation of spectrum and spectra analytics. Furthermore an advanced autonomous process performance characterisation system is presented, which utilises a collection of reconfigurable ARC signal processing tools.

4.2 Manufacturing process setup

4.2.1 CNC turning machine tool

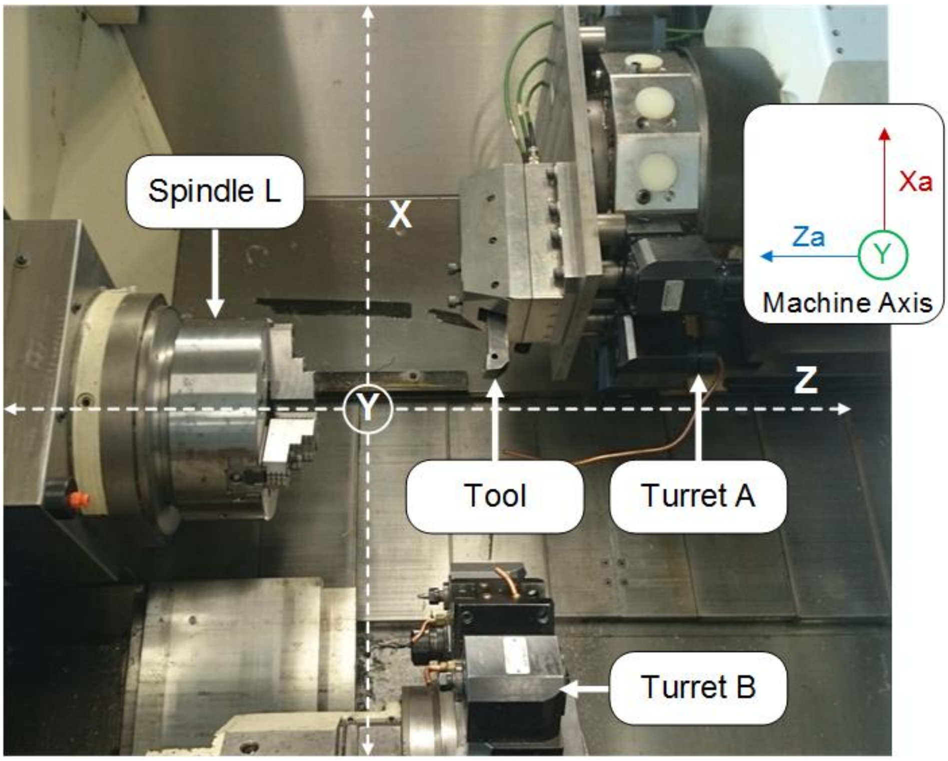


Figure 4.1 OKUMA LT15-M CNC turning lathe, axis reference

Spindles	2	X-Axis – Feedrate	0.001 to 1000 mm/rev
Tool Turrets	2	X-Axis – Feedrate - Rapid	20000 mm/min
Controlled Axis	7	X-Axis – Motor	4 kW (Xa) 3.7 kW (Xb)
No. Tools per Turret	12	Z-Axis – Feedrate	0.001 to 1000 mm/rev
Max turning diameter and length	210 x 200 mm	Z-Axis – Feedrate - Rapid	24000 mm/min
Max bar diameter	62 mm	Z-Axis – Motor	4 kW (Za, Zb, Zc)
Spindle speed	100 to 4500 rpm	Turret Indexing Motor	4.3 kW
Machine Size	3660 x 2020 mm	Spindle Power	VAC 11/15 kW

Table 4.1 OKUMA LT15-M CNC turning lathe, specifications

The CNC turning machine tool in this work was the OKUMA LT15-M, as seen in Figure 4.1, and detailed in Table 4.1. OKUMA machines operate in the aerospace, automotive, construction, oil and gas, biomedical, die and mold and wheel manufacturing areas [184]. The OKUMA LT15-M is an industrial machine tool, and provides a real representation of a manufacturing environment.

4.2.2 Tooling and materials

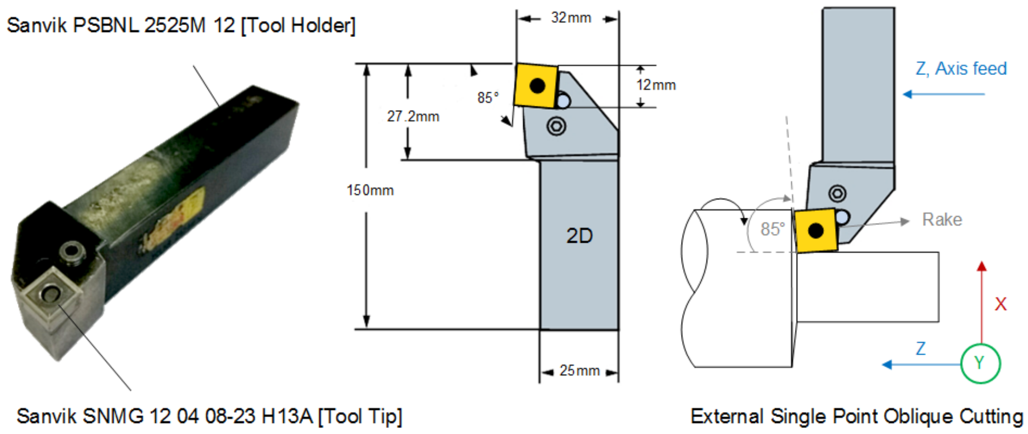


Figure 4.2 Sanvik tool tip and tool holder

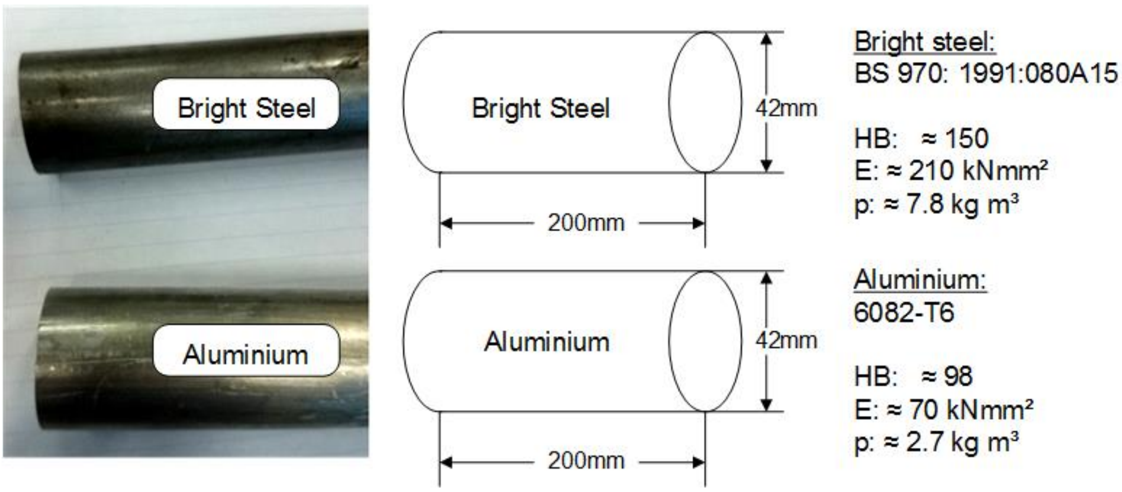


Figure 4.3 Workpieces

Oblique cutting was carried out using a Sanvik PSBNL 2525M12 tool holder and a Sanvik SNMG 12 04 08-23 H13A cutting tool tip, as seen in Figure 4.2. The workpiece material selected for testing was Steel BS 080A15 and Aluminium 6082T6. Both materials are commonly used for general machining purposes, and are suitable for machining. Dimensions of the workpieces and key material properties are illustrated in Figure 4.3.

4.2.3 Sensing systems: force, vibration, motor current

The machining variables selected for monitoring identify both cutting tool state, and the material removal process conditions; Force, Vibration, and Motor Current.

- Force is selected due to its wide utilisation in CNC turning, and dependency on the cutting process. Force is unique in this way as it is not influenced by other sources.
- Vibration is selected also due to its wide utilisation in CNC turning, and because it is reactive to both the cutting process and machine tool actions.
- Motor current was selected due to its direct relationship with the machine tool movements. Previous examples of motor current measurement in CNC turning, reviewed in the literature, focused on spindle monitoring. However electrical current drives the entire machine tool. Motor current is an active variable for machining operation, and a reactive variable due to its direct relationship with the cutting force. Subsequently motor current will be utilised to monitor the machine tools active operation, independently of the cutting process.

Sensors

<u>Force</u>

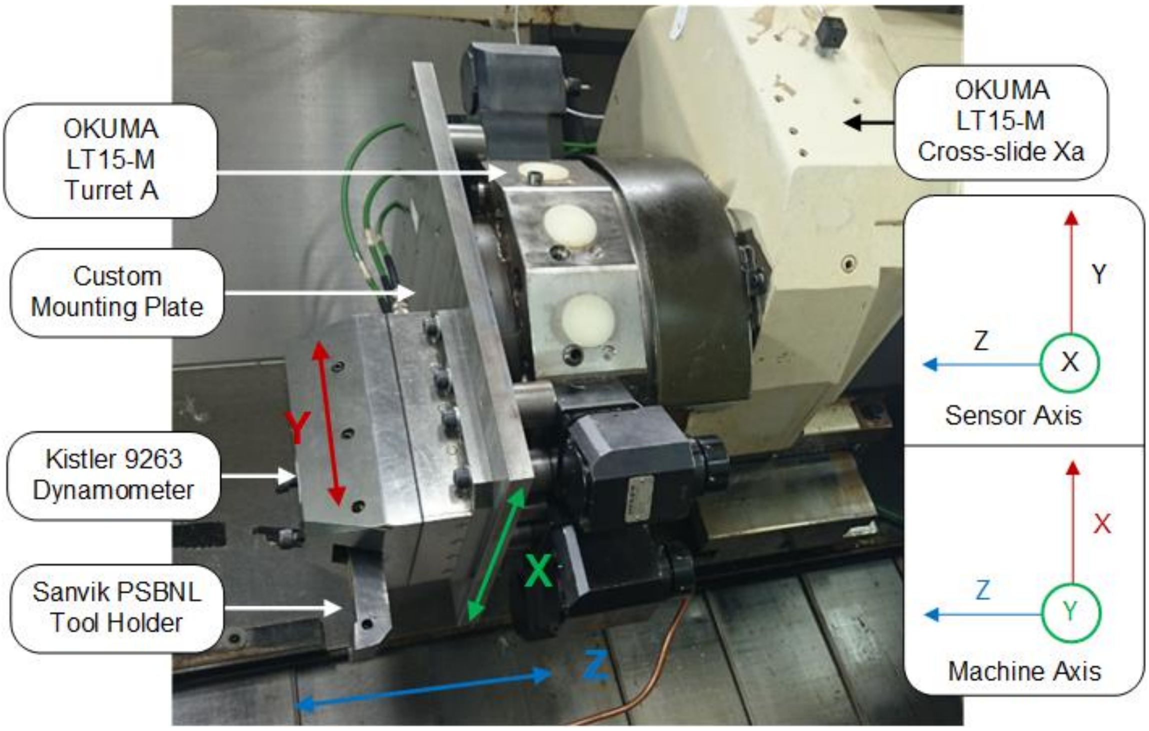


Figure 4.4 Kistler 9263 dynamometer mounting

Force measurement was achieved with a triaxial Kistler 9263 dynamometer. The dynamometer was mounted to a custom mounting plate, secured to turret A, and provided tool holder clamping, as seen in Figure 4.4. The dynamometer connected to a Kistler charge amplifier 5038A, a NI-9234 analogue input module, and a NI cDAQ 9191 WIFI data acquisition chassis. This setup enabled force on the X, Y, Z axis of the cutting tool to be measured.

Vibration

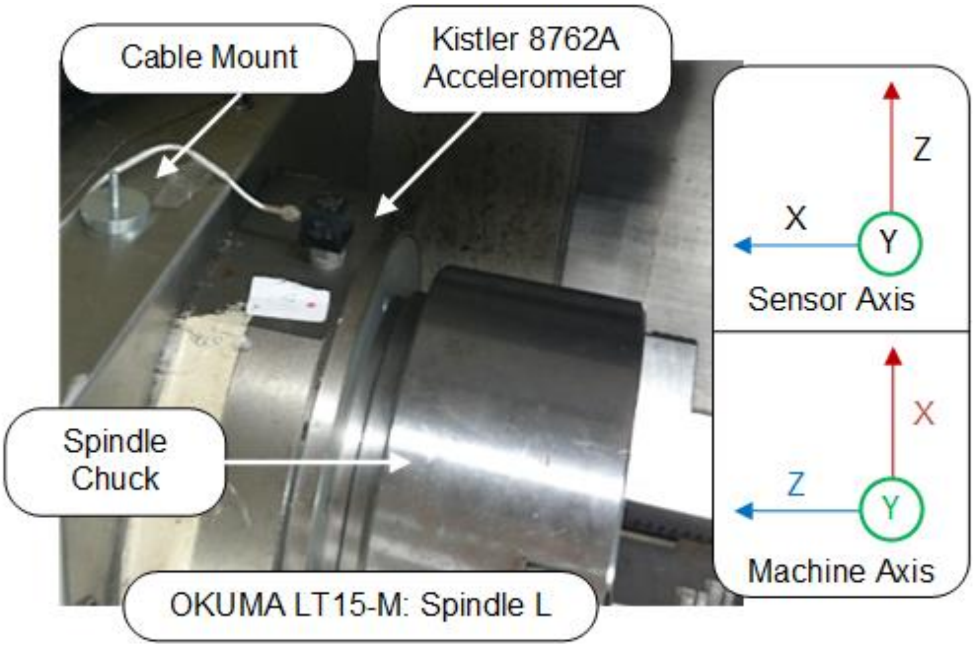


Figure 4.5 Kistler 8762A accelerometers, magnetic mounting A

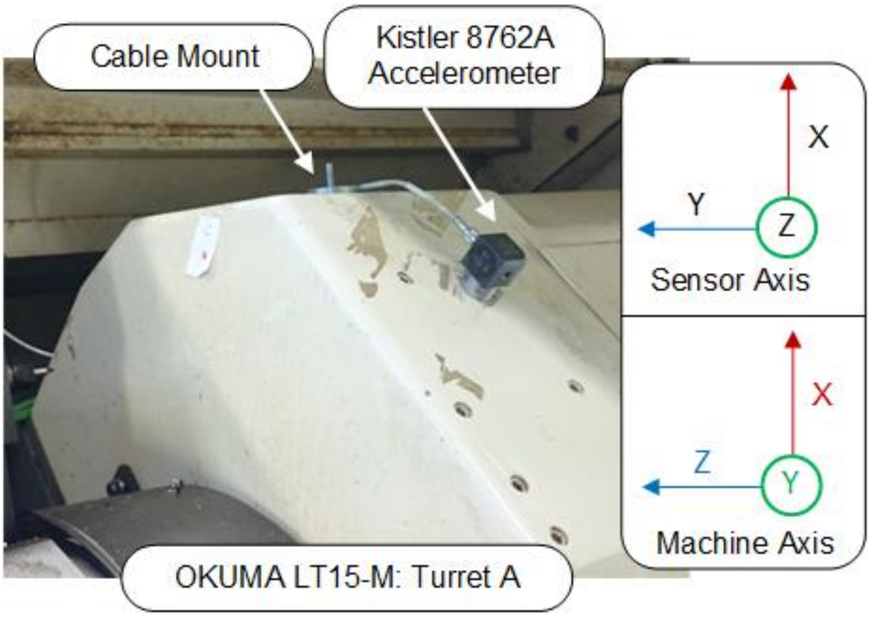


Figure 4.6 Kistler 8762A accelerometers, magnetic mounting B

Vibration measurement was achieved with two triaxial Kistler 8762A accelerometers. Accelerometer A, is magnetically mounted to the spindle, as seen in Figure 4.5. Accelerometer B, is magnetically mounted to the turret-A cross-slide, as seen in Figure 4.6. The accelerometers are connected to separate NI-9234 analogue input modules, and a NI-cDAQ 9191 Ethernet, and NI-cDAQ 9171 USB data acquisition chassis. Accelerometer B is mounted away from the tool, as the experiment is aimed at monitoring real manufacturing process conditions. Subsequently the accelerometer cannot be placed on the turret, mounting plate, or tool, because the wired connectivity of Kistler 8762A accelerometer. This wire would interfere with machine actions when the turret rotates. Subsequently Accelerometer B will explore the effects of vibration monitoring in a process as it is dispersed throughout a physical structure.

Motor current

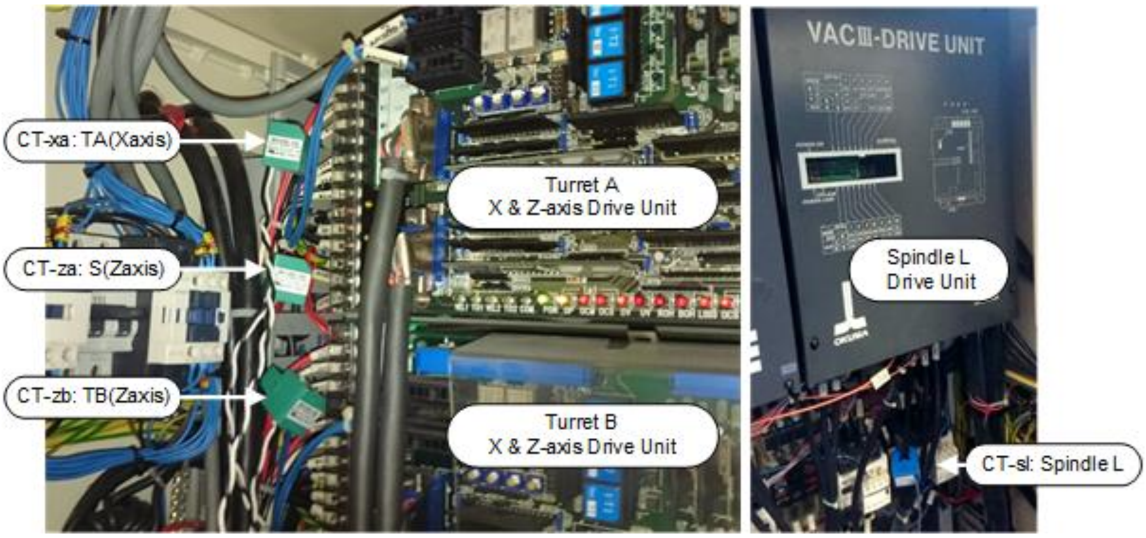


Figure 4.7 Magnelab SCT-0400-050 current transformer wire connection

Current measurement was achieved with four Magnelab SCT-0400-050, 50amp Current Transformers (CT). The current transformers are clipped around different motor winding wires in the LT15-M; spindle A, turret A x-axis, Spindle L z-axis, and turret B z-axis, as seen in Figure 4.7. The current transformers are connected to a singular NI-9239 analogue input module, and a NI-cDAQ 9178 USB data acquisition chassis. The current transformers enable AC to be measured on 1/3 motor phase connections, of each motor.

Axis

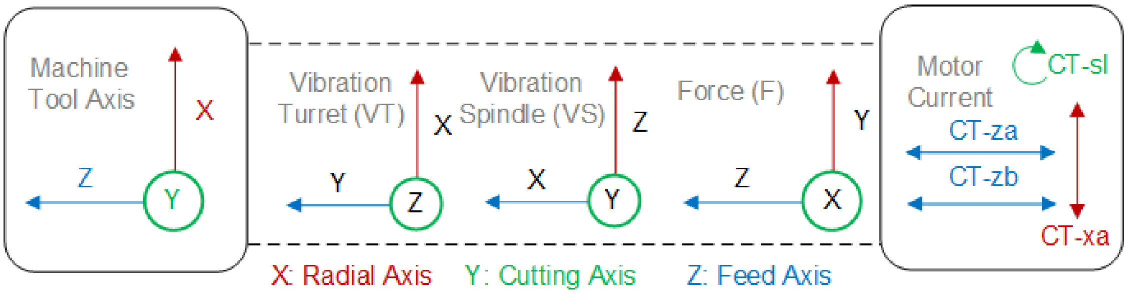


Figure 4.8 Axis reference

Each sensor is connected to CNC machine in different ways. The CNC machine has a set axis coordinate system. Each of these sensors has sensing capabilities in different axis. The cross-reference of sensor axis with machine axis can be seen in Figure 4.8.

Scale

The cross-reference of sensor sensitivity, scale, and acquisition rate can be observed in Table 4.2. A total of 13 data streams will be acquired, varying from 3kHz to 12kHz sampling rates, with a combined 102kHz sample rate, which is 829.668 kB or 6.637 Mbps. Scaling was determined through the combination of recommended settings specified to each sensor, and sensory calibration results, which are represented in Appendix B: datasheets.

Variable List:

No.	Sensor	Unit	Variable	Range	Sensitivity	Scale	Scale	Sample Rate
1	Kistler 8762A: Accelerometer A (Spindle)	Vibration (G)	X-Axis	+/- 5 g	1000 g	1000 mV/1 g	1	12kHz
2			Y-Axis	+/- 5 g	1000 g	1000 mV/1 g	1	12kHz
3			Z-Axis	+/- 5 g	1000 g	1000 mV/1 g	1	12kHz
4	Kistler 8762A: Accelerometer B (Turret)	Vibration (G)	X-Axis	+/- 5 g	1000 g	1000 mV/1 g	1	12kHz
5			Y-Axis	+/- 5 g	1000 g	1000 mV/1 g	1	12kHz
6			Z-Axis	+/- 5 g	1000 g	1000 mV/1 g	1	12kHz
7	Kistler 9263: Dynamometer (Tool)	Force (N)	X-Axis	+/- 10 kN	0.01 N	0.334 V/200N	0.00167	6kHz
8			Y-Axis	+/- 10 kN	0.01 N	0.334 V/200N	0.00167	6kHz
9			Z-Axis	0.....20 kN	0.01 N	0.334 V/200N	0.00167	6kHz
10	Magnelab SCT-0400-050: Current Transformers	Motor Current (A)	1-Xa-Axis	50 Amp	1000 Hz	0.01 V/1 Amp	100	3kHz
11			2-Za-Axis	50 Amp	1000 Hz	0.01 V/1 Amp	100	3kHz
12			3-Zb-Axis	50 Amp	1000 Hz	0.01 V/1 Amp	100	3kHz
13			4-sl	50 Amp	1000 Hz	0.01 V/1 Amp	100	3kHz

Table 4.2 Data variable reference

4.3 Cloud data acquisition

4.3.1 Prologue

Each sensor was connected to a data acquisition hardware device, which was connected to a micro-computer via a communication medium, e.g. USB, Ethernet TCP, or WIFI, as seen in Figure 4.9. These devices provided the physical measurement, and initial digital process variable measurement. The ARC acquisition-Adaptors utilised a unique hardware API to acquire data from these devices.

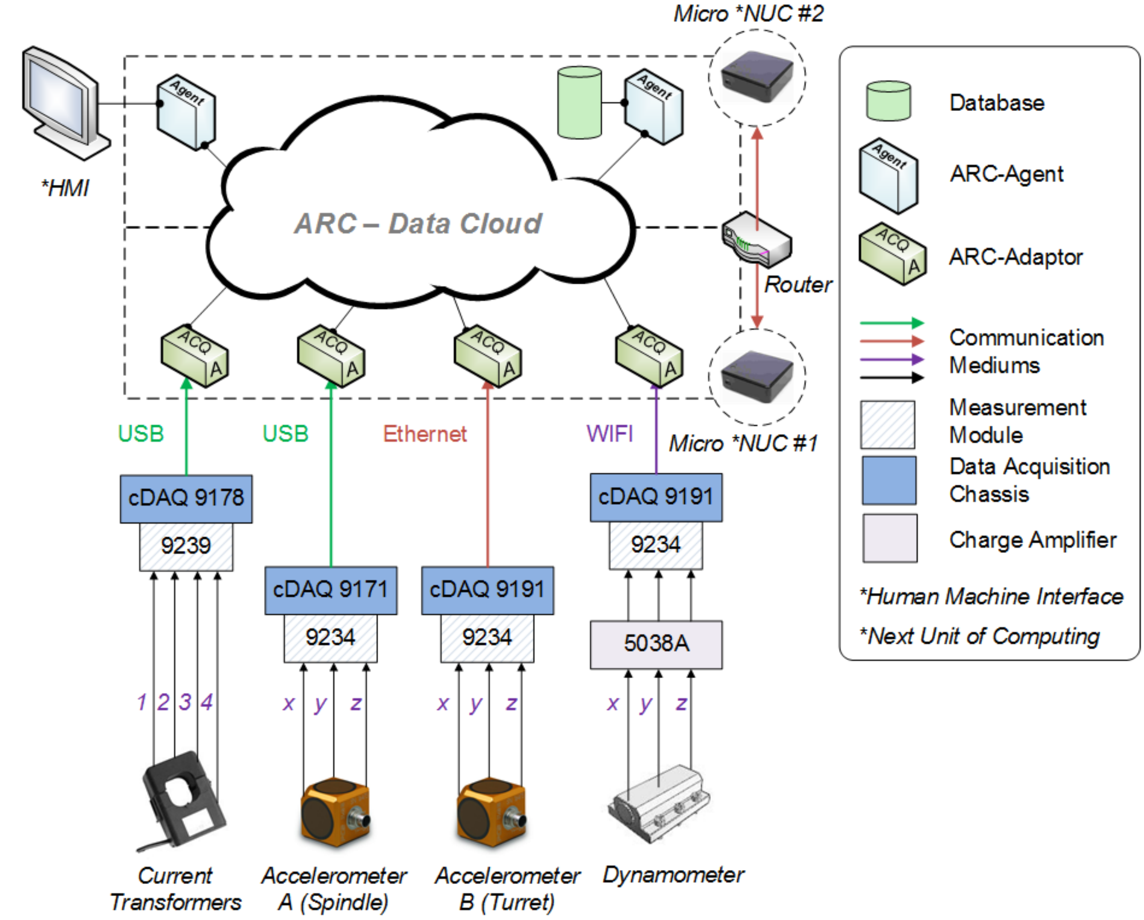


Figure 4.9 OKUMA LT15-M sensor monitoring topology

In order to achieve high speed and high data capacity data acquisition, an ARC software Adaptor was created for each data acquisition device. Data is acquired by the software Adaptor, formatted or serialised to meet the Binary Message Model (BMM), and published to the SVE data cloud, as illustrated in Figure 4.10. The SVE data cloud hosts the data and distributes it to subscribing client/Agent software applications, on Micro-computer #2. These applications can subscribe to the data in the cloud by referencing the shared variable address, as seen in Table 4.3. The data acquired is then de-serialised according to the BMM, and the required data stream in the message can be referenced via the sv-index number. The accelerometers and the force variables are represented by individual shared variables, due to their high data stream sizes. The current variables are represented by a collective shared variable, due to their lower data stream size.

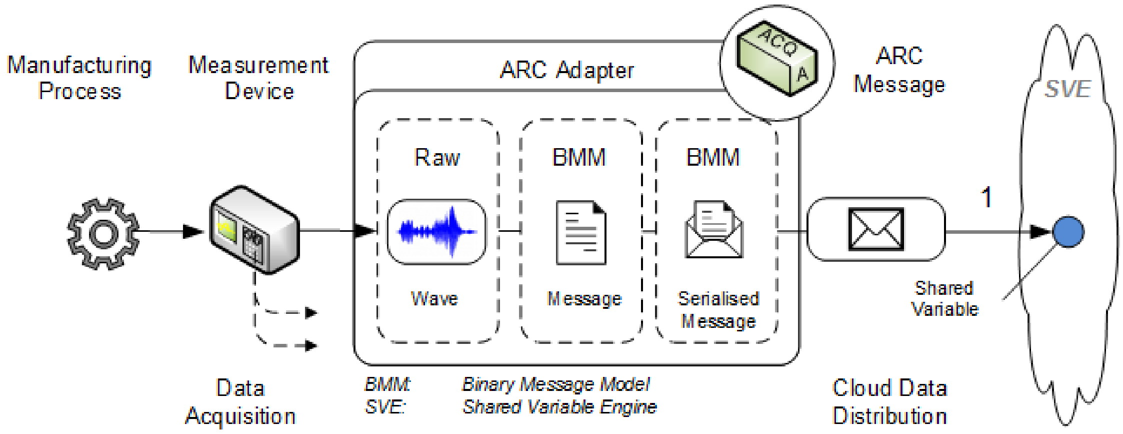


Figure 4.10 ARC acquisition-Adaptor schematic

Variable Connect

No.	Sensor	Variable	Module	DAQ	SV-Library	SV-Name	SV-Index
1	Kistler 8762A: Accelerometer A (Spindle)	X-Axis	Analogue 9234	cDAQ9191	AccelSpindle	01	0
2		Y-Axis				02	0
3		Z-Axis				03	0
4	Kistler 8762A: Accelerometer B (Turret)	X-Axis	Analogue 9234	cDAQ9191	AccelTurret	01	0
5		Y-Axis				02	0
6		Z-Axis				03	0
7	Kistler 9263: Dynamometer (Tool)	X-Axis	Analogue 9234	cDAQ9171	Force	01	0
8		Y-Axis				02	0
9		Z-Axis				03	0
10	Magnelab SCT-0400-050: Current Transformers	1-Xa-Axis	Analogue 9239	cDAQ9178	Current	Bus	0
11		2-Za-Axis					1
12		3-Zb-Axis					2
13		4-sl					3

Table 4.3 Data acquisition variable reference

Two client applications are utilised; a viewing-Agent to display the data to the user, and a database-Agent to store the data streams for post process analysis. These applications incorporate the same operating principles, as seen in Figure 4.11. Each applications unique operation is represented by a custom programming function, positioned at the end of the acquisition process. This structure acts as a default programming template, ensuring effective and efficient dynamic data acquisition of multiple process variables. This is made possible through the use of asynchronous programming.

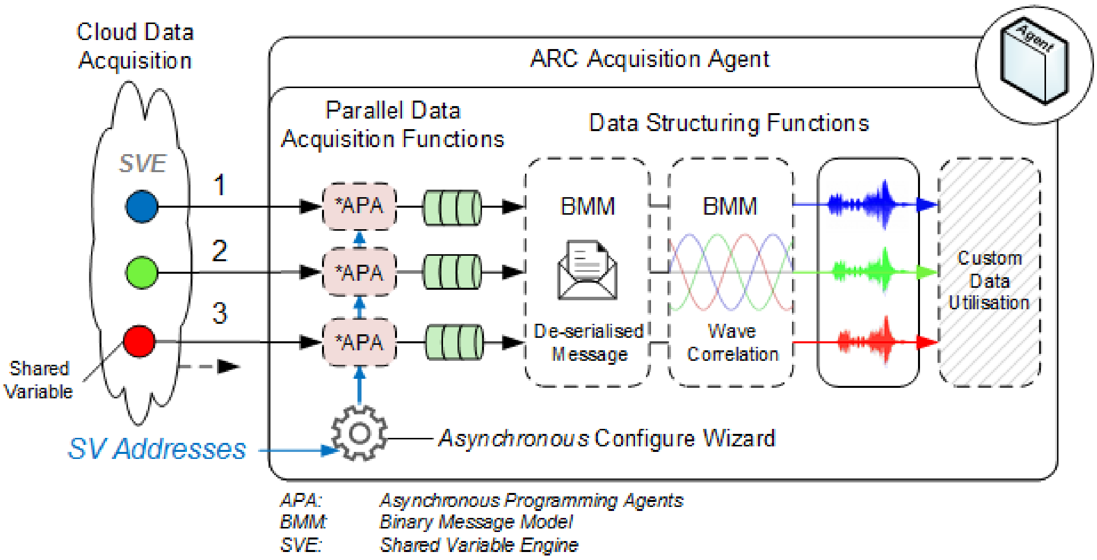


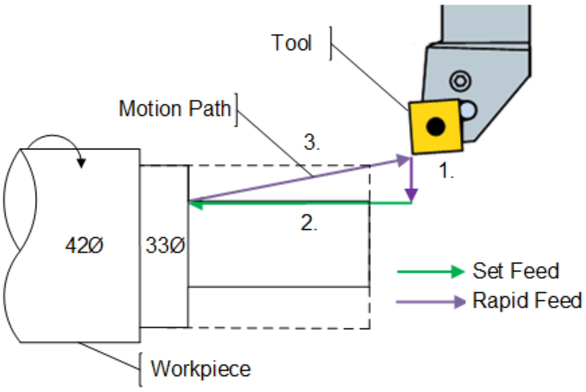
Figure 4.11 ARC Agent schematic

Asynchronous programming allows for a single primary-computation program to generate multiple sub-computation programs, which are detached from the original program. This separation allows the sub-programs to operate freely and communicate to other programs via internal communication streams. In an ARC Agent, the Asynchronous Programming Agents (APA) perform the data acquisition task from each shared variable. Asynchronous programming is imperative to this operation, as each shared variable can be from a different source, meaning their data is being transmitted at different rates. The high data sizes and throughput requirements in manufacturing process monitoring systems, means delays can cause communication bottlenecks. These bottlenecks create large data buffering queues that will lead to high computation periods, data lose, and fundamental software crashes. Bottlenecks must be avoided at all cost. If the ARC is to be used in an industrial setting, it must be resilient. Through asynchronous programming this problem can be overcome, as each shared variable has its own thread of computation, free from delay from other sources. This dedicated action ensures data cannot bottleneck within the parameters of available computation in the hardware. Additionally since asynchronous programming allows for multitudes of sub-programs to be generated, the ARC Agent is free to acquire limitless amounts of shared-variables.

4.3.2 Machining data acquisition

Operation

In order to examine the process data via the ARC, a fundamental roughing cycle machining operation was selected, as illustrated in Figure 4.12. This operation is common in turning roughing cycles to quickly remove large quantities of material from the workpiece. The machining parameters present in Figure 4.12, represent the convergence of the recommended tool machining parameters, referenced in Appendix B.4: machine tools, and OKUMA operating capability, referenced in Table 4.1. Dry cutting was selected due to the low ingress protection rating of the sensors. The workpiece is pre-machined to reduce the diameter from 42mm to 33mm, ensuring a concentric workpiece for testing. The cutting operation incorporates 3 cutting cycles, which will cut at different feed rates. This will allow for the comparative view of different cutting speeds on the process variables for analysis, for this initial phase 1 investigation.



Machining Parameters

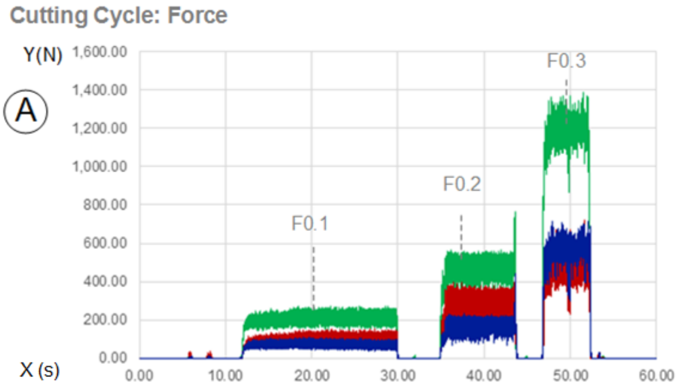
Mode	Constant Surface speed
Cutting Speed	100 m/min
Feed	0.1, 0.2. 0.3 mm/rev
Depth of cut	1 mm
Length of cut	30 mm
Cycles	3
Coolant	None

Other

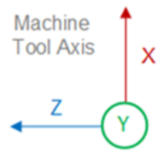
Workpiece machining length	100mm
Tool Length	40mm
Workpiece material	Aluminium, Steel

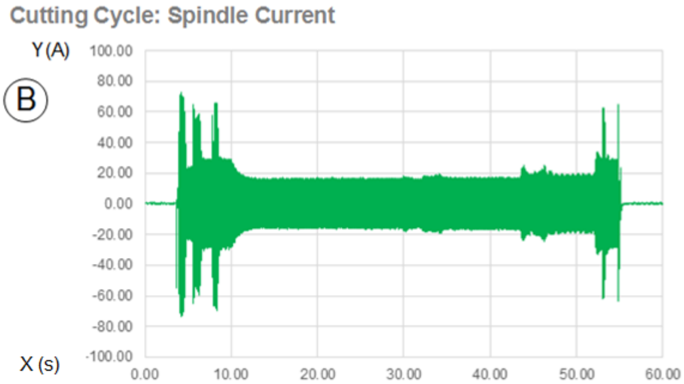
Figure 4.12 Tool canned cycle motion

Results

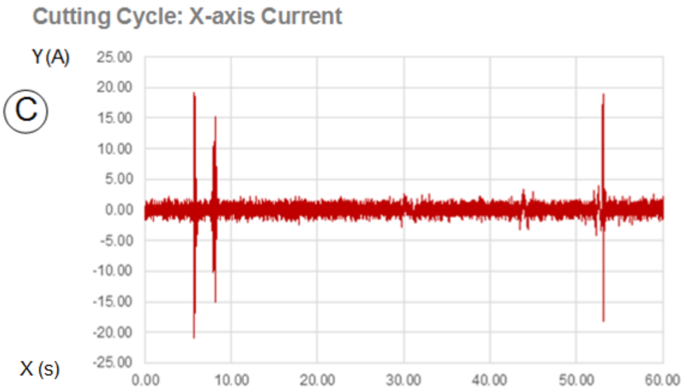


Axis	Type	Scale	Data Count
X	Force	+x1	390'592
Y	Force	+x1	390'592
Z	Force	+x1	390'592

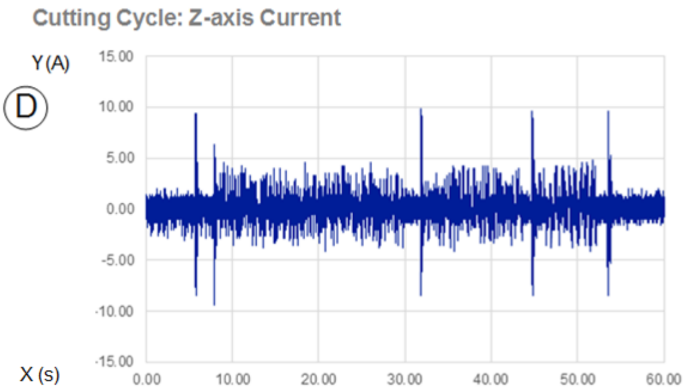




Axis	Type	Scale	Data Count
-	Spindle Current	+x1	182'987



Axis	Type	Scale	Data Count
X	axis Current	+x1	182'987



Axis	Type	Scale	Data Count
Z	axis Current	+x1	182'990

Figure 4.13 Cutting cycle varying feed steel machining results 1, A: x,y,z force, B: spindle current, C: x-axis current, D: z-axis current.

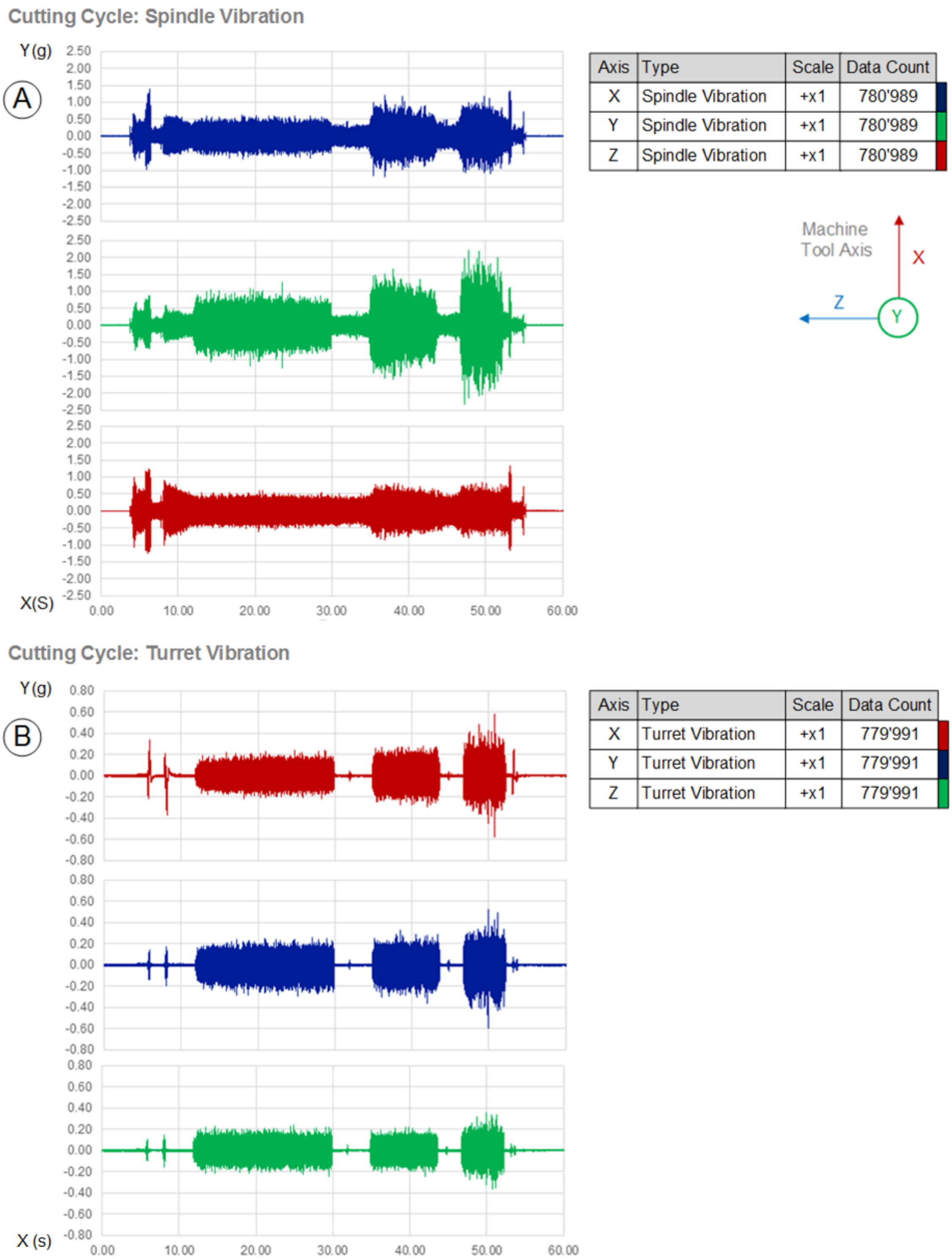


Figure 4.14 Cutting cycle varying feed steel machining results 2, A: x,y,z spindle vibration, B: x,y,z turret vibration.

The results of the cutting cycle with varying feeds for steel machining are presented in Figure 4.13, and Figure 4.14. This is the raw data acquired via the ARC, and stored in a database by the database-Agent.

The force data, as seen in Figure 4.13.A, identifies a clear machining reaction to the cutting operation, as varying feeds produce an increased force, as more material is removed in a shorter time frame. The primary of these forces is along the cutting Y-axis. The radial X-axis having marginally greater force than the feed Z-axis at F0.1 and F0.2. However feed Z-axis overtakes radial X-axis force during F0.3, as the required cutting speed reaches high cutting force levels above 1kN.

The spindle current, as seen in Figure 4.13.B, is a more complicated signal to process due to its alternating nature, reactive phenomenon, and variable operational speeds. A high inrush current is observable during process start-up, followed by multiple equal spikes in amplitude 2 seconds apart. These fluctuations are from the rapid acceleration of the spindle, initially through the process start, and variably from constant surface speed. The first acceleration is the set 160 RPM at +X 100 mm, which is the home position of the test, this is followed by a secondary acceleration as the tool is moved into its first cutting position 993 RPM at +X 32 mm. These fluctuations are followed by periods of constant acceleration, then exponential signal decay as the spindle approaches the desired speed, followed by a steady state signal to maintain the current speed. In the current unprocessed state cutting influences on the spindle cannot be observed. The only changes occur after the machining operation, from spindle acceleration and deceleration as the position of the tool changes. Finally a large spike in current can be seen during the switching off of the spindle at the end of the process. This occurrence is placed with back EMF as the energy leaves the magnetic field of the motor.

The axis current data, as seen in Figure 4.13.A/B is influenced by a base band of noise, within the <=1A, which is the minimum sensitivity of the sensor. Further signal processing may reduce this noise effect and strengthen the underline current readings. In the raw state the axis current data identifies rapid movements of the axis with large current fluctuations, movements of the feed Z-axis, and minor movements in the X-axis.

The vibration data, as seen in Figure 4.14, is highly dense due to the large data sampling rate of 12kHz. Spindle vibration varies significantly due to the acceleration of the spindle. Different spindle vibration axis identify varying magnitudes of reaction to the cutting process, which is similar to the force data. However spindle vibration is more reactive to sources other than the cutting process, as the radial X-axis shows significant signal magnitude reaction to spindle speed. A significant scale difference, of x5, can be seen in signal magnitude between the spindle and turret vibration. This is due to the location of the vibration sensors. The spindle accelerometer is located directly above the source of vibration, while the Turret accelerometer is positioned away from the tool tip, which is the dominate vibration source. However both the sources show a clear reaction to machining, with varying magnitude intensities at different feed rates, and signal fluctuations from rapid axis movements.

4.3.3 Conclusion

The ARC's high speed and high capacity interoperability, enabled the dynamic acquisition and correlation of field-level manufacturing data. Data is freely available to any subscribing software application. Data sources are replicated in the data cloud to meet the demand of multiple users. Additionally the data correlation provided a multi-dimensional view of a machines operation, which was comparable to varying modes of operation. The data produced within this phase 1 investigation can now be utilised for the development of the signal processing and analysis elements, which form the reconfigurable process monitoring system.

4.4 Cloud signal processing

4.4.1 Prologue

In order to further analyse the process, the next step in a manufacturing process monitoring system needs to be applied, i.e. signal processing. The integration of signal processing techniques within a decentralised architecture identifies a transition from a cloud-based data acquisition tool, to an ideology of decentralised collaborative cyber-physical systems. The migration of signal processing techniques into a dynamic cloud environment possesses many challenges, including; dynamic data acquisition and distribution, high computational requirements, multiple signal processing types, and customised filtering configuration sets.

Previously, the ARC Agent identified a means to dynamically acquire multiple streams of data for utilisation. However this data was consumed by the application and not redistributed. Redistribution of data identifies a transition from cloud monitoring to cyber-physical system collaboration. The data processing application is now providing its operation as a service, acting as a mechanism, or Holon, in a collaborative system, or Holarchy. In signal processing, this incorporates the dynamic signal feature extraction and subsequent distribution of process data. This enables a new resource in the collective, as process data is refined and available extensively.

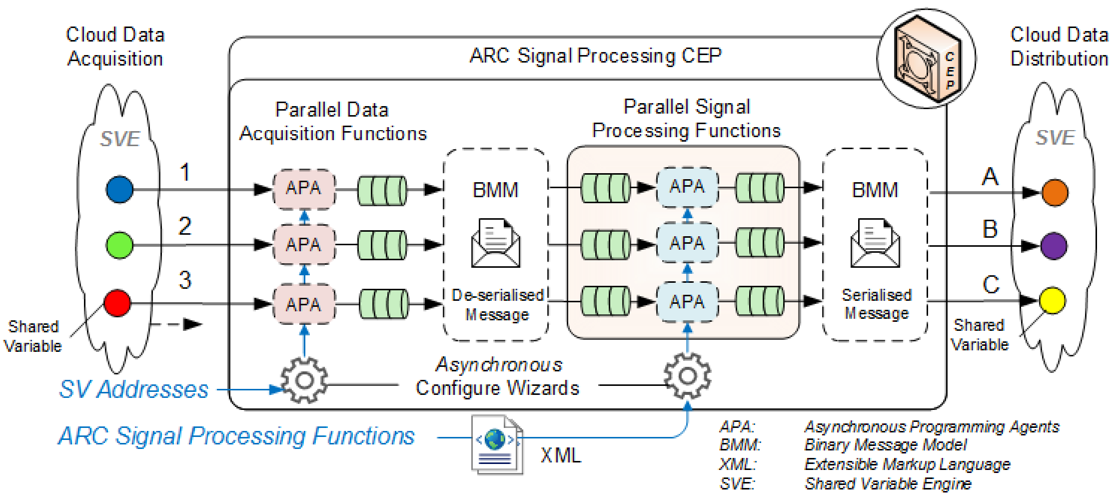


Figure 4.15 ARC signal-processing-CEP schematic

By combining both the ARC Agent and ARC Adaptor, a means for dynamic data acquisition and distribution can be formed, i.e. Complex Event Processing (CEP), as seen in Figure 4.15. Similarly to the ARC Agent, SV addresses are defined to acquire the specific process variables through an asynchronous configure wizard. The wizard generates APAs to rapidly acquire data from the cloud. The raw data is collectively deserialised from its binary representation into the BMM. After which signal processing can begin, followed by a collective data serialisation and transmission back to the SVE.

Signal processing incorporates multiple techniques with varying attributes that enable the extraction and suppression of signal attributes. Additionally the utilisation of multiple signal processing techniques in series is common practice to refine and 'filter' a signal in different ways. Subsequently the configuration and orientation of these functions can alter the outputted signal drastically. Experimentation is required to produce the desired signal feature. A flexible mechanism needs to be created to achieve this in an efficient, effective, and timely manner, which also maintains the internal and external configuration of the signal processing technique.

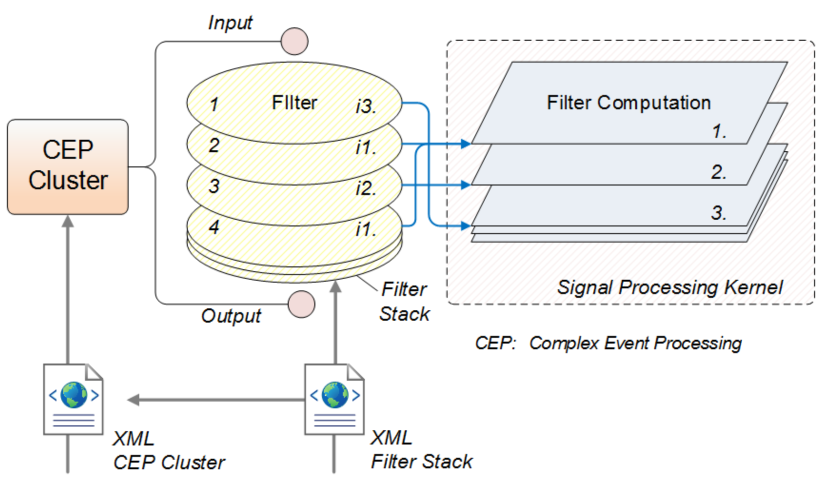


Figure 4.16 ARC reconfigurable signal processing mechanism

The reconfigurable signal processing mechanism created, as illustrated Figure 4.16, incorporates the embedding of fundamental process monitoring techniques in a programming stack format, namely the Signal Processing Kernel (SPK). The SPK is hard-coded to perform the required computation for the specific signal processing technique. The internal configuration information to enable the custom operation of these techniques are held in data layers, namely 'Filter' layers. Furthermore the external configuration or sequencing/stacking of these Filters defines the sequence/length of signal processing undertaken. Data is processed in accordance to the filter stack, selecting the SPK layer required to perform the specific technique of each filter stack layer. Once data is processed through one filter it is passed to the next. In order to further control this operation, parameters need to be set to define the required input to the first filter layer, and the output address to the each/last filter layer. In order to achieve this, the filter stack is embedded into a CEP data cluster, which defines the input and output configuration data. Filters and CEP data clusters are represented by separate XML files. Filters are linked in the CEP data cluster via XML file addresses. Subsequently all data required for customised signal processing is dynamically loaded for utilisation.

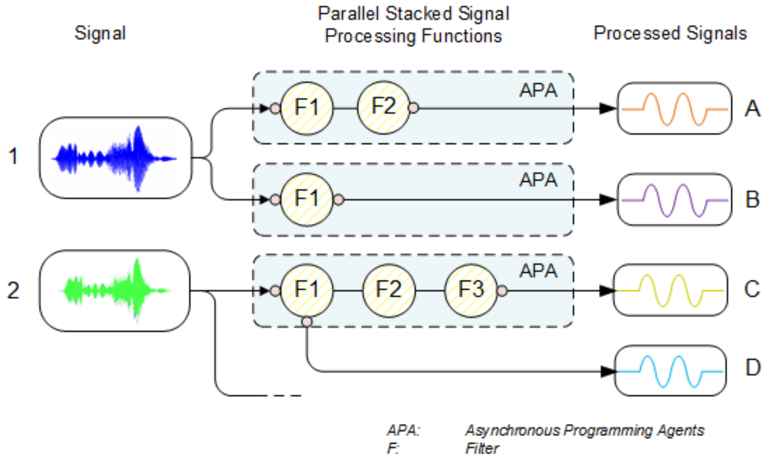


Figure 4.17 Dynamic signal processing

The utilisation of different signal processing types, with varying serial orientations, in connection with different data streams at different rates, causes varying computation requirements between signals. Additionally multiple signals in a process require processing. Subsequently the reconfigurable signal processing mechanism is embedded within an APA. Asynchronous programming will provide for effective and efficient computation of uniquely configured and stacked signal processing functions in parallel for multiple signal streams. The flow of data in the signal processing APA is defined by the CEP-cluster, and sequential orientation of the filter layers, as seen in Figure 4.17. The CEP-cluster identifies the data stream for processing into the initial filter layer. Additionally the CEP-cluster identifies which layers in the filter stack are outputted to SV for distribution. This enables a single signal to be subjected to different signal processing techniques, with parallel signal processing APAs. Additionally a single reconfigurable signal processing mechanism can provide multiple outputs, as a signal is processed at different layers.

The signal processing techniques embedded in the SPK include, but are not limited to; average, mode, standard deviation, variance, root mean square, skewness, kurtosis, rectifier, amplifier, bandpass filter, highpass filter, lowpass filter, cut-off-limit, scaling, etc. Additionally maths functions include, but are not limited to; addition, subtraction, absolute value, square root, squared, etc.

4.4.2 Machining signal processing evaluation

In order to examine the signal processing capability of the ARC signal-processing-CEP application, the process data acquired during the previous machining cutting cycle is examined. Specifically the z-axis motor current is examined, due to its multiple features. This was achieved through a virtual ARC software Adaptor that reads the process data from the database, and simulates the machining process by transmitting the data in real-time to the SVE. The ARC signal-processing-CEP application gains access to this data and processes it in real-time, exactly the same way it would process the data if machining was actively undertaken. All resulting filtered signals are recorded by an ARC database-Agent.

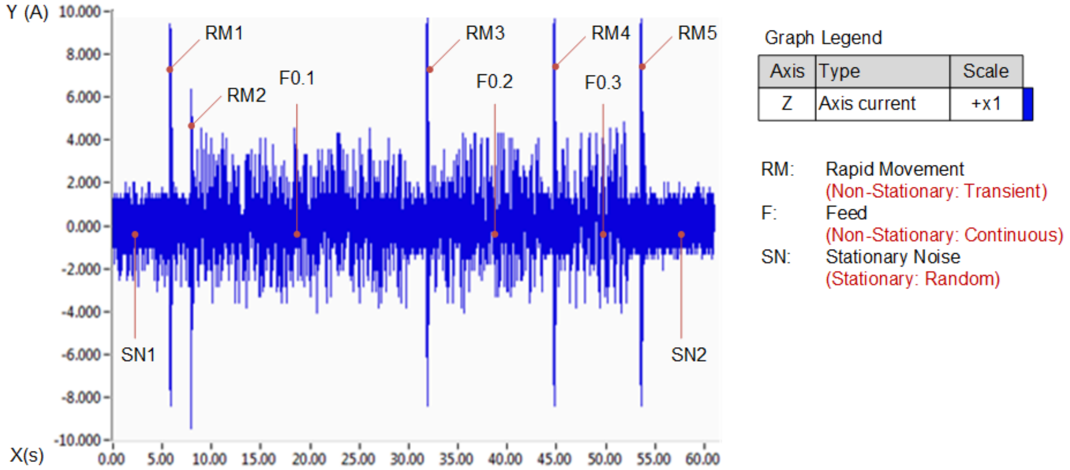


Figure 4.18 Signal processing Z-axis current: raw

The monitored Z-axis current consists of non-stationary continuous signals, due to its varying movement lengths and occurrences, varying speeds, and influences from cutting, as seen in Figure 4.18. A variety of Time-domain signal processing techniques can be utilised to extract the varying Z-axis movements of the tool. The configuration and sequence of these techniques has significant effects on the signal. In order to identify the most effective configuration and sequence, a signal needs to be evaluated.

Evaluation incorporates the utilisation of multiple signal processing techniques with different limits, in different sequences. This methodology provides a comparative signal responses, allowing for the most effective and efficient signal processing chain to be identified.

Signal processing window size

A common signal processing configuration setting is the size of the window for subjection to the technique, and whether or not the window is moving. Figure 4.19 provides a contrasting view of the effects of both of these characteristics.

Figure 4.19.A1/B1 identifies the varying window size of an averaging function across a rapid movement/feed movement, with a 'stationary' window. In order to perform the averaging technique, the window must have the required amount of data, i.e. 'window size'. At capacity the averaging function will then be undertaken. After which, the window will be emptied and filled again. The larger the window size, the more data is being average, resulting in a greater reduction of signal samples per second, and an increase in signal delay. Increasing the window size can reduce the load on the signal, from a high data rate to a low data rate. This can allow for the enhancement of the signal B1, or the suppression of signal attributes A1. The A1 rapid movement is a high frequency transient signal. Small windows can enhance this feature, and large windows dilute the signal. Oppositely the B1 feed movement is a low frequency continuous signal. Large windows can enhance this feature, while small windows have less of an effect on signal noise. Ultimately the utilisation of different window sizes can have varying effects on the signal, and should be scaled depending on desired feature extraction requirements.

Figure 4.19.A2/B2 also identifies the varying window size of an averaging function across a rapid movement/feed movement, however with a 'moving' window. Similar to perform the averaging technique, the window must have the required amount of data. At capacity the averaging function will then be undertaken. After which the window will remove a single value, and acquire a new single value to perform its operation again. This resembles a First-In-First-Out (FIFO) approach to signal processing. The unique effects this operation has include; minimal decrease in signal samples per second, and a smoothing of data transitions. A2 and B2 both demonstrate this smoothening effect, as signal features are enhanced in both movement types without loss of the signals sampling rate.

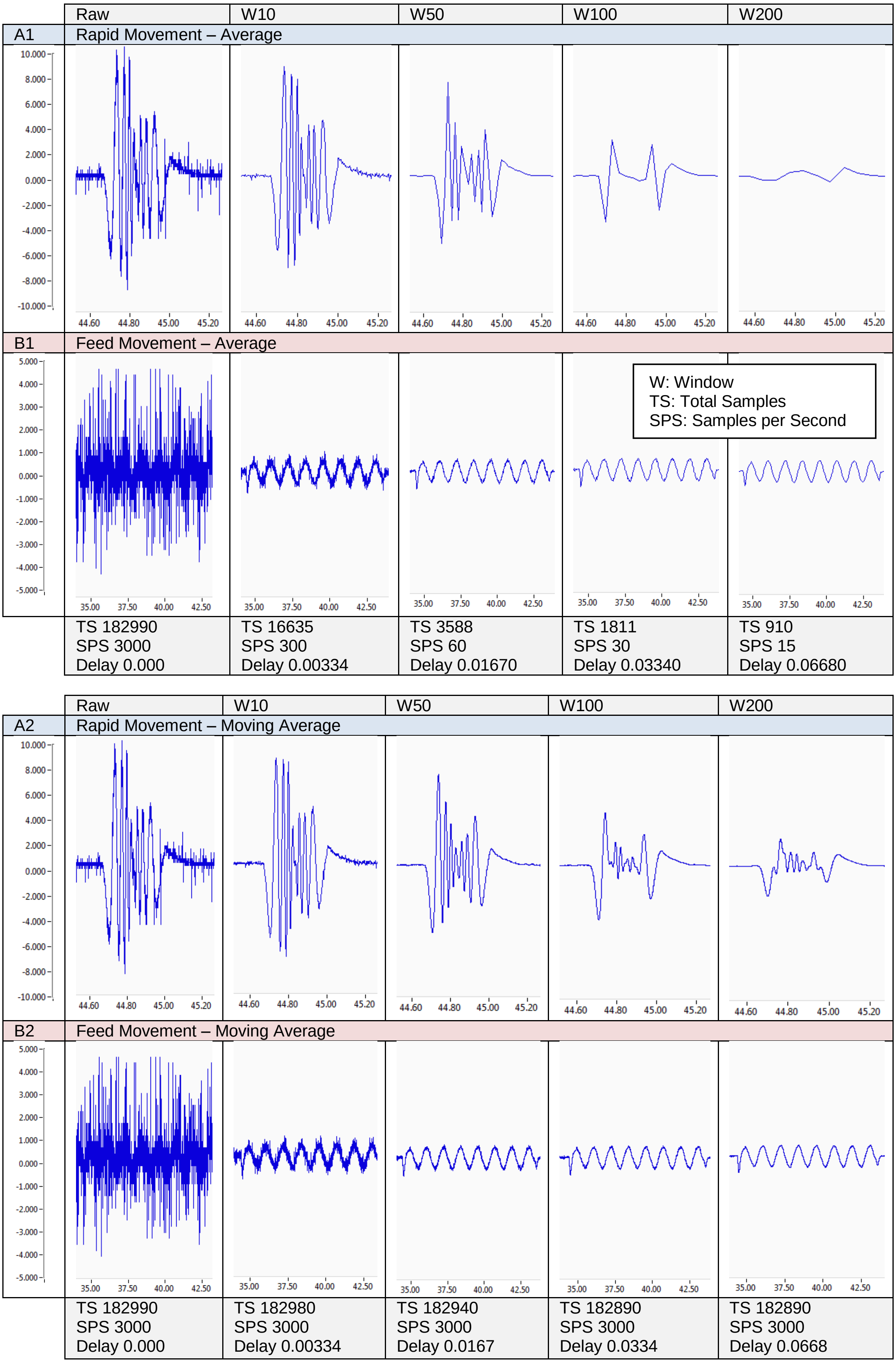


Figure 4.19 Signal processing averaging window size and mode variation

Figure 4.20.C1/D1 demonstrate the signal processing techniques of standard deviation / variance, with varying window sizes. The suppression of feed movement and enhancement of rapid movement can be achieved by varying the window size of either the standard deviation or variance. The larger window allows for more data to be utilised in the function, and a bigger scope of the process operation to be considered. This allows for the large variation present in rapid movements to be identified. Subsequently in this example, the required window size for rapid movement identification is achieved at W50, and further window extension has little effect.

Figure 4.20.E1 demonstrate the signal processing technique of RMS, with varying window sizes. RMS identifies the power in an alternating signal and the window size is imperative for effective utilisation. Small window sizes allow for the identification of high frequency signals, as the full magnitude of the alternating amplitude is measureable. In low frequency signals, the full magnitude of the amplitude is not measurable. A RMS is taken incrementally as the amplitude of the signal rises and falls, producing a semi-elliptical pattern. This pattern is formed from the iteration of the amplitude and inverting of the negative phase of the signal. Low frequency signals can be measured by increasing the window size. However the magnitude of transient signals are reduced due to dilution of the mean.

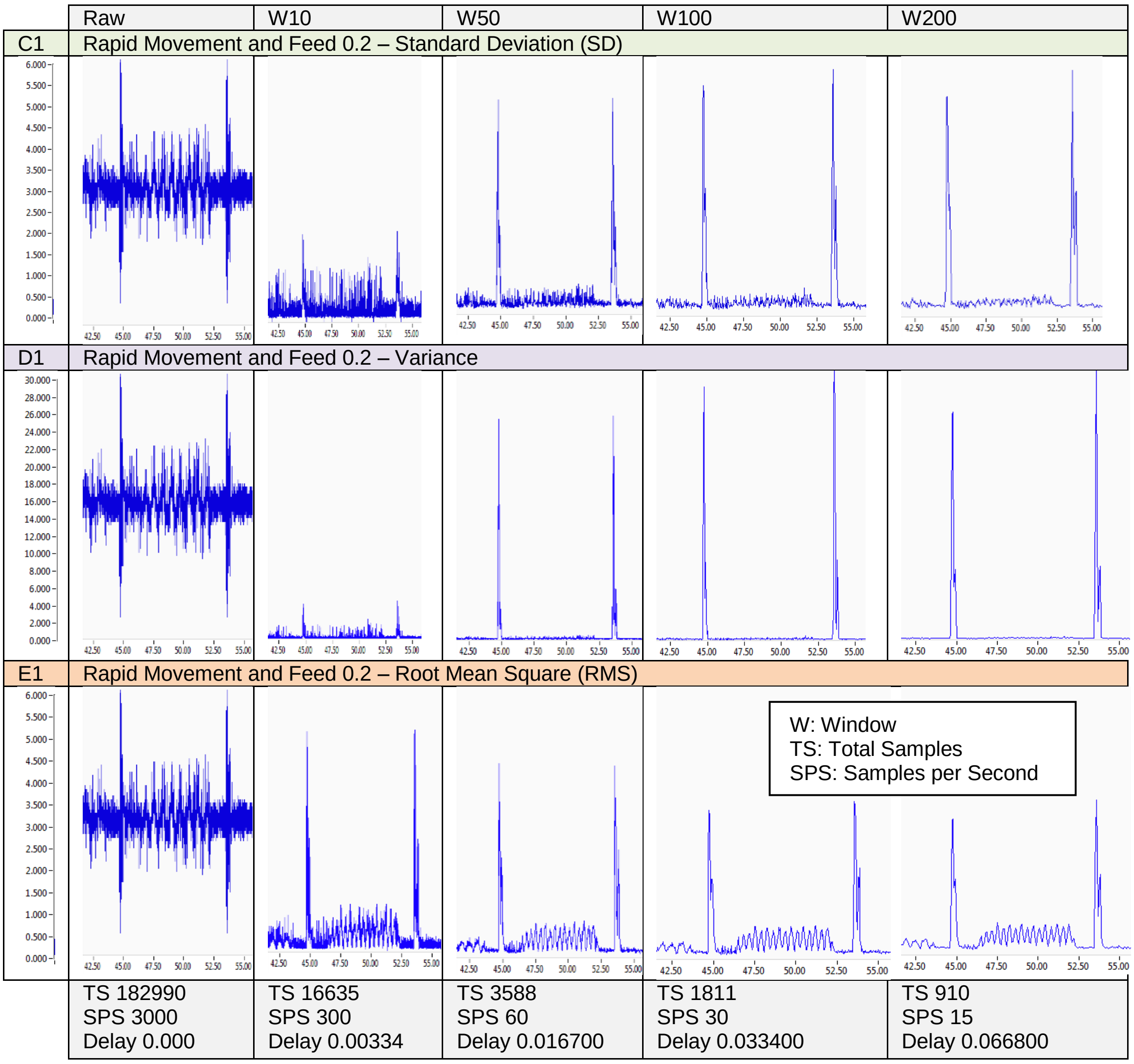


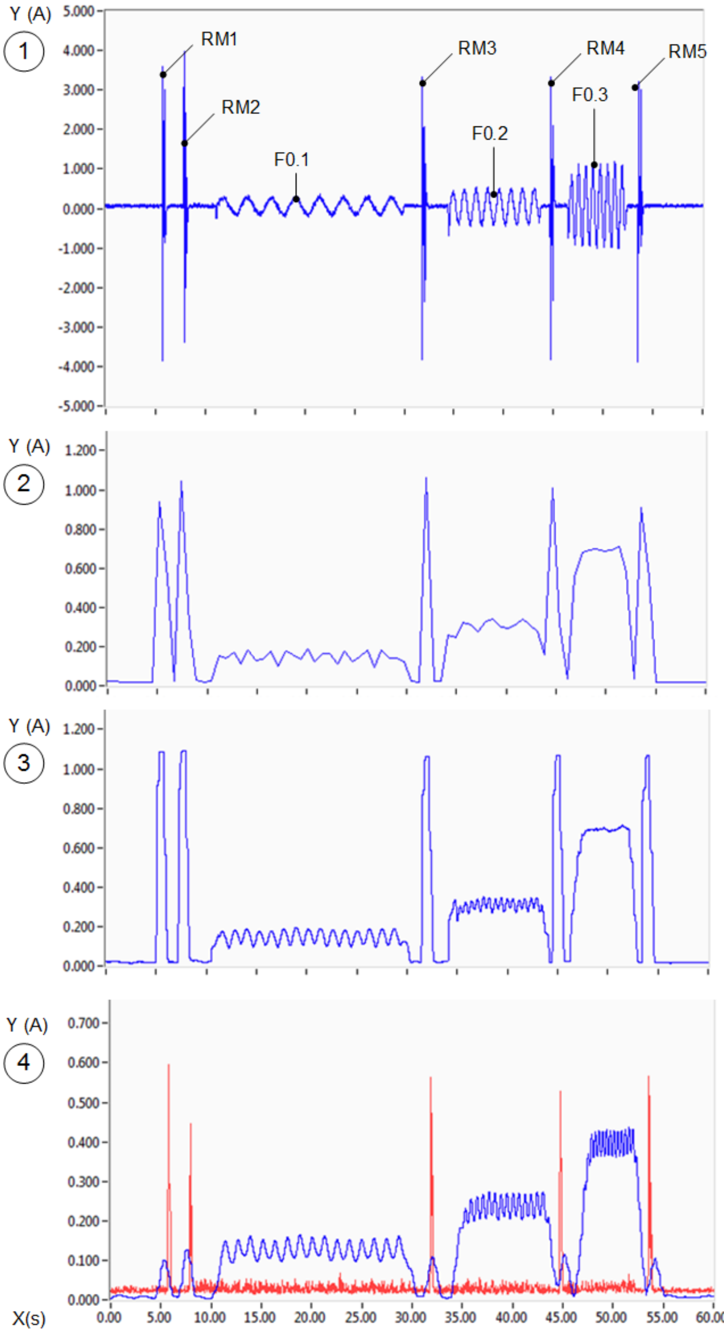
Figure 4.20 Signal processing techniques with varying window sizes

Signal processing sequencing

The sequencing of signal processing techniques can achieve the highest resolution of desired signal features. Pre-signal processing can enable a new signal processing technique to produce a more desirable response. Figure 4.21.1 identifies that the combination of both an average and moving average function can yield smooth signal features with a reduced sample load. In order to achieve this result the overall magnitude of the amplitude of the signal was reduced. However, this can be compensated for with a signal amplifier function if required. Further signal processing can now be undertaken with a refined Z-axis current signal.

Figure 4.21.2 identifies the incorporation of a RMS, to identify the power in the signal and convert the alternating current into direct current. The result display a clear distinction in amplitude at the different feed rates. However the resultant signal load is extremely low, at 1.5 samples per second. Additionally the RMS window size required to get a clear amplitude at different feeds, has begun merging operations, as feed and rapid movements converge due to the low signal load. In order to overcome this, a moving window is utilised in the RMS, ensuring a high resolution signal, while maintaining the required RMS window size to identify the feed and rapid movement features, as seen in Figure 4.21.3. The moving RMS identifies a separation in machining movements and produces a clear direct current response to axis movement. Subsequently, this sequence of signal processing is the most effective and efficient to measure the overall power in the z-axis movements of the CNC machine tool.

Figure 4.21.4 identifies the capability of signal processing to extract different features from the same signal, as rapid movements are suppressed in one signal and magnified in another. In order to achieve this, a unique sequence of averaging functions, with stationary and moving windows, is utilised to identify feed movements. The rapid movements are then extracted through a standard deviation function. These two signals can now be utilised by analysis tools for the correlation of data to different machining operations.



Graph Legend

Axis	Type	Scale	RF
Z	Axis current	+x1	1.1

RM: Rapid Movement
F: Feed

Graph Legend

Axis	Type	Scale	RF
Z	Axis current	+x1	1.2

Graph Legend

Axis	Type	Scale	RF
Z	Axis current	+x1	1.3

Graph Legend

Axis	Type	Scale	RF
Z	Feed Movement	+x1	1.4
Z	Rapid Movement	-x10	1.5

RF: Reference Filter
TS: Total Samples
SPS: Samples per second
Avg: Average
RMS: Root Mean Square

Signal Processing Legend

FR	Layer 1	Layer 2	Layer 3	Layer 4	SPS	Delay
1.1	Avg(10)	Avg(M10)	-	-	300	0.036
1.2	Avg(10)	Avg(M10)	RMS(200)	-	1.5	0.708
1.3	Avg(10)	Avg(M10)	RMS(M200)	-	300	0.708
1.4	Avg(10)	Avg(M100)	Rectifier(1)	Avg(M250)	300	1.209
1.5	SD(100)				30	0.0334

Filter Type (Window Size) [Info] (M100) = Moving Window, size 100

Figure 4.21 Signal processing sequencing and optimising

4.4.3 Conclusion

The internal and external re-configuration capability in the ARC signal-processing-CEP application, enables the dynamic custom signal processing of multiple manufacturing variables. Process data streams can now be manipulated on-the-fly within the soft-real-time capabilities of the architecture. The unique customisation of signal feature extraction is achieved through a signal processing evaluation, which does not require any programming knowledge. The manufacturing process monitoring environment is now open to not only multiple data sources, but open CEP services.

The manipulation of data streams through signal processing will further propagate varying acquisition rates and data types in the system. The ARC facilitates this operation due to the dynamic meta/data model, namely the BMM. The incorporation of processing monitoring signal processing functionalities with the ARC network forms the first step in manufacturing cyber-physical system collaboration. Data interoperability provides the capability for this collaboration, however the unique services built above it provides the desired intelligence to the process.

4.5 Cloud signal frequency analysis and processing

4.5.1 Prologue

In order to further analyse the process, more advanced signal processing features need to be applied. The integration of frequency domain analysis functions requires the integration of spectrum analysis. This functionality transforms a 1 dimensional wave into a 2 dimensional spectrum, which viewed overtime becomes a 3 dimensional spectra. This data structure is outside the scope of the BMM and subsequently cannot be utilised within a CEP to distribute the spectrum. However feature selection and transformation into 1 dimensional wave from the spectrum would allow for redistribution. Subsequently spectrum analysis is utilised for signal analysis and subsequent decision support in the ARC. Through spectrum analysis the signal processing of alternating signals can be evaluated, e.g. vibration. Furthermore, specific frequency bands can be identified and if required isolated through 'pass' filters that are present in the ARC signal-processing-CEP.

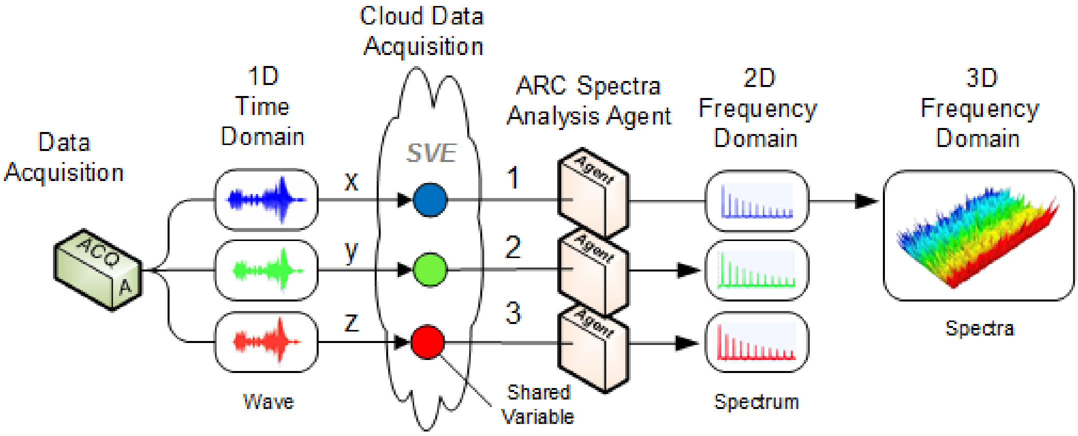


Figure 4.22 Cloud signal spectra analysis

In order to achieve spectrum analysis an ARC spectra-analysis-Agent was created. This Agent can only acquire a single shared variable, to perform amplitude or power spectrum analysis via a FFT. Single shared variable processing removes the complexity of previous Agents, as data correlation functions, and asynchronous program is not required. Single value processing further demonstrates the re-configurability within the ARC, as a single software application can be replicated multiple times and utilised in parallel to analyse different process variables, as seen in Figure 4.22. Through utilisation of these configuration options, a data stream can be analysed in a multitude of ways. Furthermore, the integration of these functions within the ARC, allows these functions to be applied to any data stream.

In order to perform spectrum analysis the following settings need to be defined:

(1) Type of spectrum required, i.e. amplitude spectrum or power spectrum
(2) Sensitivity frequency (Sf), what is the sensitivity of the sensor, e.g. 6kHz
(3) Nyquist frequency (Nf), what is the sampling rate, e.g. 12kHz/2 = 6kHz
(4) Window size (W), i.e. how much data to apply the FFT to, the size of the spectrum produced is half the window size, e.g. 12kS = 6kHz spectrals in a spectrum.
(5) Spectral density, whether to represent the each spectral band as the mean of its bandwidth
(6) Window type, what type of window should the data be in, i.e. rectangular, Hanning, etc.
(7) Multiple-In-Multiple-Out (MIMO), is the FFT a moving average with varied window size.

Amplitude and power spectra analysis provide a 3D frequency map of alternating signals. This enables a user to identify not only a change in amplitude/power, but also a change amongst the various frequencies contributing to the signal. This frequency map can enable the identification of process specific frequencies of interest that can be isolated for monitoring in real-time, without full spectrum evaluation. Isolation can be achieved through the utilisation of various ‘pass’ filters. These filters operate in real-time, across a range of sampling rates, and with high resolution capability.

The filtering types of high pass, low pass, band pass, and band stop, are Butterworth filters, and are embedded within the signal processing kernal of the ARC signal-processing-CEP. Butterworth was selected due to its wide application use within process monitoring. Furthermore other filtering techniques can be easily integrated within the SPK, but is currently outside the scope of this work.

In order to perform pass filtering the following settings need to be defined:

(1) Type of pass filter, i.e. low pass, high pass, band pass, and band stop
(2) Window size, i.e. how much data to apply the filter to
(3) Nyquist frequency (Nf), what is the sampling rate, e.g. 12kHz/2 = 6kHz
(4) Limits, what are the frequency limits of the filter,

e.g. band pass 1000 – 2000 Hz

(5) Order, identifies the level of attenuation at the frequency limits, the higher the order steeper the slope of power reduction at frequency limits.

By integrating these filters into the ARC signal-processing-CEP multiple pass filters can be utilised on the same signal to extract specific features, or on a variety of process variables dynamically.

4.5.2 Machining signal frequency analysis

In order to examine cloud-oriented signal frequency analysis, the process data acquired during the previous machining cutting cycle is examined. This was achieved through a virtual ARC software adaptor that reads the process data from the database, and simulates the machining process by transmitting the data in real-time to the SVE. The ARC spectra-analysis-Agent and signal-processing-CEP gain access to this data and process it in real-time, exactly the same way it would process the data if machining was actively undertaken. The spindle cutting Y-axis is subjected to spectra analysis as it is most reactive axis to the machining process. Subsequently this data stream can provide unique insight into machining operations.

Spectra analysis

The amplitude spectra and power spectra provide contrasting views of the machining processes, as seen in Figure 4.23. The amplitude spectra displays the changing amplitude of the various frequencies in the signal. This is achieved by estimating the amplitude by expanding the RMS value obtained, $\sqrt{2}$*RMS. The power spectra displays the changing power of the various frequencies in the signal, of which the square-root of the sum of all power in the spectrum is equal to the signals RMS. The power spectrum is obtained through the squaring of the FFT, $RMS^2 = MS$. The subsequent squaring of the spectrum reduces the lower impacting frequencies and increases the higher impacting frequencies on the spectrum.

Spindle cutting Y-axis amplitude and power spectra analysis provides a 3D map of vibration during a machining process. In this example the configuration of both the amplitude and power spectrum is set to achieve the highest resolution of frequency analysis in the spectra, i.e. a spectral band a width of 1 Hz.

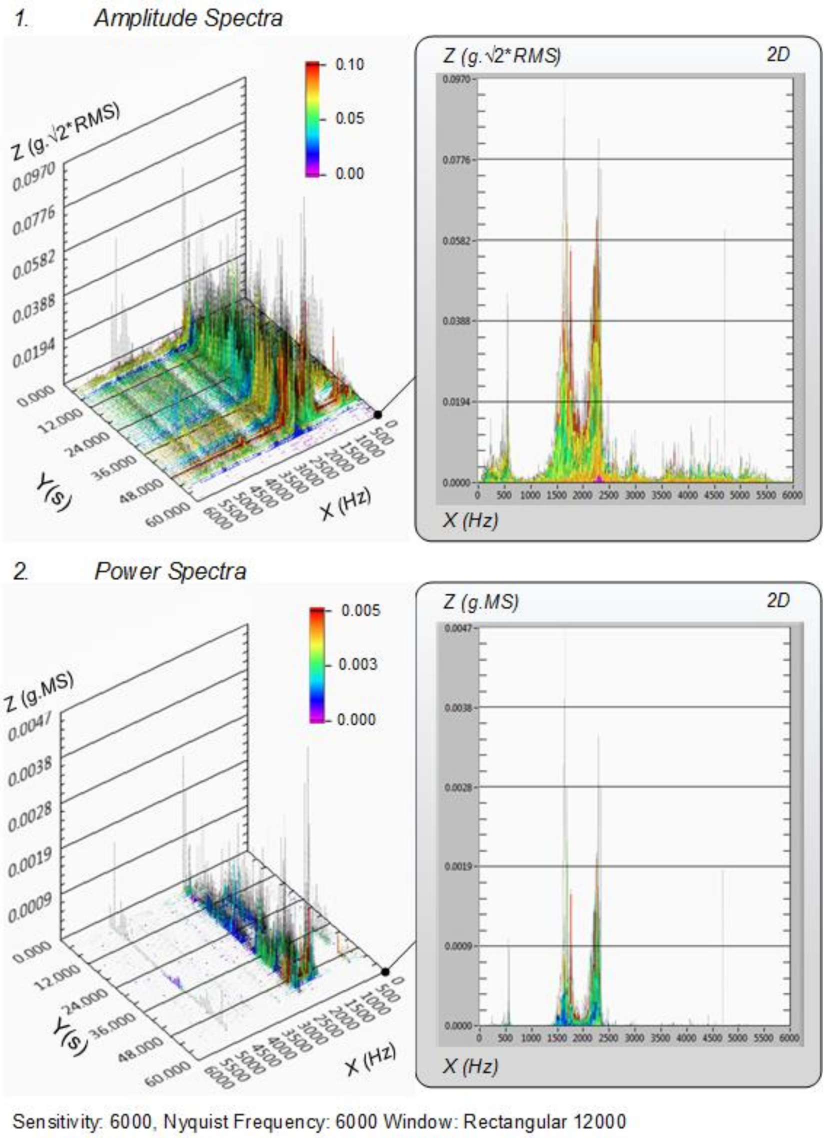


Figure 4.23 Spindle cutting Y-axis, 1. amplitude spectra, 2. power spectra

The 12kHz sampling rate represents the Nyquist rate, i.e. the minimum sampling rate to achieve a Nyquist frequency to meet the 6kHz sensitivity range of the accelerometer. By processing the data at a window size of 12k samples a spectrum range of 6kHz is produced. If the sampling rate of the sensor was set to 12kHz and window size set to 24k samples, the spectrum range would be 12kHz. A full measurement range is achievable. If the sampling rate of the sensor was set to 6kHz and window size set to 24k samples, the spectrum range would also increase to 12kHz. A full measurement range is not achievable as the sensor is only capable of measurement up to 6kHz. However, the extra sampling rate can ensure that the high frequency signals at not missed.

The 12kHz sampling and 12k window size of the spectrum produces a high resolution spectrum but at a low rate of 1 spectrum per second. If a high rate was required, the spectrum would need to be generated by smaller windows. However decreasing the window size also decreases the resolution of the spectrum. The Band width (Bw) per spectral, and Cut-off band (Cb) for which the spectrum provides a measured value is proportional to the Sensitivity frequency (Sf), Window size (W), and Nyquist frequency (Nf), as seen in Figure 4.24.

$$[(Sf / (W / 2)) * (Nf / Sf)] = Bw \qquad [(Sf / Bw)] = Cf$$

Band width (Bw) per spectral
Sensitivity frequency (Sf)
Window size (W)

Cut-off band (Cb)
Nyquist frequency (Nf),

Figure 4.24 Spectrum scaling

For example;

A: sensitivity of 6kHz, Nyquist frequency 6kHz, a window size of 12000

(6000/(12000/2))*(6000/6000) = 1 Hz Band width

(6000 / 1) = 6000 Cut-off band (6000 Hz range)

B: sensitivity of 6kHz, Nyquist frequency 6kHz, a window size of 600

(6000/(600/2))*(6000/6000) = 20 Hz Band width

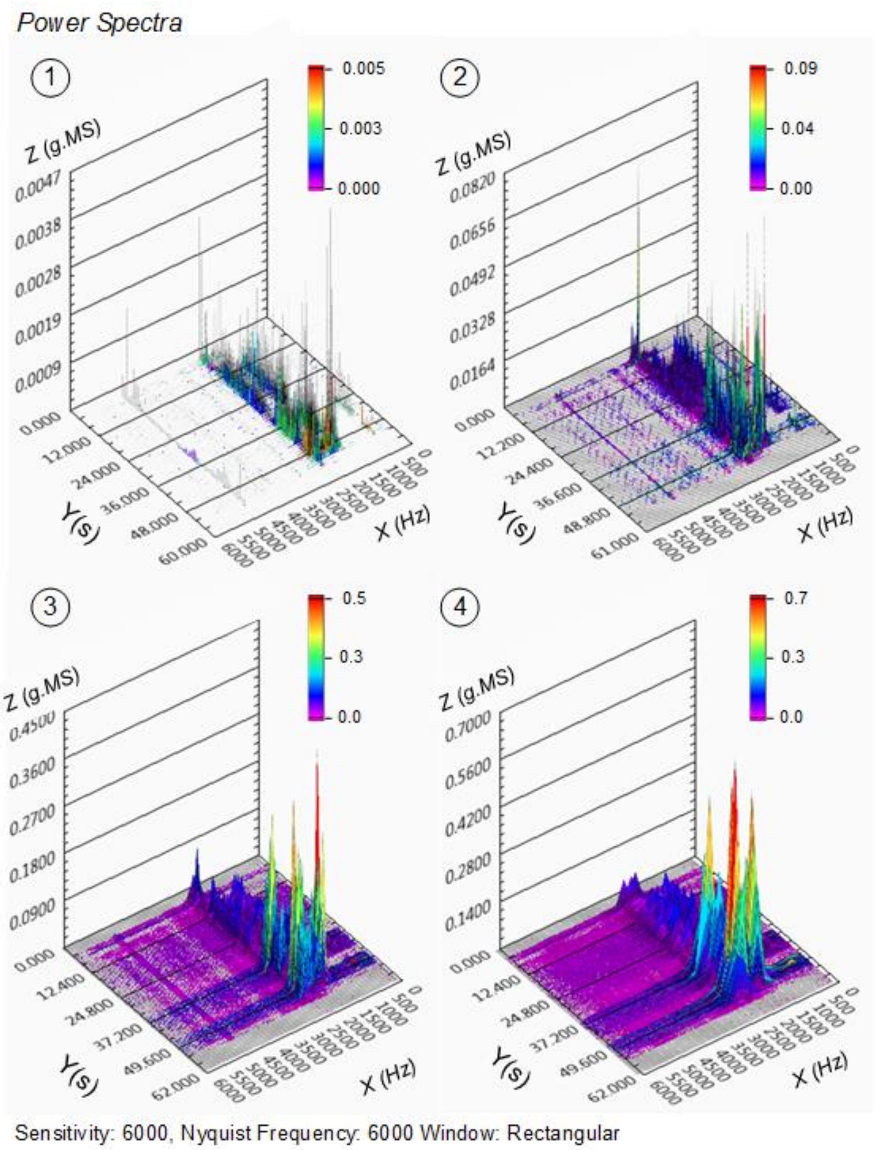
(6000 / 20) = 300 Cut-off band (6000 Hz range)

C: sensitivity of 6kHz, Nyquist frequency 12kHz, a window size of 1200

(6000/(1200/2))*(12000/6000) = 20 Hz Band width

(6000 / 20) = 300 Cut-off band (6000 Hz range)

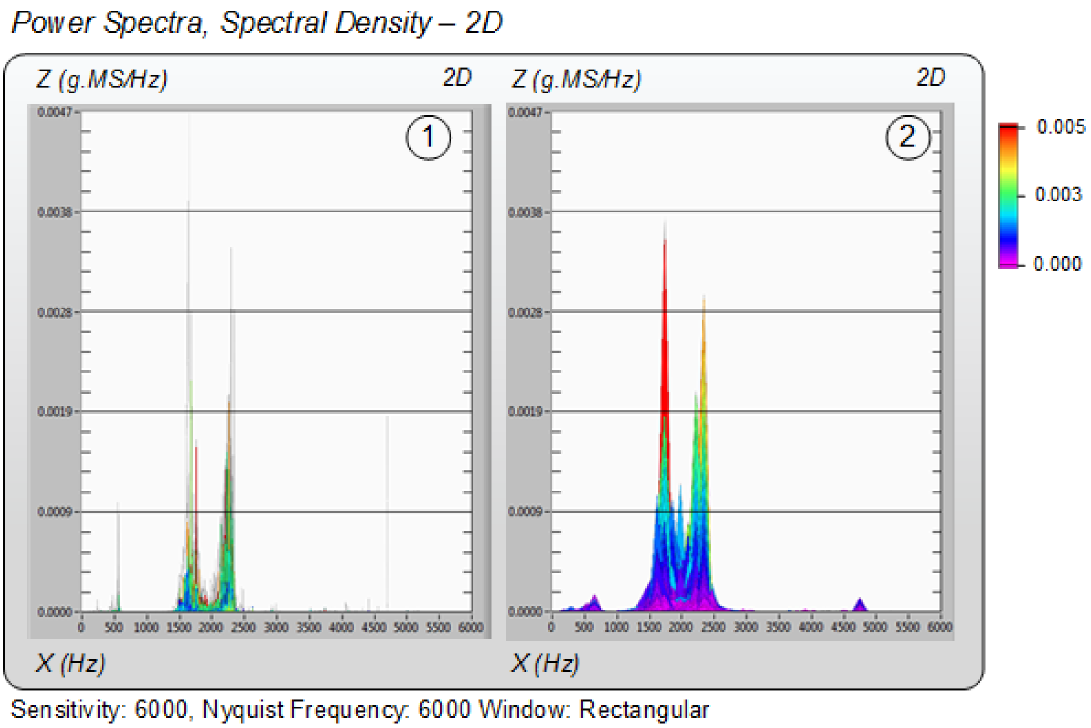
Both the B and C examples cover the sample time period of 100 milliseconds, however B has twice the sampling rate, and window size. The greater window size will yield a larger spectrum, however the higher frequencies in the spectrum are not obtainable as the sensitivity rate is the same in both applications. Subsequently the cut off band is the same for both instances. However increasing the sample size can become difficult as large data sets require high computation, and can lead to large data storage or ‘big data’ requirements.



	Sampling:			Power:		
	Samples (X)	Band Width	Layers (Y)	Max g.MS	Sum g.MS/s	Sum g.RMS/s
1	12000	1 Hz	65	0.0047	0.048	0.22
2	600	20 Hz	1302	0.0820	0.048	0.22
3	100	120 Hz	7810	0.4500	0.048	0.22
4	50	240 Hz	15620	0.7000	0.048	0.22

Figure 4.25 Spindle cutting Y-axis power spectra; varying sample sizes

A demonstration of reduced window sizes can be seen in Figure 4.25. The window size is decreased from 12kHz to 50 Hz at different increments. As the window size decreases the band width increases, spectrum layer output increases, and subsequently the power in each spectral increases. At a 12k window size the highest reading is 0.0047 g.MS, at a 100 window size the highest reading is 0.45 g.MS. This is due to the fact that as the bandwidth per spectral increases, the power in each band is added together. No power is lost in the process as the sum of all power in both spectrums is equal to 0.048 g.MS/s. Increasing the bandwidth provides a collective perspective of neighbouring spectral. As a 100 window size provides a 50 spectral spectrum with a band width of 120 Hz per spectral.



	Sampling:			Power:		
	Samples (X)	Band Width	Layers (Y)	Max g.MS	Sum g.MS/s/Hz	Sum g.RMS/s/Hz
1	12000	1 Hz	65	0.0047	0.0480	0.22
2	100	120 Hz	7810	0.0038	0.0004	0.02

Figure 4.26 Spindle Y-cutting-axis power spectral density

In order to compensate for the widening of spectral bands and subsequent collective of frequency power, Power Spectral Density (PSD) is utilised. PSD represents the power of each spectral on a spectrum as the mean of its band width. The PSD of both a 12k and 100 sample window are presented in Figure 4.26. The spectral band width of the 12k sample window is 1Hz, subsequently the averaging has no effect. The spectral band width of the 100 sample window is 120Hz, subsequently the averaging has significant effect. PSD represents the power in a low resolution spectrum, >1Hz bandwidth, equivalently to a high resolution spectrum, =1Hz bandwidth.

In order to improve the spectral resolution when performing spectrum analysis at periods below 1Hz, a moving spectrum analysis through a MIMO operation is required. A moving spectrum operates like a moving average, new data is combined with a window of previous data producing a collective result. Unlike previous moving average examples that operate on a FIFO operation, the moving spectrum utilises a MIMO operation. A FIFO operation would be unrealistic in this operation as new the computational requirements would be extremely high to achieve the rapid FFT. More advanced hardware, such as FPGA could yield these high data computation results, but are outside the scope of the current work. In order to demonstrate this operation a window size of 600 was selected, which generates a bandwidth of 20 Hz. By utilising a MIMO of window size 600 and sensitivity of 6000, the 600 data samples are added to the previous 11400 samples, creating a full 6kHz spectrum with a bandwidth of 1 Hz, 20 times a second, as seen in Figure 4.27. The MIMO operation of FFT enables a high resolution at a higher analysis rate of 20 Hz. However the computation and data requirements increased significantly, causing the process data to be segmented for collective analysis. This utilisation of this method without buffering the spectrums would remove this overhead, as all computation would be dedicated to performing the FFT, and not forming large data arrays for display.

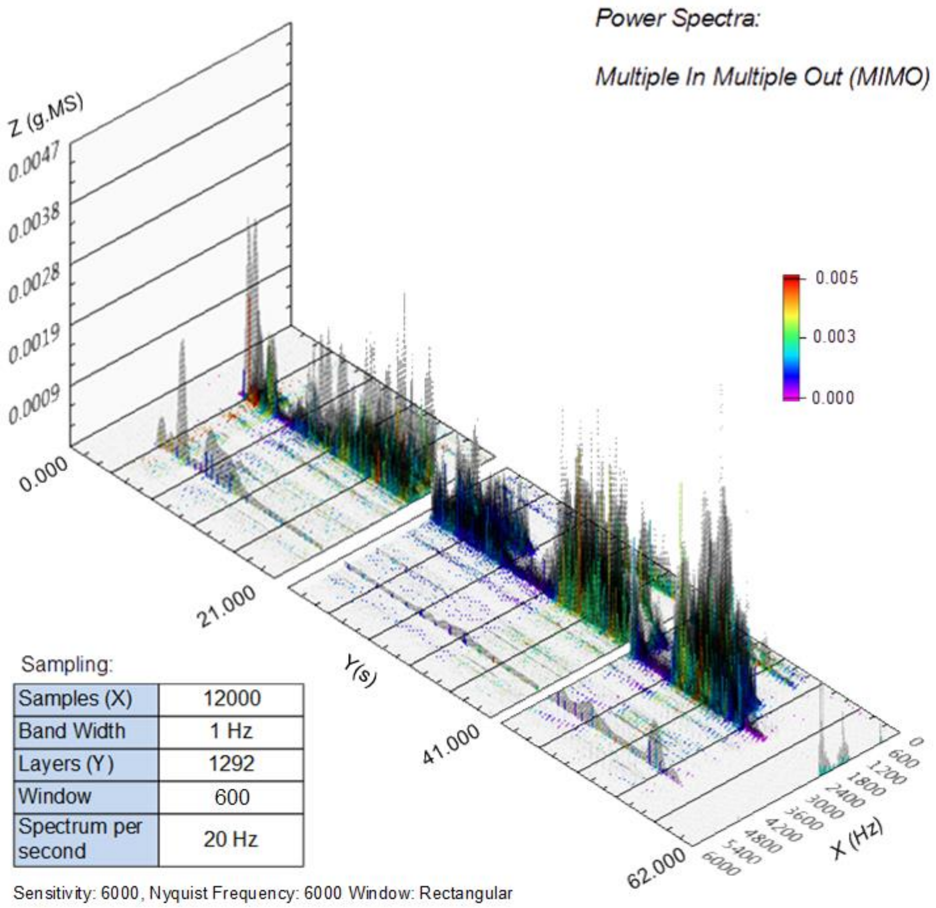
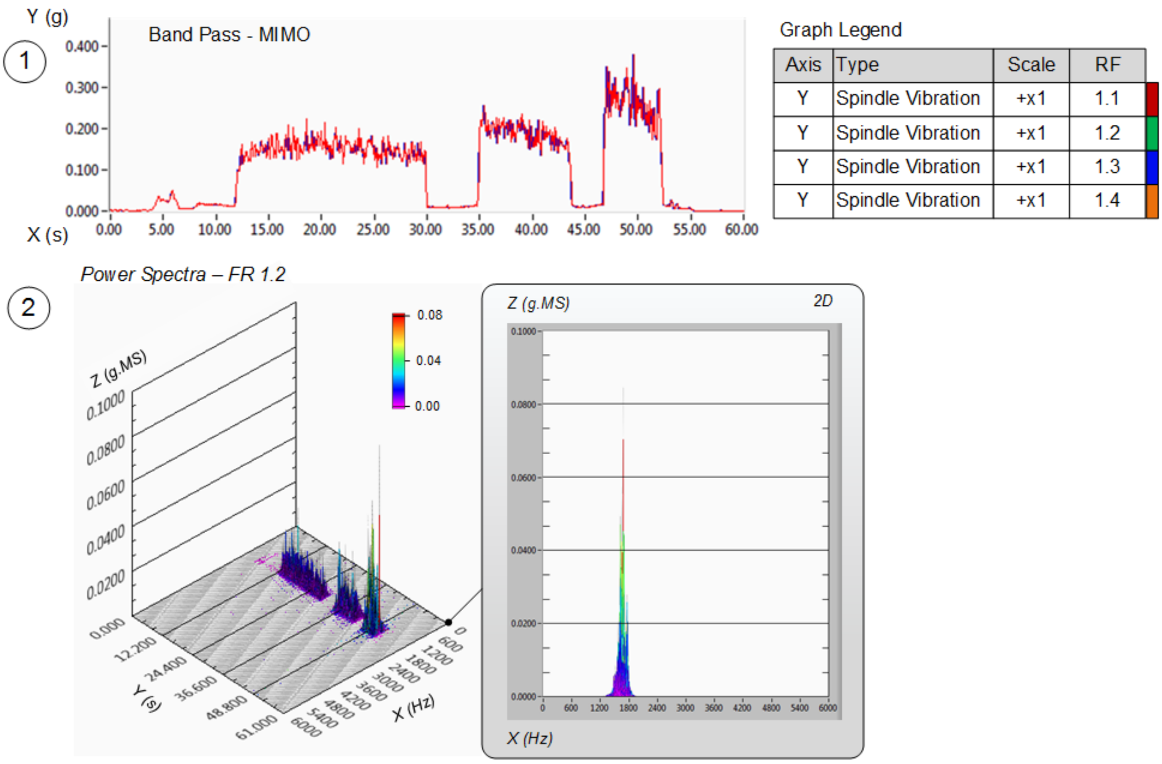


Figure 4.27 Spindle cutting-Y-axis power spectra; MIMO

Signal filtering

In order to demonstrate the frequency filter configuration specifics within the ARC signal-processing-CEP, a band pass filter was selected to isolate the most reactive frequency range within the spindle Y-cutting axis vibration, i.e. 1200 to 1800 Hz. The bandpass filter operates similarly to spectrum analysis, but produces an accumulative time domain output signal corresponding to specific frequency limits. This reduces the high data load and computational requirements of spectrum analysis, but without the wide range, as the function is frequency specific.



Graph Legend

Axis	Type	Scale	RF
Y	Spindle Vibration	+x1	1.1
Y	Spindle Vibration	+x1	1.2
Y	Spindle Vibration	+x1	1.3
Y	Spindle Vibration	+x1	1.4

Sensitivity: 6000, Nyquist Frequency: 6000 Window: Rectangular 600

Signal Processing Legend

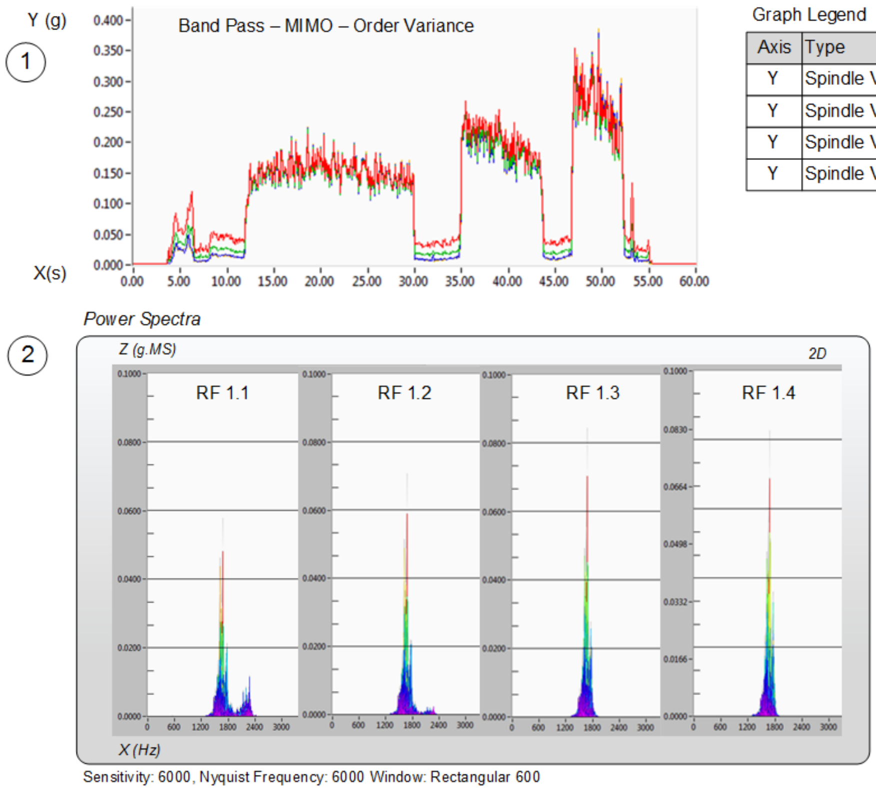
FR	Layer 1		Layer 2
1.1	BP (M12000)	[L(1200–1800), Nf:6000, O:5]	RMS(1000)
1.2	BP (M600)	[L(1200–1800), Nf:6000, O:5]	RMS(1000)
1.3	BP (M100)	[L(1200–1800), Nf:6000, O:5]	RMS(1000)
1.4	BP (M50)	[L(1200–1800), Nf:6000, O:5]	RMS(1000)

Filter Type (Window Size) [Info] (M100) = Moving Window, size 100

RF: Reference Filter
RMS: Root Mean Square
BP: Band Pass
L: Limits
Nf: Nyquist Frequency
O: Order

Figure 4.28 Signal filtering, 1. window size variation, 2. power spectra

The frequency filtering operation in the ARC signal-processing-CEP is specifically MIMO, which enables a high resolution and high frequency signal output. A demonstration of this accuracy at different window sizes can be seen in Figure 4.28. In Figure 4.28.1, the window size varies between 12000, 600, 100, 50, and results in a near identical time domain output signal. Furthermore the band-pass filter type successfully isolates the frequencies within the 1200-1800 Hz, as seen in Figure 4.28.2.



Graph Legend

Axis	Type	Scale	RF
Y	Spindle Vibration	+x1	1.1
Y	Spindle Vibration	+x1	1.2
Y	Spindle Vibration	+x1	1.3
Y	Spindle Vibration	+x1	1.4

Signal Processing Legend

FR	Layer 1		Layer 2
1.1	BP (M600)	[L(1200–1800), Nf:6000, O:1]	RMS(1000)
1.2	BP (M600)	[L(1200–1800), Nf:6000, O:2]	RMS(1000)
1.3	BP (M600)	[L(1200–1800), Nf:6000, O:5]	RMS(1000)
1.4	BP (M600)	[L(1200–1800), Nf:6000, O:10]	RMS(1000)

Filter Type (Window Size) [Info] (M100) = Moving Window, size 100

RF: Reference Filter
RMS: Root Mean Square

BP: Band Pass
L: Limits
Nf: Nyquist Frequency
O: Order

Figure 4.29 Signal filtering order variation, 1. time domain, 2. frequency domain

Other configuration capabilities within frequency filtering include, types, limits, and the order. Types and limits operate within the previous defined example, as the filter type will identify modes of frequency isolation, and the limits define the specific frequency border/s. However, the order is unique as it identifies the “roll-off” or slope outside the pass limits in the frequency domain. The higher the order the higher the slope in the transition period between isolated and un-isolated frequencies. In order to demonstrate the order effect identical band pass filters are applied to the cutting Y-axis vibration data with varying orders of; 1, 2, 5, and 10, as seen in Figure 4.29. The time domain output signal, represented in Figure 4.29.1, identifies a small decrease in power between cutting operations. This observation becomes clearer in the frequency domain, as seen in Figure 4.29.2, as low order filters allow for more power from neighbouring frequencies to be present. As the order increases the slope of transition in increased removing neighbouring frequencies, and increasing the resolution of frequencies within the isolation area.

4.5.3 Conclusion

The transition of advanced signal processing techniques, specifically frequency domain analysis, within the ARC, identifies a major benefit for reconfigurable process monitoring systems. Internal reconfiguration parameters enables application adaption to a wide range of processes, and the flexibility to change with a varying process. Furthermore, the integration of this functionality with the ARC has provided an external reconfigurability. Sophisticated analytics are now applicable to any process variable in the data cloud. The replication of Agents within the architecture, ensures parallel signal processing of multiple data sources. A complex task has now become a building block in a larger collaborative system. This multi-dimensional reconfiguration enables the incorporation of effective and efficient, simplistic and complex functions, into any manufacturing process monitoring system.

4.6 Cloud process performance characterisation

4.6.1 Prologue

The measurement, data acquisition, and signal processing steps, provided varying degrees of decision support within manufacturing systems. During online and off-line analysis, a skilled engineer can review this data and make decisions for process management and operation, with the aim to improve the process. However this process can be complex and extremely time consuming. Within a high production volume environment more autonomous means of process analysis and decision support is required. Sensor fusion is required to achieve this, providing multiple perspectives on process operation, subsequently identifying windows of analysis for comparative review and decision support. This autonomous characterisation also requires the automation of all other previous process monitoring steps, in order to provide the system with the raw/filtered data it needs.

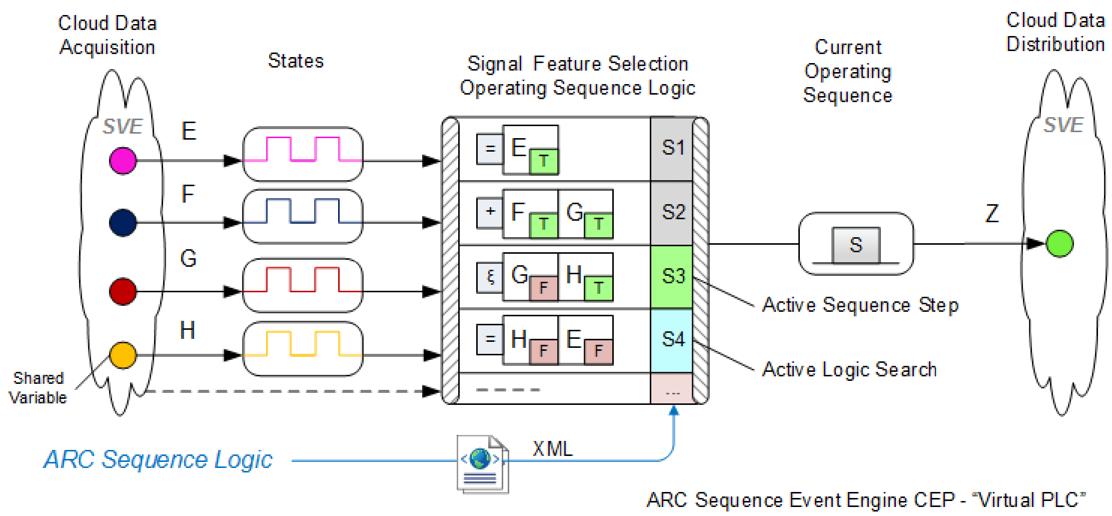


Figure 4.30 ARC sequence-event-engine-CEP

A unique CEP was created to achieve autonomous characterisation within the ARC; the ARC sequence-event-engine-CEP, as seen in Figure 4.30. This application utilises multiple digital Boolean signals to generate an operating sequence of sequential events. These events act as windows of analysis, and process metrics can be defined within their specific occurrences, providing a processes performance to be autonomously monitored. The ARC sequence-event-engine-CEP utilises a similar topology as the ARC signal-processing-CEP. Multiple process signals are acquired via APAs from the cloud, processed, and a signal is then redistributed to the cloud. Diversely however, the functionality of the event engine is to correlate the data acquired and subject it to a Boolean logic mechanism to identify the operating sequence. Each operating sequence has a Boolean logic set, consisting of multiple signals with different states, “on” or “off”, with different logic rules, i.e. states are equal in parallel, serial sequence, or randomly. If the logic set is met the sequence becomes active. The application searches sets in succession. For example if sequence set N is active, then sequence set N+1 is being actively searched for. Once sequence set N+1 is identified, it becomes the active state, and sequence set N+2 becomes the active search set. Once all sequence sets have been found, the search resets to the first sequence set N, unless specified otherwise. The sets are reconfigurable, and the sequence of sets is represented in an XML format for importing and exporting on-the-fly.

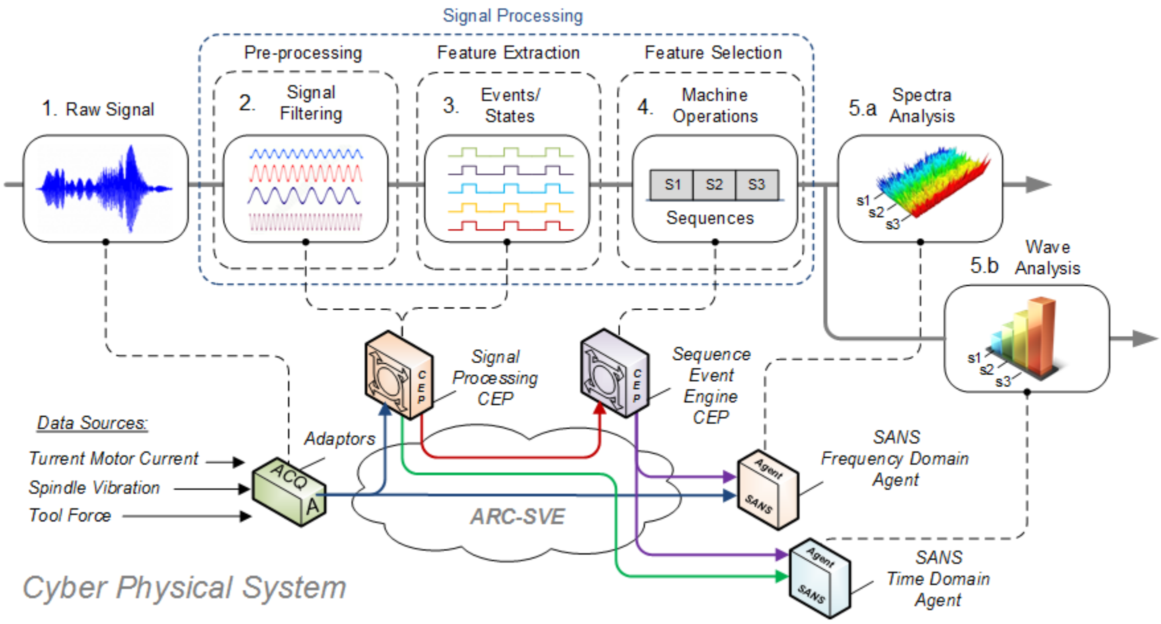


Figure 4.31 Cyber physical process performance characterisation system

The active sequence is communicated to a shared variable, allowing multiple Sequence-oriented ANalySis (SANS) Agents to synchronously correlate their analysed data to the processes operation. These SANS-Agents follow the schematic of the ARC Agents, enabling cloud acquisition and correlation of multiple data streams. Diversely the SANS-Agents also acquire the sequence shared variable from the ARC sequence-event-engine-CEP. This variable identifies the active sequence with a timestamp of initial occurrence. Once a new state is active the window of analysis of the previous sequence is closed, enabling a machining operation to be quantified within the measured timeframe.

Two SANS-Agents were created to provide time and frequency domain analysis. These Agents utilise the previously explored signal processing and frequency analysis techniques. The SANS frequency domain Agent utilises spectra analysis to quantify the total energy and power across the spectrum of frequencies in each sequence of operation. The SANS time domain Agent quantifies multiple process signals in relation to the signal features of; sum, average, maximum, and variance. The utilisation of the ARC signal-processing-CEP enables the dynamic pre-isolation and enhancement of process signals for utilisation in the SANS time domain Agent application.

The unique collaborative environment of the ARC has produced a collective signal processing and analysis chain, as seen in Figure 4.31. Each software application has a localised goal which is internally reconfigurable to provide a range of bespoke outputs. However, the globalised goal is achieved through the collaboration between these software applications provided by the ARC. The complexity of each step on the signal processing step is localised within a singular interchangeable entity, or ‘holon’. The produced outputs of this entities are further utilised on a higher plain or domain of holonic influence.

4.6.2 Machining process performing characterisation

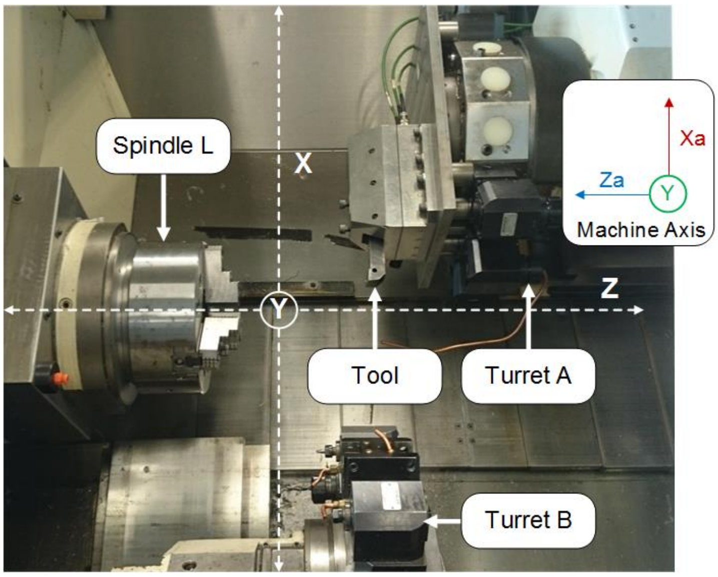


Figure 4.32 OKUMA LT15-M CNC turning lathe, axis reference

In order to examine autonomous cloud-oriented process performance characterisation, the process data acquired during the previous machining cutting cycle is examined. This was achieved through a virtual ARC software Adaptor that reads the process data from the database, and simulates the machining process by transmitting the data in real-time to the SVE. All ARC software applications gained access to this data and process it in real-time, exactly the same way it would process the data if machining was actively undertaken. In order to provide context, the OKUMA CNC machine axis reference is shown in Figure 4.32.

Process sequence generation

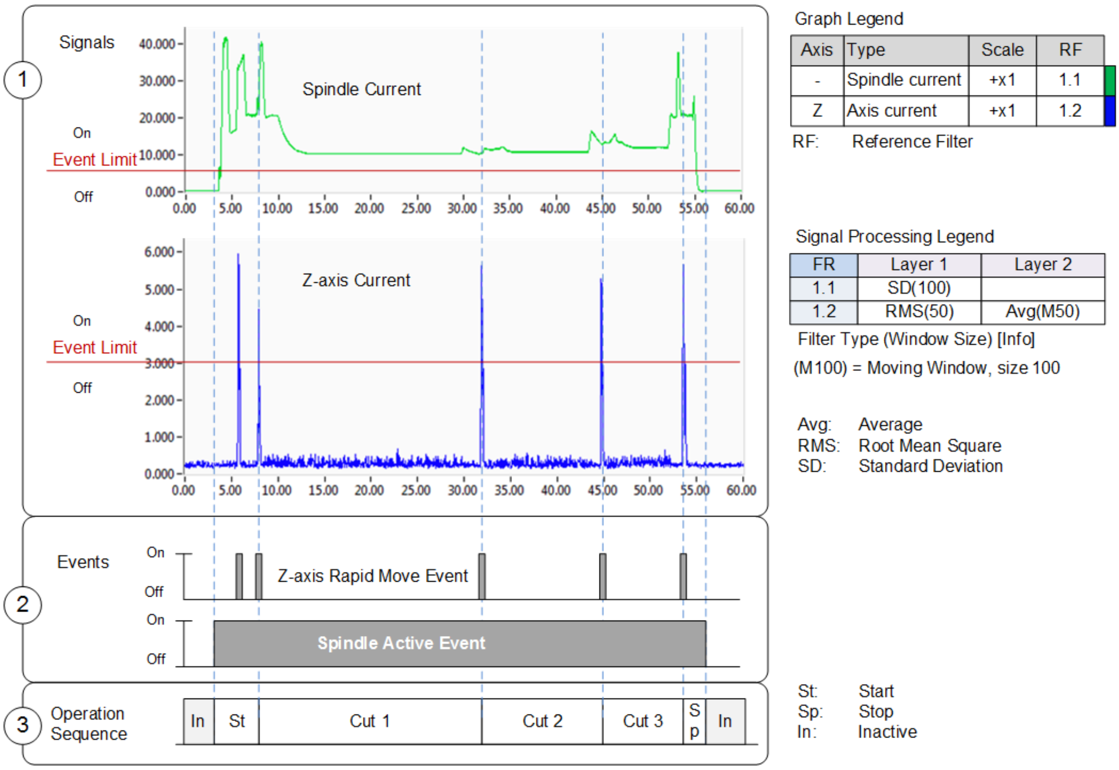


Figure 4.33 Process characterisation; operating sequence identification: 1. process signals, 2. derived events, 3. operating sequence

Boolean process signals are required to achieve process sequencing. Manufacturing processes typically consist of various Boolean and numeric data streams which enable the process to be controlled. The OKUMA LT15-M CNC Turning Lathe did not provide any of these data points for external measurement. Subsequently Boolean process operations needed to be extracted from the external sensors. This was achieved through signal processing and limit setting of spindle and turret motor currents, as seen in Figure 4.33.1. Specific process attributes were extracted via signal processing, converting alternating current to direct current. Spindle current identified the occurrence of spindle activation, and Turret rapid movements were isolated to identify the start and end of process operations. The Boolean output was achieved by setting limits on the signals, which identify the occurrence of different events in the process, as seen in Figure 4.33.2. If the signal was above the limit the event was active, Boolean value “true” or numerically “1”. If the signal was below the limit the event was inactive Boolean value “false”, or numerically “0”. The correlation of these events in sequence define the sequence, i.e. sequence 1 Start: Spindle “True”, sequence 2 cut 1: Spindle “True” Rapid Movement “True”, as seen in Figure 4.33.3. The rapid movement is an ideal signal to divide the sequences, as it is a clear stable signal. Rapid movement reactions do not differ between machining parameter settings, and subsequently the sequence does not require modification if machining parameters change, e.g. cutting speeds. The defined sequence consisted of start and stop sequences, and 3 cutting sequences, to autonomously quantify the varying effects different cutting speeds have on spindle vibration and tool force.

Process performance analysis

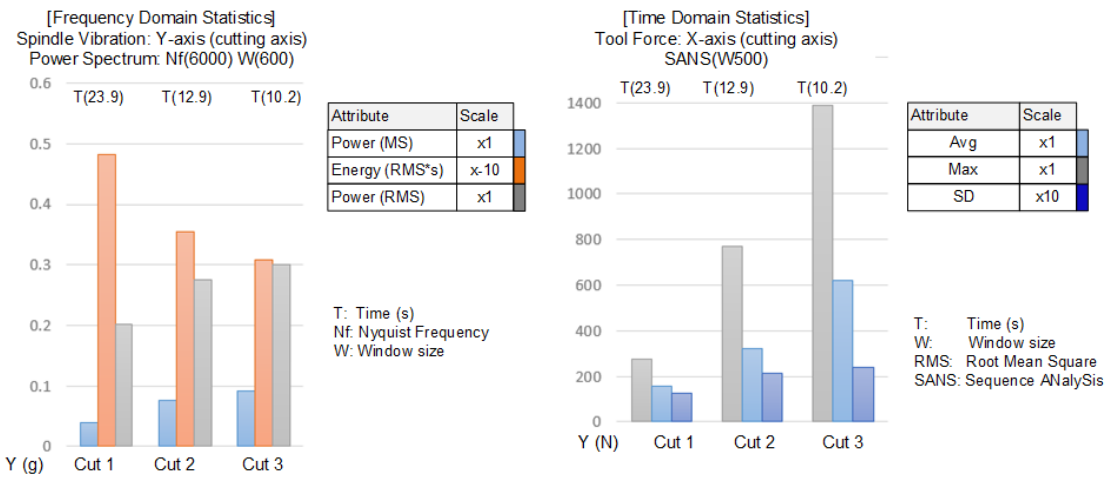


Figure 4.34 Process characterisation; sequence time-domain performance metrics, 1. vibration energy and power, 2. cutting force

Sequence specific time domain performance analysis for both spindle cutting vibration, and tool force is identified in Figure 4.34. Spindle vibration identified an decreasing energy distribution between the different cutting speeds. Each cut had the same length and depth, however the speed of the tool feed changed. This is made evident with the root of the power of the vibration, unit RMS/S. Vibration power increases with the increase in cutting speed linearly. The force also shows an increase in cutting force with an increase in cutting speed, however the plot resembles an exponential change. The only reactive variable in vibration that similarly responds to the exponential force, is the standard deviation, indicating variance in the signal.

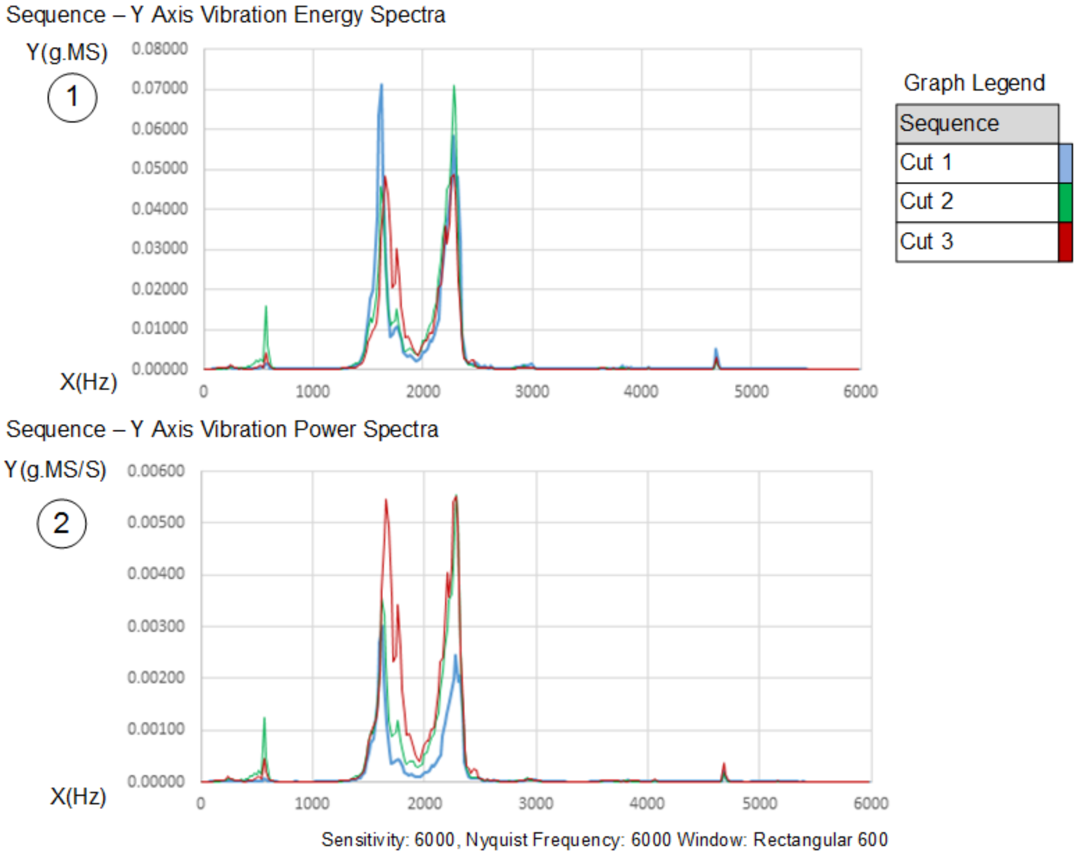


Figure 4.35 Process characterisation; sequence frequency domain performance metrics, 1. energy spectra, 2. power spectra

Sequence specific frequency domain performance analysis for spindle cutting vibration is identified in Figure 4.35. Figure 4.35.1 identifies the energy spectrum and Figure 4.35.2 identifies the power spectrum of spindle cutting Y-axis vibration over the sequence time period. The two dominant vibration frequency bands; A:1500–1900, B:2100–2400, provide performance metrics for frequency reaction to changing machining parameters within this turning process. Previous time domain analysis identified the even distribution of energy between cutting processes. The frequency energy spectra identifies an equal energy peak in band B, and an unequal peak in band A. The energy in band A widens during Cut 3. The sequence power spectrum also identifies a difference in frequency response in band A, as it not only widens in cut 3, but increases in magnitude significantly. Subsequently, frequency analysis provides a new performance metric, as vibration can be quantified in both power and frequency.

4.6.3 Conclusion

The configuration and collaboration of the unique ARC entities has resulted in the autonomous characterisation of a manufacturing process. This phase 1 investigation has demonstrated the capability of the ARC to be assembled into a cyber-physical production system. Data acquisition, signal processing, and data analytic software applications are distributed in a decentralised architecture, and collaborate together to create a unified process monitoring system.

The goals of the signal processing chain are configured to meet the unique requirements of the CNC turning machine. By identifying key machining actions a sequence of operations are extracted through sensor fusion. This process removes the need for manual segmentation of data by a user, and enables the autonomous dynamic identification of machining operations. The core fundamental operation of this analytical system is achieved through Boolean logic, in connection with monitored process variables, which are pre-processed to extract process features. Locally, each step in this signal processing chain incorporates intelligent techniques, mechanisms, and analytics. However, collaboration empowers a global intelligence, as windows of analysis are correlated to machining actions. A wide range of process signals can now gravitate to these key moments in time. The result is comparative performance metrics, which enable competent decision support for real-time production systems.

4.7 Summary

This chapter, has identified the complexity present in manufacturing process monitoring systems. This complexity is evident in; the multitude of sensory technologies, variation in production equipment, and the sophistication of data acquisition medium, signal processing techniques, and data analytics. The utilisation of decentralised design aims to overcome this complexity, through the establishment of reconfigurable process monitoring tools.

This phase 1 investigation set out to identify the capability of the ARC to achieve reconfigurable process monitoring within an engineering environment. Evidently the ARC enabled the data acquisition of multiple process variables from a CNC turning machine. This data was hosted as a service by ARC acquisition Adaptors, to enable the dynamic distribution of digital resources across a network. A test case was undertaken to machine a workpiece at different feed rates, and examine the reactions from; tool force, axis and spindle motor current, and spindle and turret vibration. Each data source was represented by individual hardware/software components. The unification of these data sources was achieved through the remote acquisition of cloud data via data sourcing Agents. Effective and efficient data acquisition, and signal correlation was achieved with key software architecture techniques, namely asynchronous programming.

The process data acquired in the industrial case-study, provided a point of reference for the design and development of decentralised signal processing and analysis techniques. Signal processing techniques were encapsulated within a reconfigurable mechanism, to enable customised signal processing sequencing and configuration. Frequency analysis entities were created with reconfigurable controls. For efficient parallel computation, these signal processing mechanisms and reconfigurable analytics were designed with asynchronous programming. The resultant ARC signal-processing-CEP and ARC signal-spectra-Agent applications, enabled reconfigurable and dynamic signal processing within the decentralised process monitoring architecture.

In order demonstrate the utilisation and collaboration capability of the reconfigurable process monitoring system entities, an autonomous cyber-physical process characterisation system was created. Process characterisation was achieved through utilisation of a Boolean logic sequencing mechanism, namely the

ARC sequence-event-engine-CEP. This application enabled the identification of process operations through the correlation of multiple process events. The global dispersion of current machine operations, enabled the analysis of sequenced operations by other Agents. Both frequency and time domain sequence analysis Agents were created, resulting in autonomous multi-dimensional manufacturing process performance characterisation.

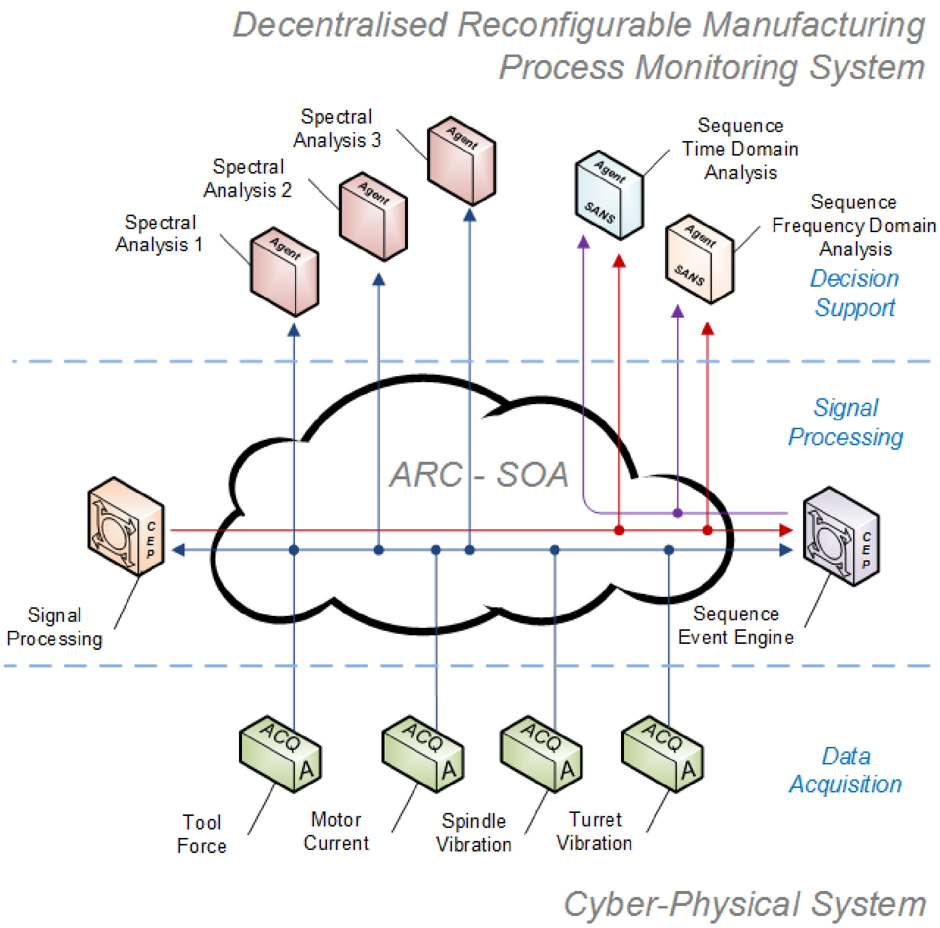


Figure 4.36 Reconfigurable process monitoring system topology

The resultant reconfigurable manufacturing process monitoring system is a dynamic borderless collective of interactive software entities, or tools, as illustrated in Figure 4.36. Localised intelligence is integrated within every individual architecture entity, which represent common process monitoring tools. However, global intelligence is achieved through configurable orchestration, resulting in generation of a custom process specific signal processing chain.

Chapter 5

Application investigation into CNC turning characterisation and dry machining

5.1 Introduction

The establishment of an interoperability foundation for manufacturing process monitoring has provided an advantageous multi-scalable reconfigurable environment. The further integration of signal processing techniques, advanced signal analysis, and intelligent monitoring applications, provide building blocks for custom process performance characterisation. Process adoption of these advanced signal processing and decision support mediums is dependent on the effective framework assimilation into the specific process. Subsequently, a case study was undertaken to identify the capability of the ARC process monitoring components to achieve process insight.

This phase 2 investigation focuses on the characterisation of CNC machining operation inside and outside cutting operations. The investigation involves the characterisation of the process through the measured process monitoring variables and evaluation of effective application for production monitoring. Machine operation parameters are varied to identify their effects on spindle vibration, turret vibration, tool force, and turret movements. Furthermore the effects of undesired machining parameters, namely tool wear, was quantified in respect to the defined machining performance.

5.2 Machine characterisation

5.2.1 Machine operation

The characterisation of machining operation is important for the health monitoring and management of manufacturing machines. By identifying normal operating parameters, the onset of faults can be comparatively identified and targeted for preventative maintenance. Process characterisation requires the varied measurement of multiple machining operation procedures, in a controlled manner. This process allows for a comparative map of machine operation reactions to be defined. This map can be utilised to not only define a baseline for normal operation, but also identify key operating characteristics/events for windows of analysis and potentially autonomous monitoring.

In order to provide context to analysis figures, the OKUMA CNC machine axis reference is shown in Figure 5.1, and Figure 5.2.

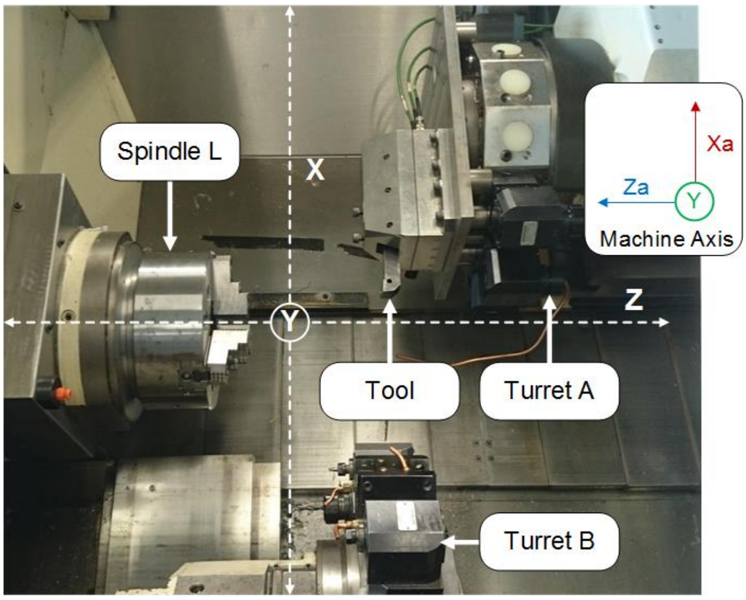


Figure 5.1 OKUMA LT15-M CNC turning lathe, axis reference

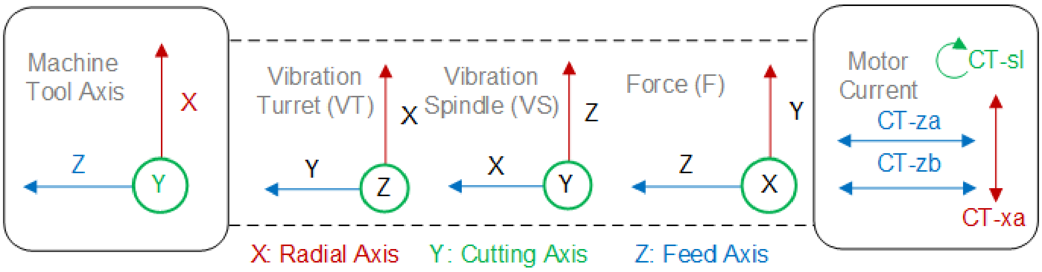


Figure 5.2 Axis reference

Spindle Rotation

Signal Processing Legend

RF	1	2	3	4	5	6	SPS	Delay
1.1	RMS(1000)	-	-	-	-	-	3	0.333
1.2	Avg(10)	Avg(M10)	Rectifier	Var(25)	Square	Avg(M5)	51	0.145
1.3	HP(100) {F:60} [N:1500 O:10]	RMS(100)	Avg(50)	Square	-	-	30	0.301
1.4	RMS(1000)	-	-	-	-	-	12	0.083
1.5	RMS(200)	Square	Avg(M10)	-	-	-	64	0.187
1.6	BP(100) {F:1800-1200} [N:6000 O:5]	RMS(100)	Avg(50)	-	-	-	130	0.101

Filter Type (Window Size) [Info] (M100) = Moving Window, size 100

RF: Reference Filter
SPS: Samples per second
Avg: Average
RMS: Root Mean Square
Var: Variance
HP: High Pass Filter

Table 5.1 Machine operation: Spindle rotation, signal processing legend

Motor current

Figure 5.3.1 represents the spindle motor current during a rotating operation from a station position. By converting alternating current to direct current with a RMS, the spindle operating states can be identified, as seen in Figure 5.3.2. Spindle states include;

- Off– Spindle is inactive
- Start– Spindle has been switched on
- Acceleration– Spindle is accelerating
- Transient– Spindle in decreasing acceleration
- Steady– Spindle is maintaining speed
- Stop– Spindle has been switched off

With signal filtering these states can be extracted by feature recognition, as seen in Figure 5.3.3. Each of these state can provide a window for analysing a specific machining operations, or collectively analysing a total machining operation.

The requirement for constant surface speed machining causes multiple spindle accelerations. The forced acceleration of the spindle can be reviewed in Figure 5.3.4. The spindle is accelerated from stationary to 300 RPM, and then incrementally to 2000 RPM. This acceleration is characterised by the spike in current and period of large signal amplitude, as the spindle transitions between operating states. The steady state amplitude does not show a significant change with varying speed. Additionally the amplitude and duration of acceleration periods, does not scale proportionally with acceleration.

Vibration

The vibration response to spindle operation is similar to the motor current, as seen in Figure 5.4.1. However the triaxial signals respond differently to the process, as seen in Figure 5.4.2. Axis X and Z, the movement axis, resemble the spindle operating states. While the cutting axis Y, identifies a response to spindle vibration, but without variation between spindle acceleration, transient, and steady-state. A potential explanation to this occurrence is the structural restraints of the CNC, stiffening the cutting axis.

With signal filtering, some process states can be extracted by feature recognition, as seen in Figure 5.4.3. Furthermore the time domain vibration response to varying spindle speed/acceleration, as seen in Figure 5.4.4, is incremental in steady state operation, with a reduced initial peak.

The frequency domain, represented in Figure 5.5, further identifies the variance in vibration reaction to spindle operation, as each axis identifies a different response frequency. These vibrations represent stationary deterministic signals from a combination of the spindles bearings, gears, and motor windings. The Y and Z axis are both restrained structurally in different ways, but provide no movement to machining operations. The Y axis is the most unreactive to vibration compared to the other axis. Axis X is an unrestrained axis, as it provides the Z axis movements to the machine tool. Subsequently the X axis identifies the most variation in frequency, including peaks in 1 Hz spectra from rapid movements.

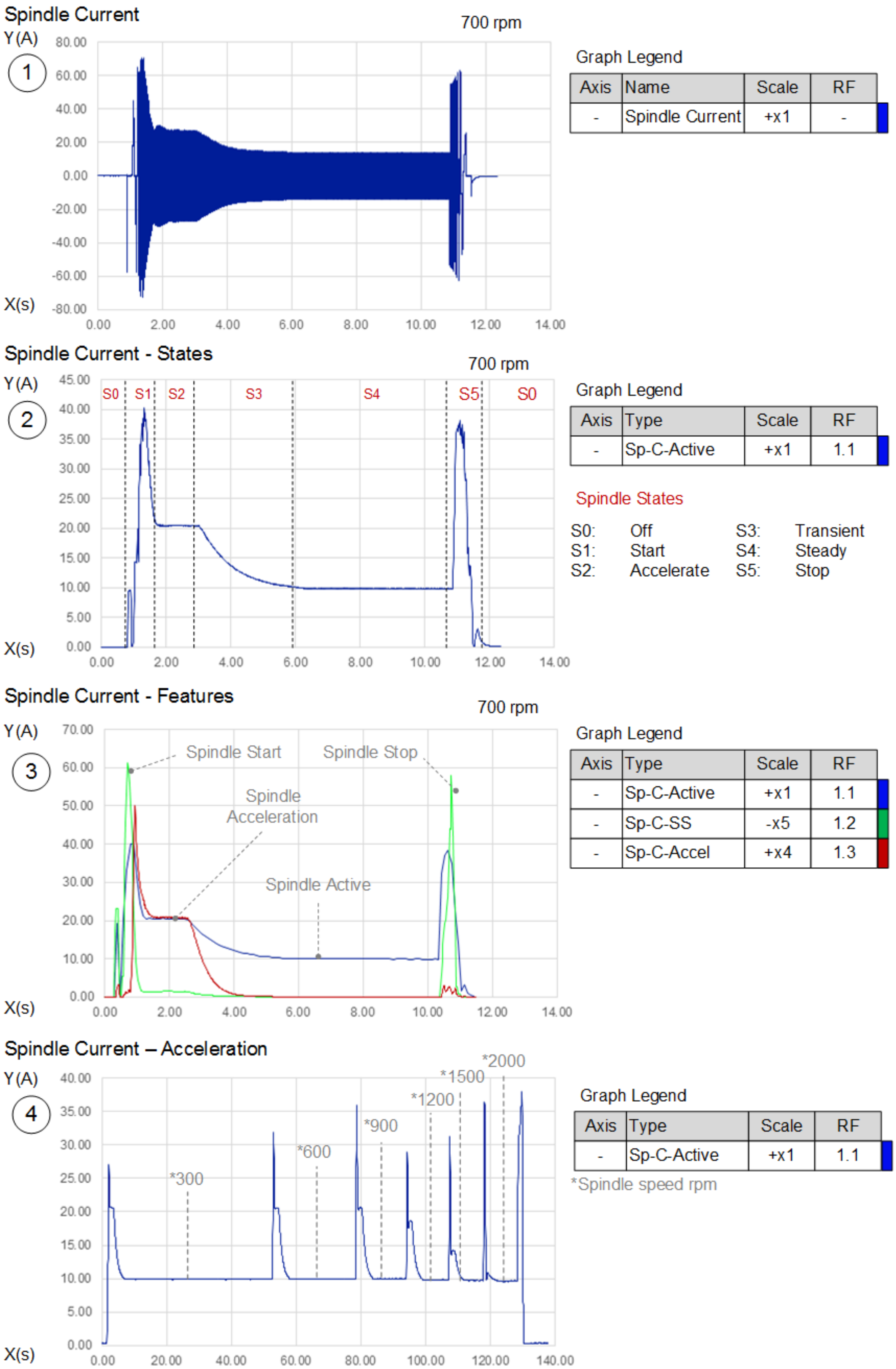


Figure 5.3 Machine operation: spindle operation, motor current

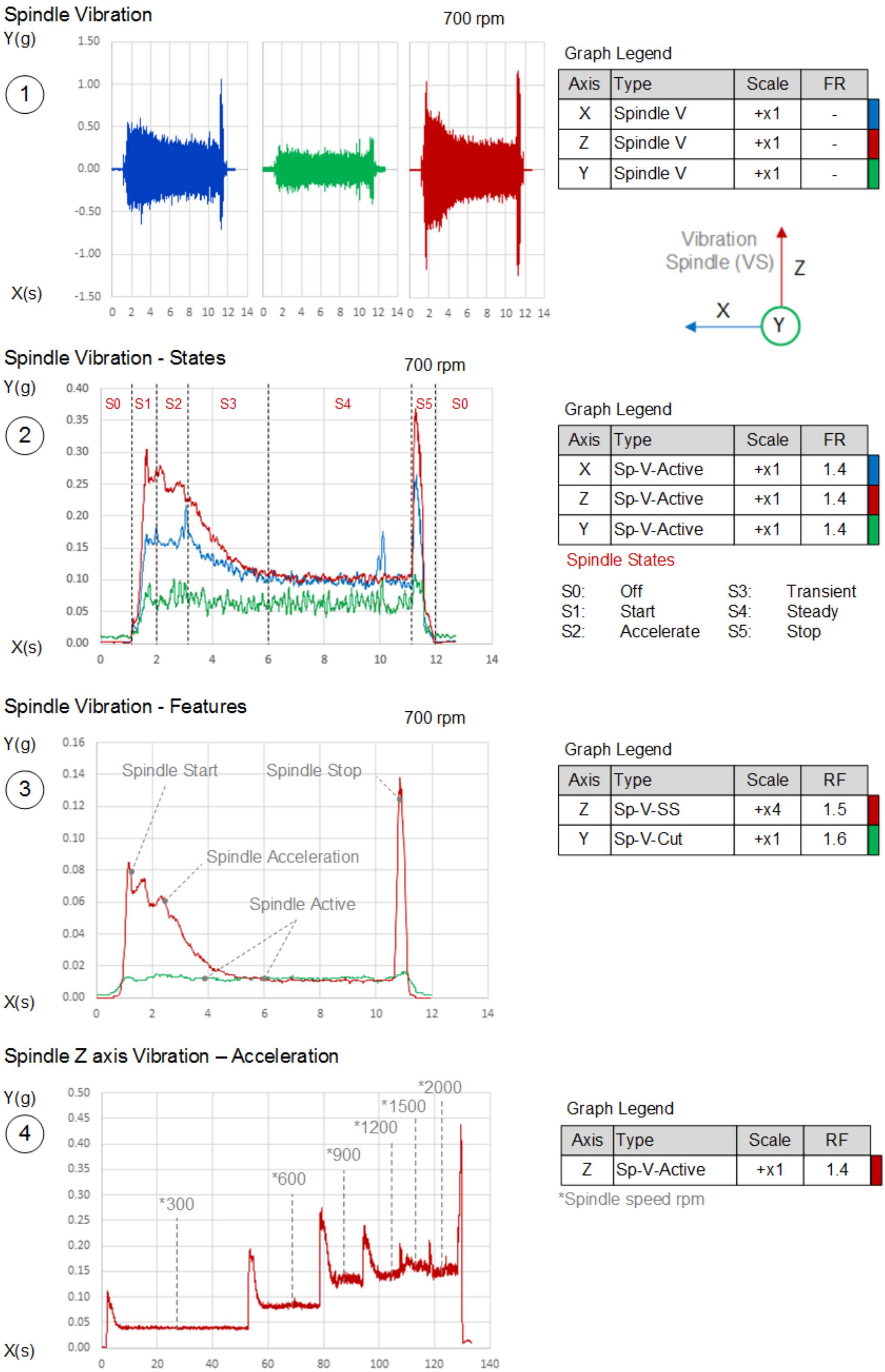


Figure 5.4 Machine operation: spindle operation, triaxial vibration, time domain

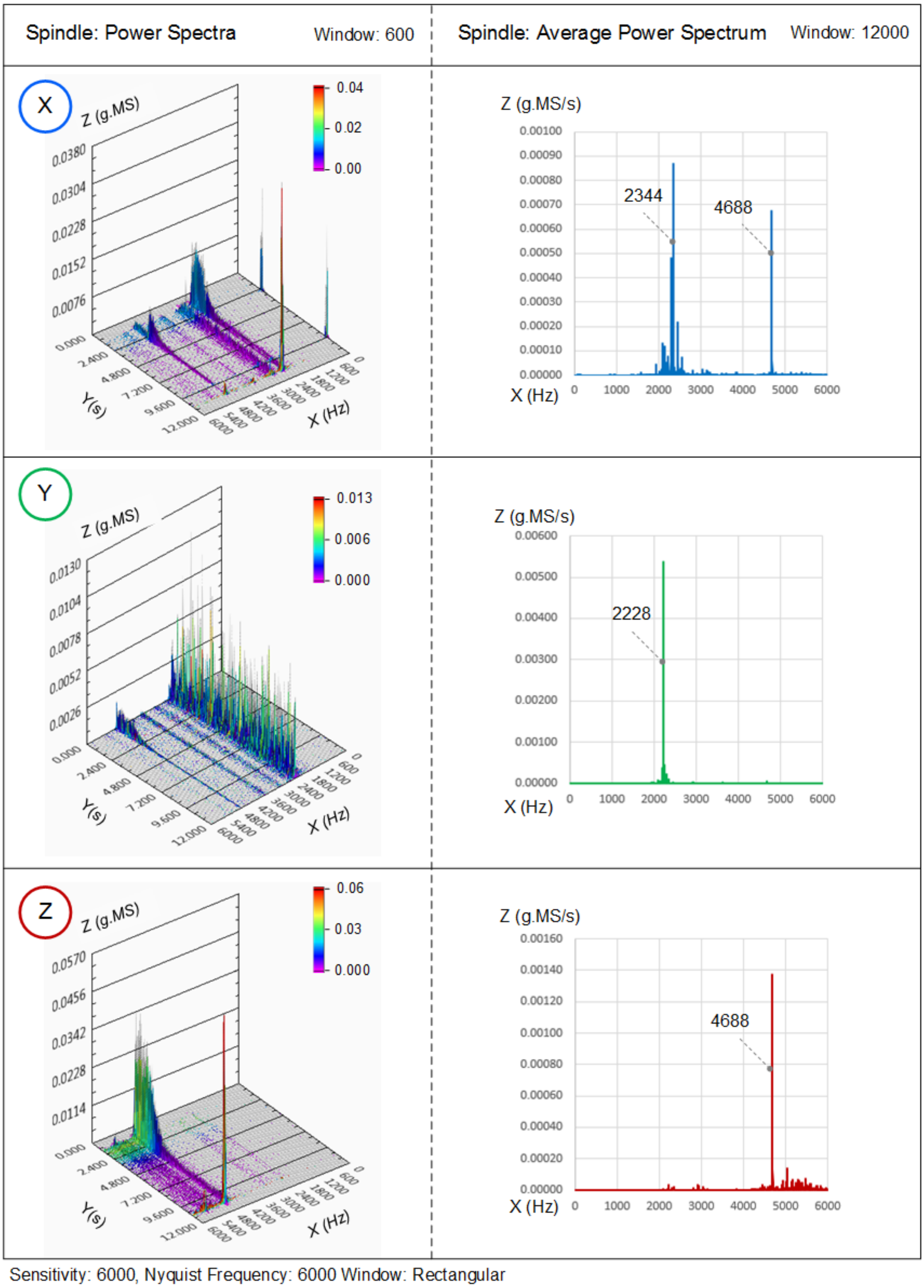


Figure 5.5 Machine operation: spindle operation, triaxial vibration, frequency domain

Z Axis Movement

Signal Processing Legend

RF	1	2	3	4	5	6	SPS	Delay
2.1	Avg(3)	Avg(M100)	Rectifier	Avg(10)	Avg(M200)		300	0.878
2.2	SD(100)						30	0.033
2.3	LP(100) {F:2} [N:6000 O:5]	RMS(100)	Avg(50)				130	0.405

Filter Type (Window Size) [Info] (M100) = Moving Window, size 100

RF: Reference Filter
SPS: Samples per second
Avg: Average
RMS: Root Mean Square
SD: Standard Deviation
LP: Low Pass Filter

Table 5.2 Machine operation: Z axis movement, signal processing legend

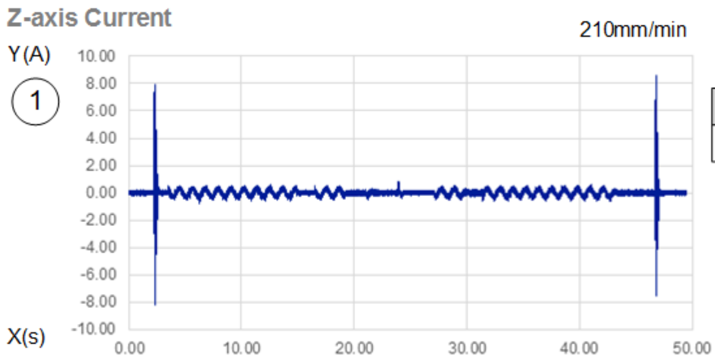
Motor current

Figure 5.6.1 represents the machine Z-axis motor current during 4 incremental movements, in both the positive and negative directions. The first movement is a rapid movement, followed by 3 set speed movements, covering 50mm, 10mm, and 1mm. Signal processing enables the alternating current to be converted into direct current, which identifies different movements, as seen in Figure 5.6.2. Furthermore the occurrence of rapid movements can be separated from the signal, enabling the creation of multiple windows of analysis from the individual signal. Subsequently large and small movements of the machine Z-axis can be effectively identified through single phase motor current measurement.

The speed of the machine Z-axis is proportional to the feed rate, and the spindle speed. Feed-rate is the distance travelled per revolution of the spindle. Varying the feed rate produces different amplitudes and frequencies of current, as seen in Figure 5.6.3. Also varying the spindle speed produces different amplitudes and frequencies of current, as seen in Figure 5.6.4. At 700 RPM the signal processing chain created can identify a wide range of different feeds. However the varying spindle speeds, as seen Figure 5.6.4, identify slower axis movements, identifying an incapacity to produce a stable direct current. The capability of a signal processing chain to produce the direct current response is dependent on the size of the moving average window. A low moving average window will produce a fast output signal, and is more responsive to high frequency alternating signals. A large moving average window will produce a slower output signal, and is more responsive to low frequency alternating currents. Subsequently to produce a smooth direct current at low speeds would require a larger moving average. Currently the signal processing chain is ideal for measuring spindle speeds >=900 RPM at feed rates >=0.1, which is in scope for the machining tests within this work.

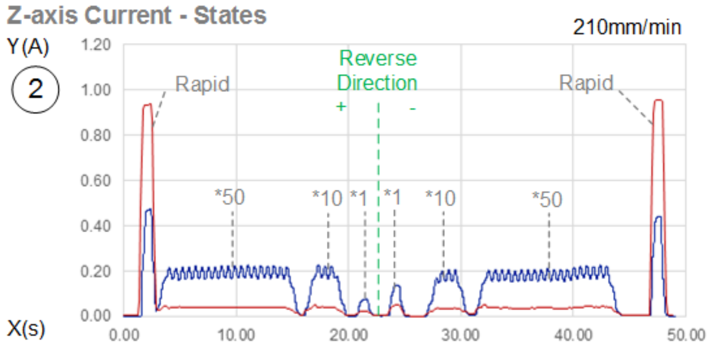
Vibration

The machine Z-axis vibration is measured by the spindle accelerometers X-axis, as seen in Figure 5.7.1. Since the spindle itself is moved to produce Z-axis movements, the vibration of spindle revolution is combined with Z-axis movement. In order to measure the vibration/acceleration response to Z-axis movements, a Lowpass filter is utilised to isolate movements below 2Hz. The acceleration response across; axis movements Figure 5.7.2, varying feed rates Figure 5.7.3, and varying spindle speeds Figure 5.7.4, have identified no significant response controlled speed movements, and only identify rapid movements. Subsequently the current vibration/acceleration measurement system in this work can only utilise windows of analysis from rapid movements.



Graph Legend

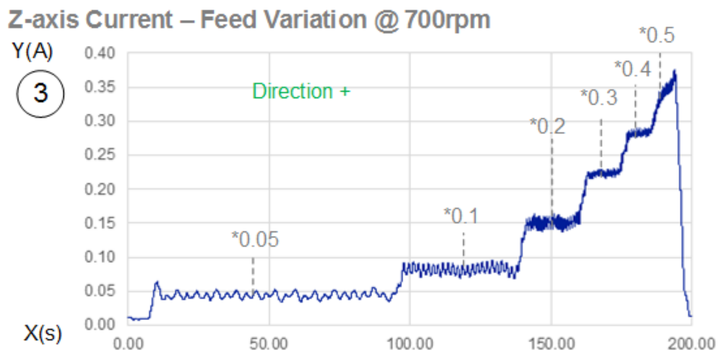
Axis	Name	Scale	RF
X	Current Z	+x1	-



Graph Legend

Axis	Name	Scale	RF
X	Z-C-Active	+x1	2.1
X	Z-C-Rapid	+x1	2.2

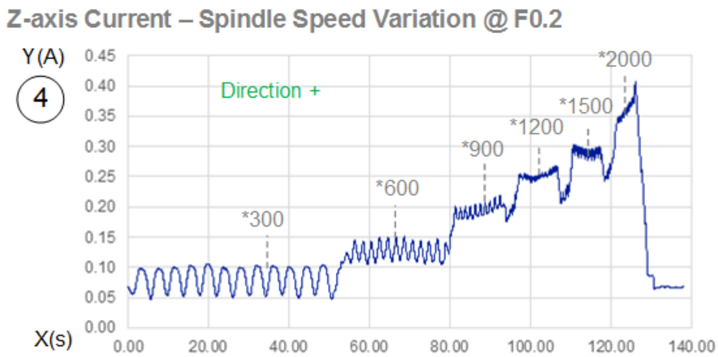
*Distance Travelled mm



Graph Legend

Axis	Name	Scale	RF
X	Z-C-Active	+x1	2.1

*Feed mm/rev
Distance Travelled 50mm



Graph Legend

Axis	Name	Scale	RF
X	Z-C-Active	+x1	2.1

*Spindle Speed rpm
Distance Travelled 50mm

Figure 5.6 Machine operation: Z axis movement, motor current

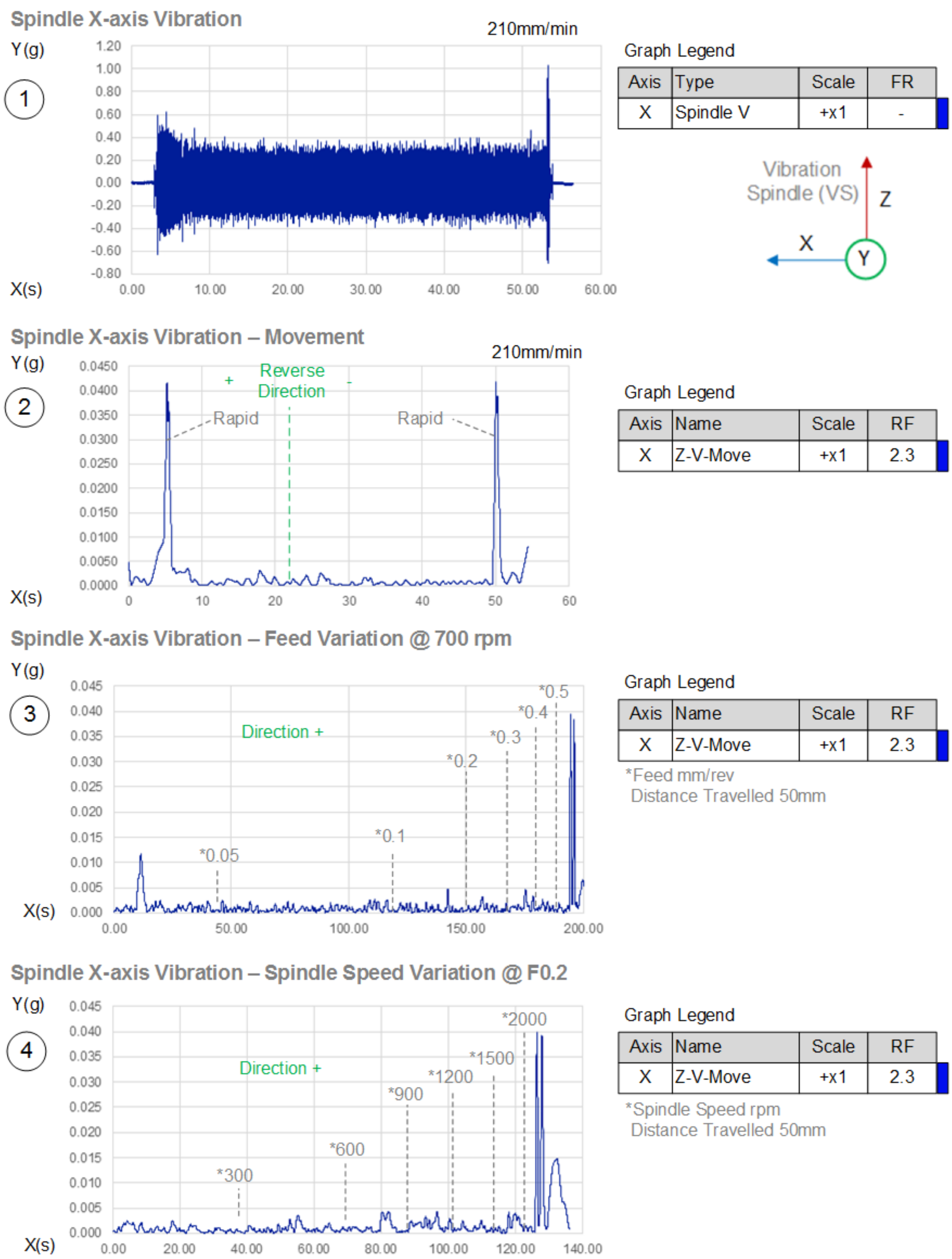


Figure 5.7 Machine operation: Z axis movement, Spindle X-axis vibration, Time domain

X Axis Movement

Signal Processing Legend

RF	1	2	3	4	5	6	SPS	Delay
3.1	Avg(3)	Avg(M100)	Rectifier	Avg(10)	Avg(M200)		300	0.878
3.2	SD(100)						30	0.033
3.3	LP(100) {F:2} [N:6000 O:5]	RMS(100)	Avg(50)				130	0.405

Filter Type (Window Size) [Info]   (M100) = Moving Window, size 100

RF: Reference Filter
SPS: Samples per second
Avg: Average
RMS: Root Mean Square
SD: Standard Deviation
BP: Band Pass Filter

Table 5.3 Machine operation: X axis movement, Signal processing legend

<u>Motor current</u>

Figure 5.8.1 represents the machine X-axis motor current during 4 incremental movements in both the positive and negative directions. The first movement is a rapid movement, followed by 3 set speed movements, covering 25mm, 5mm, and 1mm. With signal processing the alternating current can be converted into direct current identifying the different movements, as seen in Figure 5.8.2. Furthermore the occurrence of rapid movements can be separated from the signal, enabling the creation of multiple windows of analysis from the individual signal. Subsequently large and small movements of the machine X-axis can be effectively identified through single phase motor current measurement.

Uniquely the X-axis draws a significantly larger current amplitude than the machine Z-axis. Potentially this is because of the weight difference between the spindle and the turret. Additionally the negative movements of the X-axis result in a higher current amplitude. This is due to the angle of the CNC bed, as the X-axis moves on a slope downwards, towards the workpiece, for positive moves, and upwards for the negative moves. The extra force requires a greater current amplitude to do the work.

The X-axis operates similarly to the Z-axis. Subsequently varying the feed rate or spindle speed produces different amplitudes and frequencies of current, as seen in Figure 5.8.3 and Figure 5.8.4.

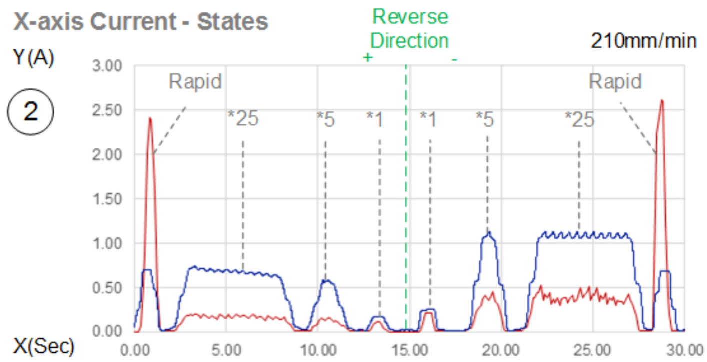
<u>Vibration</u>

The machine X-axis vibration is measured by the turret accelerometers X-axis, as seen in Figure 5.9.1. In order to measure the vibration/acceleration response to Z-axis movements, a Lowpass filter is utilised to isolate movements below 2Hz. The acceleration response across; axis movements Figure 5.9.2, varying feed rates Figure 5.9.3, and varying spindle speeds Figure 5.9.4, have identified small responses to controlled speed movements, and large responses to rapid movements. Uniquely the X-axis is not significantly influenced by the spindle rotation, reducing the noise in the acceleration signal. Subsequently small acceleration spikes can be observed in the signal at initial movement, acceleration, and movement stops.

The triaxial frequency response to acceleration during the incremental movements of Figure 5.9.2, can be observed in Figure 5.10. The results identify significant low levels of vibration outside of rapid movements, e.g. below 0.2×10^{-5} g.MS/s. A varied range of small frequencies is observed, with the X-axis exhibiting the highest stationary signal at 1244 Hz, and a variety of frequency spikes induced from rapid movement acceleration and braking. Furthermore the spindle rotation is faintly observable on the turret acidometers Y and Z axis at 4688 Hz.

Graph Legend

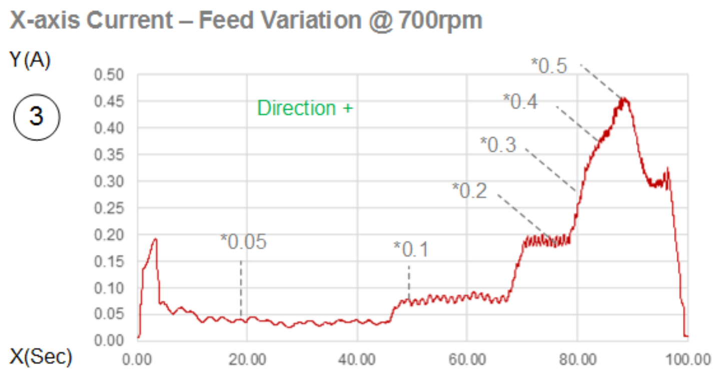
Axis	Name	Scale	RF
X	Current X	+x1	-



Graph Legend

Axis	Name	Scale	RF
X	X-C-Active	+x1	3.1
X	X-C-Rapid	+x1	3.2

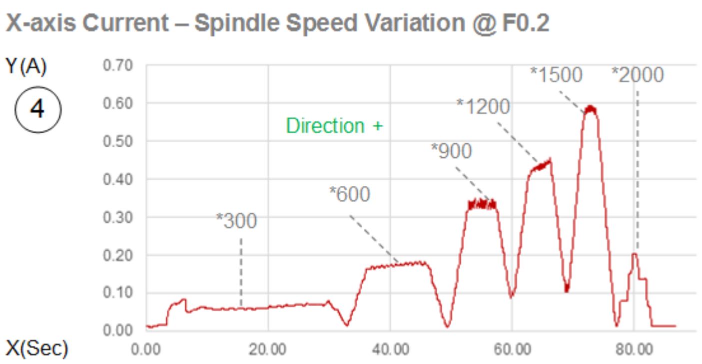
*Distance Travelled mm



Graph Legend

Axis	Name	Scale	RF
X	X-C-Active	+x1	3.1

*Feed mm/rev
Distance Travelled 50mm



Graph Legend

Axis	Name	Scale	RF
X	X-C-Active	+x1	3.1

*Spindle Speed rpm
Distance Travelled 50mm

Figure 5.8 Machine operation: X axis movement, motor current

Figure 5.9 Machine operation: X axis movement, turret x axis vibration, time domain

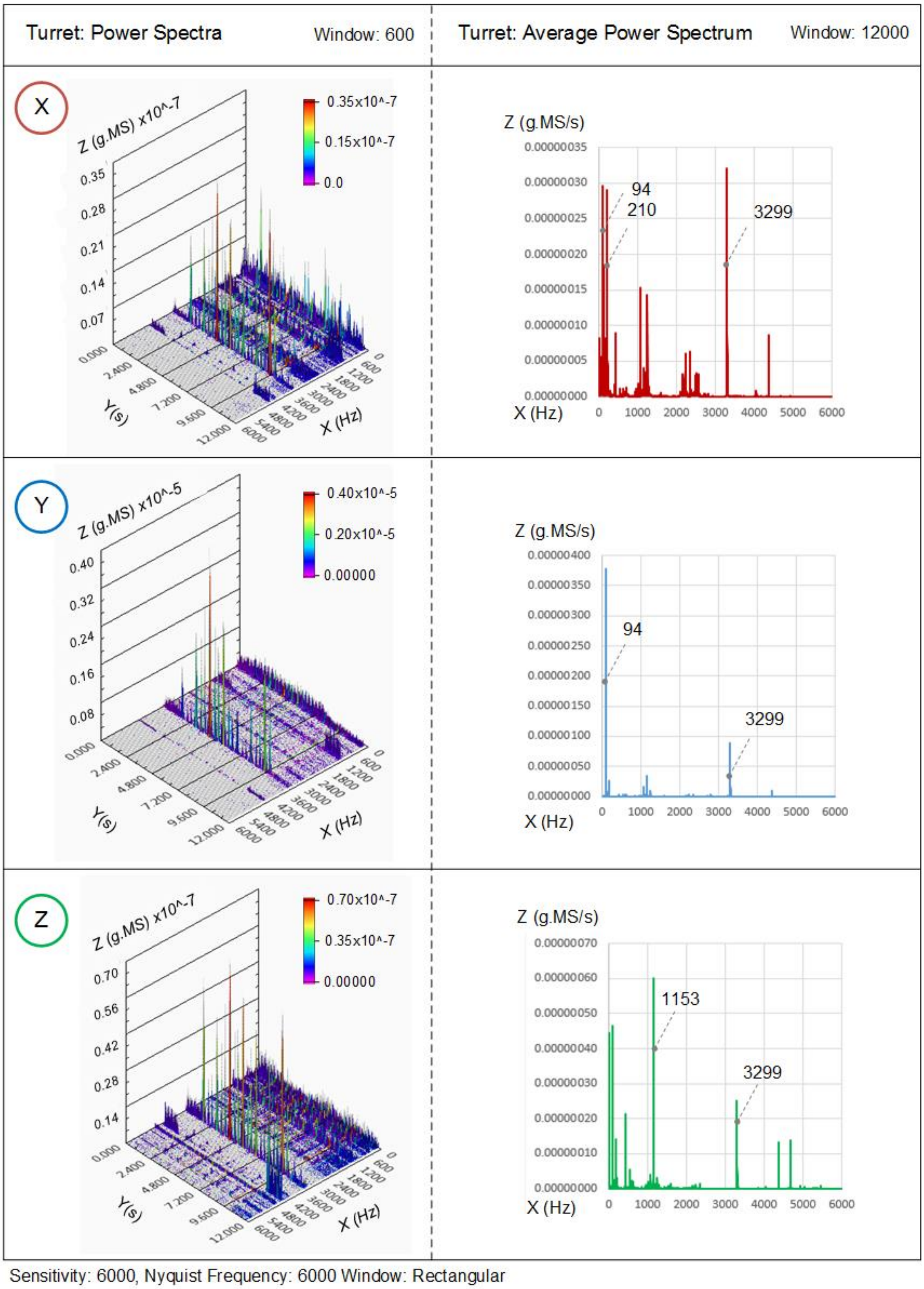


Figure 5.10 Machine operation: X axis movement, turret triaxial vibration, frequency domain

5.2.2 Machine resonance

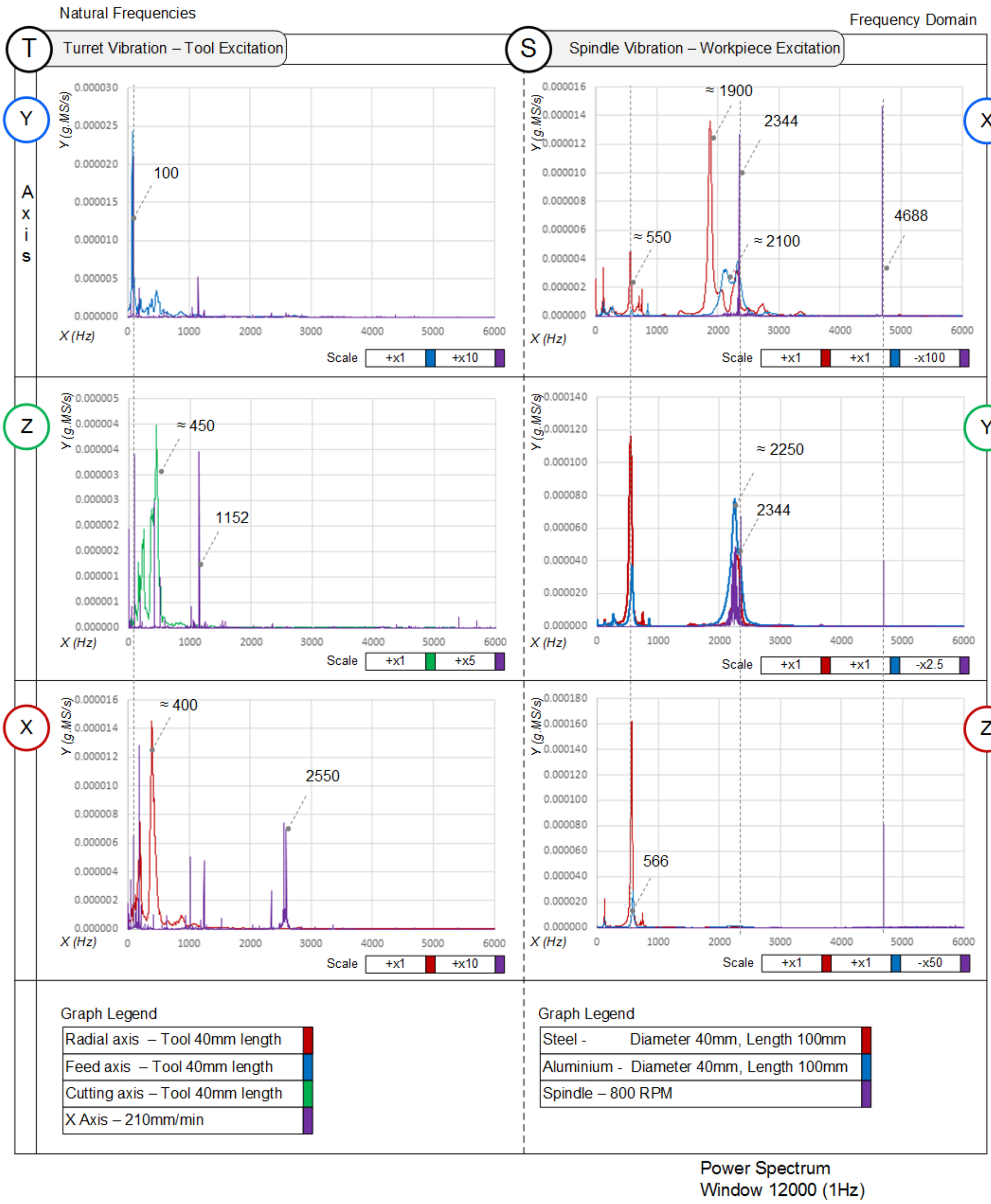


Figure 5.11 Machine resonance: turret and spindle, natural frequencies

In order to further identify the natural frequencies within CNC turning, a bump test was carried out. This test required the external excitation of the tool, and both aluminium and steel workpieces. The spindle accelerometer monitored the workpiece vibration, and the turret accelerometer measured the tool vibration. External excitation was achieved with a force hammer. The result of the external excitation are plotted with the natural vibration recorded during machine operation, i.e. spindle rotation and machine X-axis movement, as seen in Figure 5.11. The results identify a multitude of frequency responses to the spindle rotation, tool and workpiece vibration.

The natural tool resonance resides in a low frequency band <1000 Hz for the Turret X, Y, and Z axis. The turrets movement resonance are below <1300 Hz, at 1246 Hz in the unrestrained X-axis. Also spindle rotation frequencies are measureable on Turret Y 2344 Hz and Z 4688 Hz

The spindles resonance is identified in X 2344 and 4688 Hz, Y 2344 and 4688 Hz, and Z 4688 Hz. The natural workpiece resonance of aluminium and steel both have low resonant frequencies at 600 Hz, measureable across X, Y, and Z. Diversely steel exhibits a X axis resonant peak at 1900 Hz, and a lesser peak at 2300 Hz, which is the resonant frequency of the spindle. Aluminium also exhibits two peaks but at closer frequency bands and equal power, X 2100 and 2300 Hz. Both aluminium and steel resonant at the similar frequencies in the cutting Y axis, 550 - 566 Hz, and 2250 – 2300 Hz. The lower frequency reaction is present in the X, Y, and Z axis, with the steel workpiece having the greatest power. The higher frequency reaction is present on both the X and Y axis, with the aluminium workpiece having the greatest power.

5.2.3 Conclusion

The measurement of machine operations outside of cutting operations has defined the normal/natural spindle and axis current and vibration response. These natural machining responses allow for windows of analysis to be identified for in-processing machining. Key process indicators include; spindle activation, spindle acceleration, spindle braking, and axis movements. Furthermore a unique key process indicator identified to provide sequential windows of analysis is the rapid movement of the axis. These rapid movements are easily extracted from the motor current, and are not influenced by changing machining parameters. Subsequently these operations are repeatable and reliable, can be utilised to characterise the machining of multiple parts, and will not require updating if machining parameters change.

Both vibration and current enable the monitoring of machining actions. The current is the most accurate and reliable measurement for machine action monitoring, due to its direct relationship with the motors that perform the operations. Spindle vibration does however provide a measurement of physical movements, and the kinematic response to various operations. These measurements are key to monitoring the internal bearing and gears during physical machining.

By performing machining actions and motions demonstrated in this work, specific insight into unseen mechanics can be observed. Subsequently comparing the results to the previously defined normal operating responses, can isolate areas of concern in the spindle, and both axis. This alignment of machine health datums can ultimately become a periodic preventative maintenance task, resulting in more insightful decisions into machine operation and maintenance.

Furthermore, the identification of the natural resonance of the machining components has enabled frequency spectrum to be separated into areas. These areas consist of tool, workpiece, spindle, and turret vibration. The identification of these areas allows for the effective monitoring and understanding of their excitation during machining.

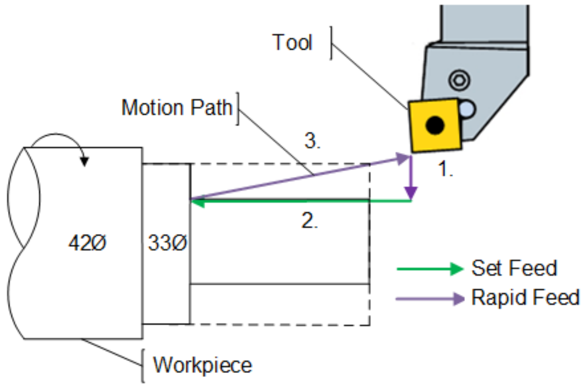
5.3 Machining investigation

The following machining operations were undertaken to measure the triaxial responses of tool force, spindle vibration, and turret vibration, in both the time and frequency domain, for active machining operations. The machining area of focus, is roughing cycles in CNC turning, which remove large quantities of material. These operations typically utilise the same machining parameters to remove the bulk of the material in a turning operation. Fundamentally these operations are the most consistent operations, due to the limited variation observed between iterations. Logically, performance characterisation should be obtainable by measuring these windows.

The aim of this study is to compare the tool force, spindle vibration, and turret vibration during dry turning roughing cycles of both aluminium and steel workpieces. Furthermore, a tool wear mode will also be investigated to provide a contrast in cutting performances. Key process indicators are sought out to identify the tool wear mode in both the time and frequency domains.

5.3.1 Case 1: fixed cutting parameters

Machining setup



Machining Parameters

Mode	Constant Surface speed
Cutting Speed	100 m/min
Feed	0.2 mm/rev
Depth of cut	1 mm
Length of cut	30 mm
Cycles	4
Coolant	None

Other

Workpiece machining length	100mm
Tool Length	40mm
Workpiece material	Aluminium, Steel

Figure 5.12 Machining: Feed variation, setup

The initial machining operation was undertaken to; identify the required signal processing configuration/resolution for comparable signal analysis throughout the testing regime, and to provide an initial contrast for machining both aluminium and steel. An aluminium and steel workpiece was cut using the machining parameters represented in Figure 5.12.

Resolution

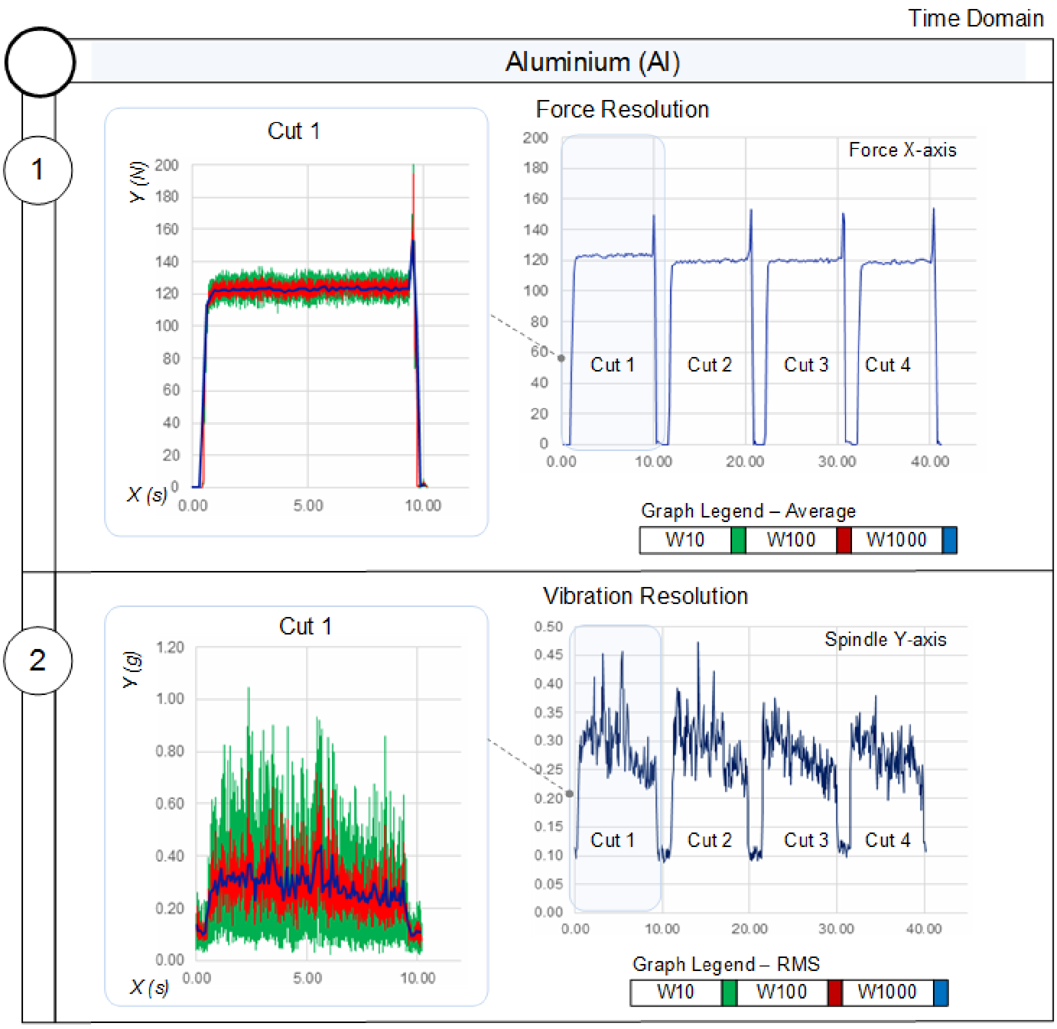


Figure 5.13 Machining: analysis resolution, time domain

Figure 5.13, identifies the time domain force and spindle Y-axis vibration response to 4 cutting operation in series, with an aluminium workpiece. A clear analysis signal is required for comparison. Subsequently an average value is sought to remove the larger variations in measurements, and represent the response as the mean power. Force provides a more stable response to the cutting process than vibration. Both signals are represented by kHz sampling. By reducing both signals to Hz a visually comparable signal is produced. This was achieved by averaging the force data, and performing a RMS on the vibration data, with windows of 1000 samples. The produced force signal is very consistent, as the constant surface speed of the turning operation aims to achieve a uniform cutting speed at different workpiece diameters. The produced vibration signal however, shows a degree of variation as the vibration of the spindle appears to vary throughout the cutting process.

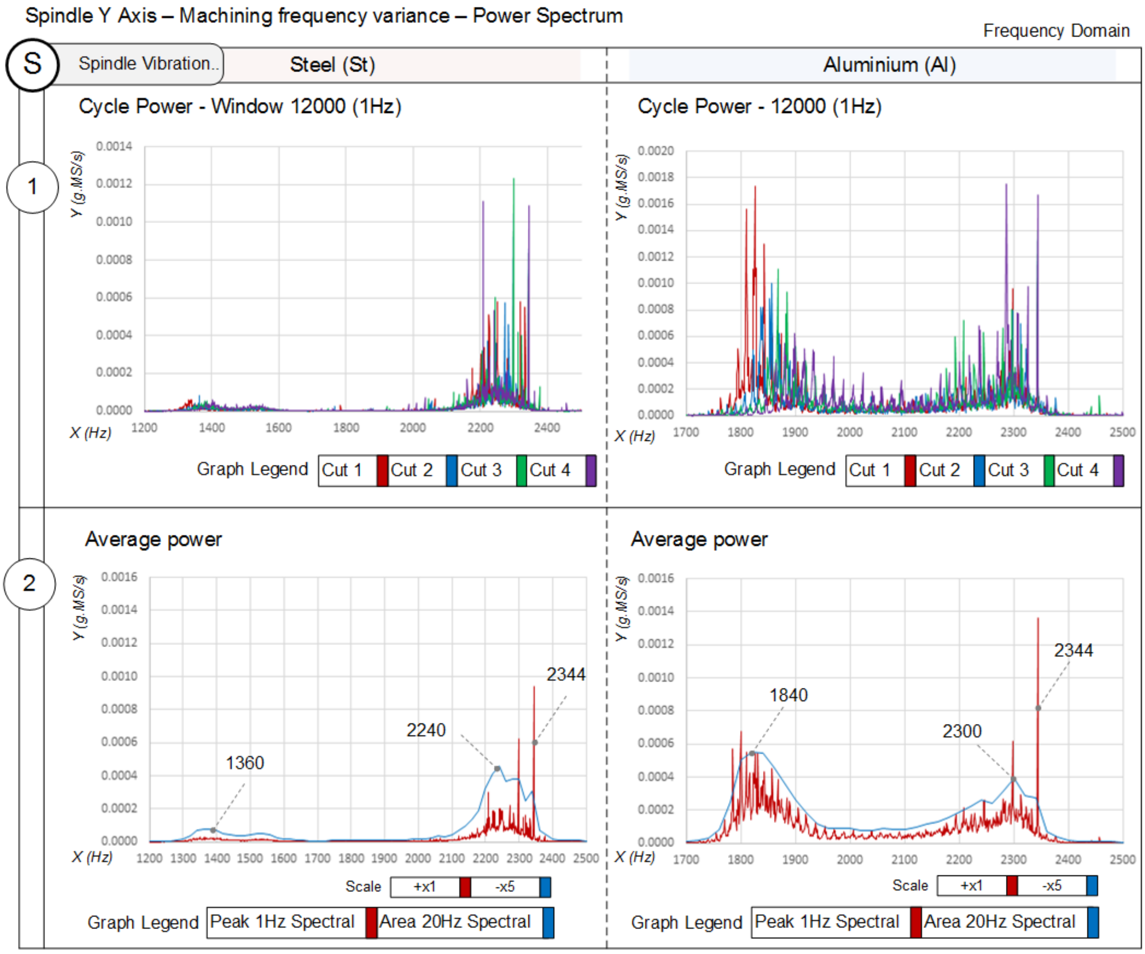


Figure 5.14 Machining: analysis resolution, frequency domain

A frequency window with the peak power of the vibration is reviewed to observe the vibration frequency response between cuts, 1200 – 2500 Hz, of both aluminium and steel, as seen in Figure 5.14. A clear variation in vibration frequency between cuts is observable in both materials, as seen in Figure 5.14.1. Subsequently an average value is required to represent the signal as a mean of this variation, producing a more stable and comparable signal. Two methods can be utilised to achieve this, time dimensional averaging, and spectral bandwidth widening. Time dimensional averaging maintains the high resolution spectral bandwidth of 1Hz, and gets total power across all cutting iterations. Spectral bandwidth widening condenses the power within a specific bandwidth to represent the sum of the power in all frequencies. Obtaining an average of multiple cuts identifies the cutting process as a collective. This improves the robustness of the analysis regime to not be affected by minor random anomalies. Widening bandwidths compensates for small frequencies shifts, and is useful for the analysis of random stationary signals, and continuous and transient non-stationary signals. Time dimensional averaging maintains the peak frequencies response, as the bandwidth is maintained at 1Hz. Spectral bandwidth widening represents the frequency response as an area, >1Hz. The utilisation of both methods is dependent on the application area. In turning machining, viewing the frequency response of the cutting axis on the spindle as a peak and an area identifies contrasting results. Peak results, identify the dominant frequency of the deterministic spindle at 2344Hz. Area results, identify the dominate frequency of the resonance of the material between two peaks which differs between materials; steel 1360 – 2240Hz, aluminium 1840 – 2300 Hz. Area analysis is beneficial to processes that demonstrate drifting frequency responses. Furthermore, un-deterministic vibration frequency responses represent the sum of the frequencies, which enables a clear comparison to be achieved.

Results

The results are displayed and individually reviewed in the following; time domain Figure 5.15, spindle vibration frequency domain peak Figure 5.16, turret vibration frequency domain peak Figure 5.17, and spindle and turret vibration frequency domain area Figure 5.17.

Time domain

There is a significant difference in the tool force required for cutting the two materials. This difference is expected due to the difference in hardness. Both materials provide stable and repeatable force measurements between cycles with minimal variance in the signals.

Aluminium has an increase in spindle vibration amplitude compared to steel, in both the feed and cutting axis. However, considerable variance is observed in spindle vibration for aluminium machining, as steel maintains a minimal reaction to machining with near equal measurement on all axis.

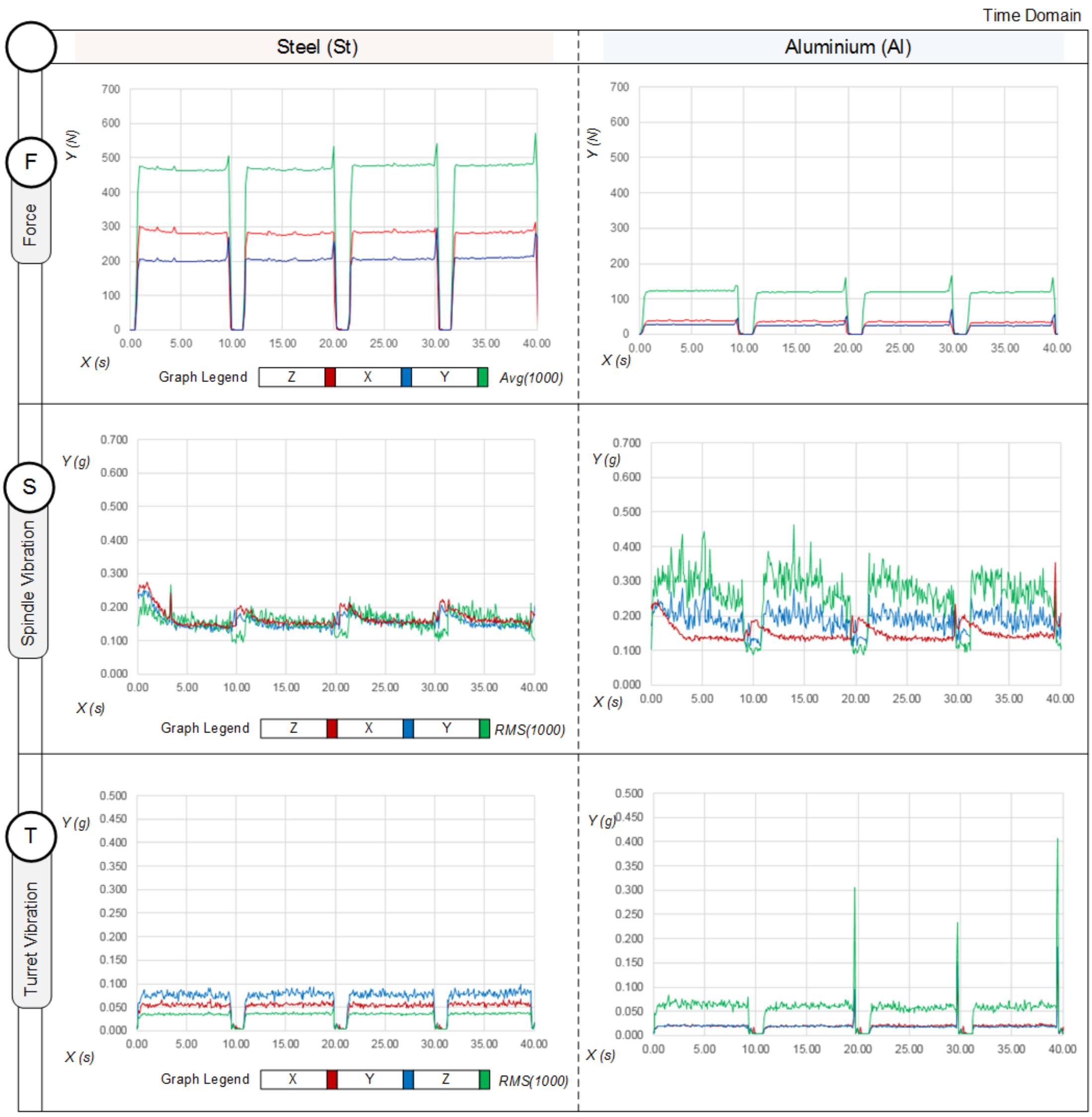
Aluminium also has an increase turret vibration amplitude compared to steel, however only in the cutting axis. The feed and radial axis are consistently higher during steel machining. Aluminium is prone to vibration over steel due to its lower density and Young’s modulus. However aluminium is more easily machined due to its lower hardness. The volatility in machining the harder material could be identified in the increase in turret feed and axial vibration. Furthermore, steels reluctance to vibrate can also be seen in the lack of turret vibration peaks that are observed at the end of cutting cycles. The cause of these peaks can be contributed to the accuracy of the CNC to move the required distance in the Z axis, and the rapid movement at the end of the roughing cycle. If the tool overshoots the distance it will strike the end of the workpiece at 2mm+ cutting depth. The rapid movement can also slightly swing the tool into contact to the wall as it reverses direction rapidly.

Frequency domain

In spindle vibration, both aluminium and steel identify peak power in the X, Y, and Z axis at the spindle resonating frequencies of 2344 and 4688 Hz. Similarly to the time domain, aluminium has the highest cutting axis power, while steel has the highest feed and radial axis power.

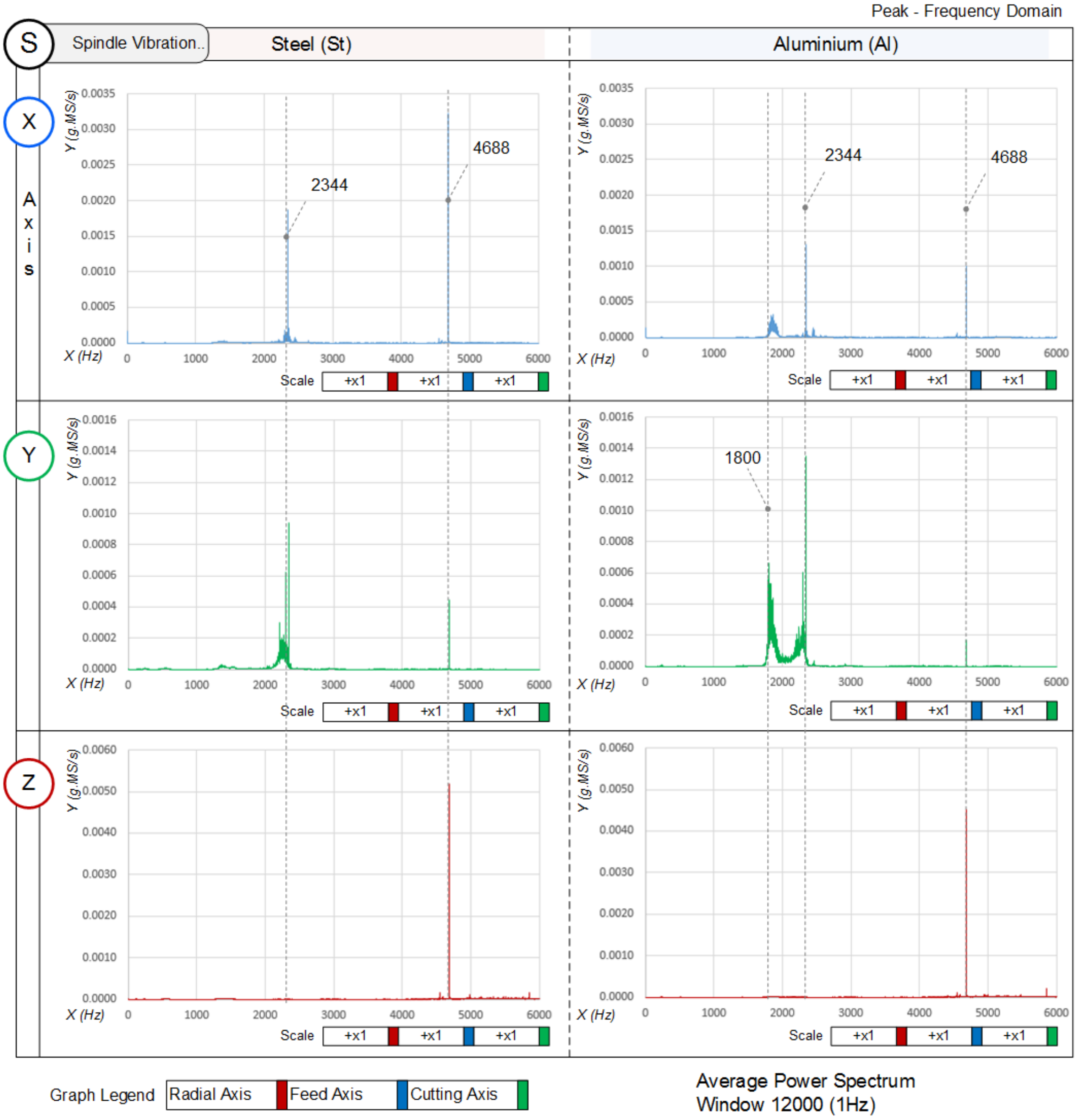
Turret vibration provides a unique view of machining vibration. All frequency responses are not significantly reactive to the previously defined natural resonance frequencies, observed in tool excitation and machine movement. The frequency responses do not resemble deterministic peaks, but do resemble concentrated areas of vibration within frequency bands. Subsequently the vibration is a collection of turret components under resonance induced via machining. Comparatively both materials identify a separation in frequency and power response to different material machining. Aluminium has high frequency response in the cutting axis. Steel has a varied frequency response amongst axis, with significantly larger areas of power in the feed and radial axis than aluminium.

To further compare the resonance of the materials, area frequency analysis is presented in Figure 5.18, with spectrals consisting of a 20Hz bandwidth. Each spindle and turret vibration axis of both materials are plotted against one another. The lack of peak reaction for turret vibration means area frequency analysis provides a less variant frequency spectrum. However, area frequency analysis for spindle vibration, provides a very clear and comparable material frequency response to aluminium and steel. A difference in spindle peak reaction between the materials, at 2340 Hz, is still observable, however the sum of the frequency shifting material resonance is now visible. This identifies a separation in spindle vibration frequency response between materials, with steel peaks of 1360 and 2340 Hz, and aluminium peaks of 1840 and 2340 Hz.



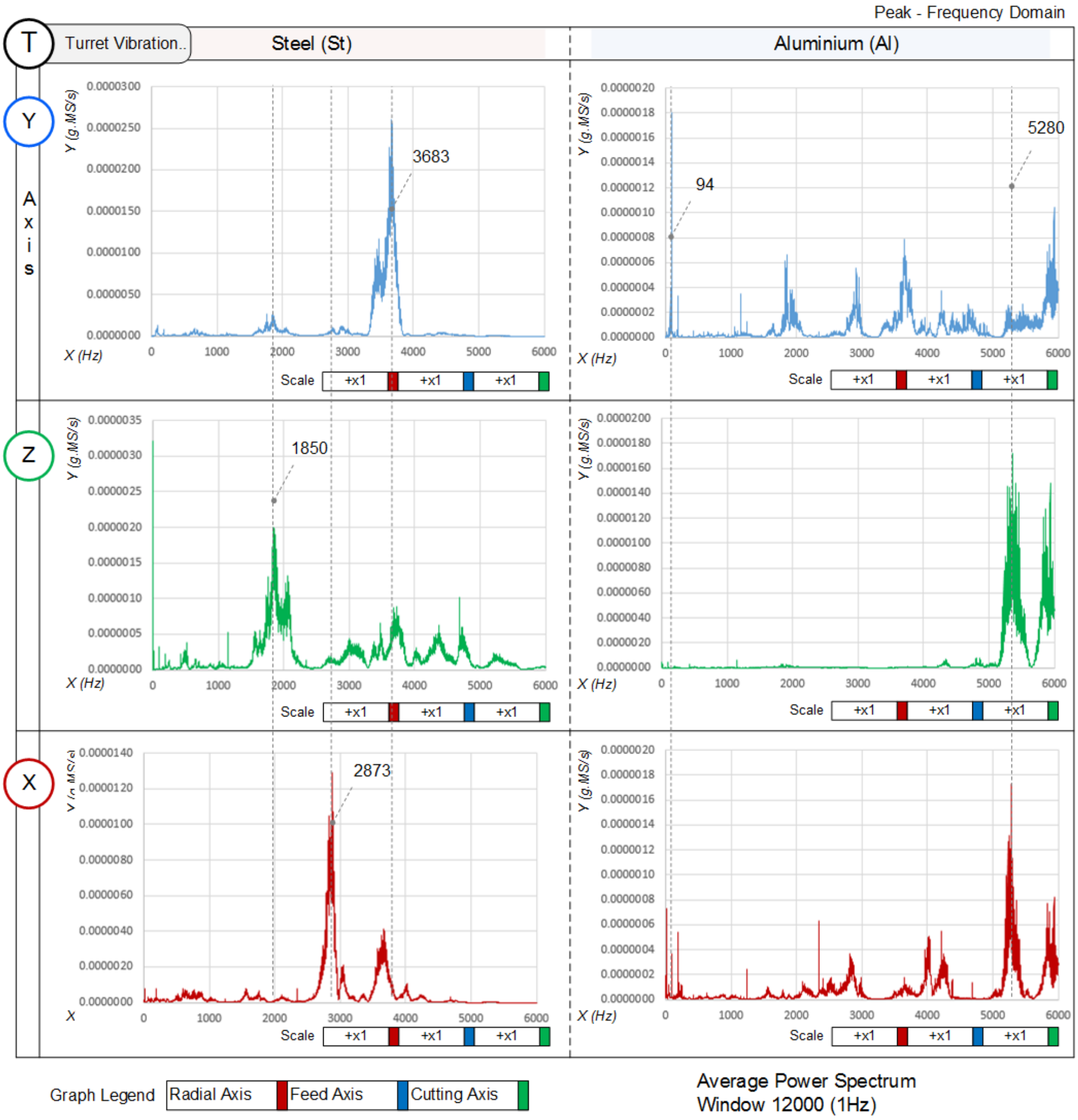
Steel	Aluminium
• Spindle vibration is very unreactive, all axis near equal in value • Consistent and similar turret vibration amplitude between axis	• Variance in spindle vibration between cuts • Turret vibration peaks observable after cut 1, low feed and radial axis amplitude
• Minimal variance in force between cutting cycles • Significantly higher force required for steel machining • Spindle vibration is greater during aluminium machining • Turret vibration peaks observable during aluminium machining	

Figure 5.15 Machining: initial cut, time domain



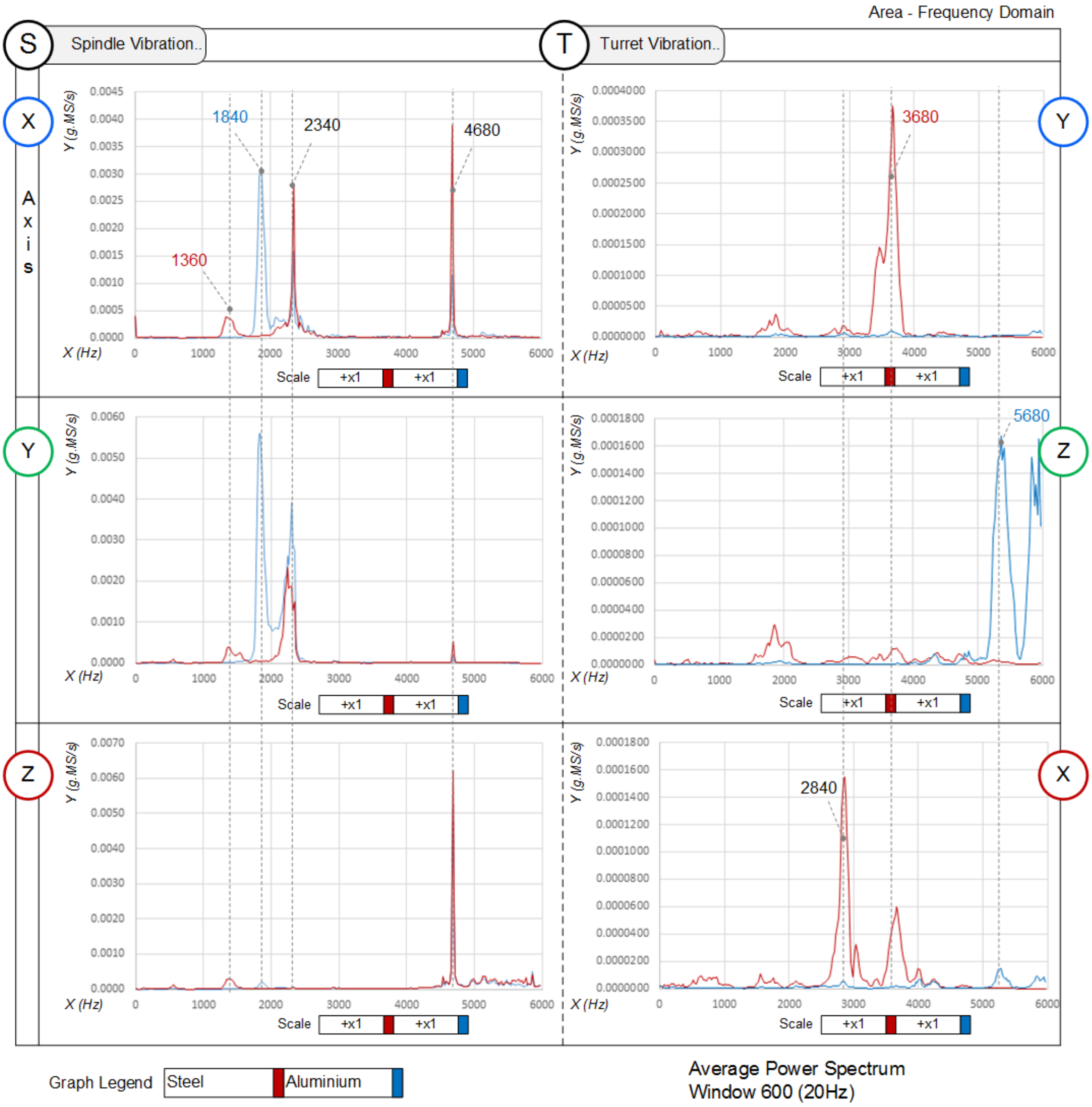
Steel	Aluminium
• Minimal peak power in cutting axis Y	• Minimal peak power in feed and cutting axis X & Y
• Peak power of both materials at X Y Z axis are all at spindle resonating frequencies; 2344, 4688 • Increase in peak power in steel at X Z axis • Higher cutting axis vibration in aluminium Y axis • Higher area power observable in aluminium X Y axis, at ≈1800 Hz material resonance	

Figure 5.16 Machining: initial cut, spindle vibration, frequency domain peak



Steel	Aluminium
• Minimal power in cutting axis Y	• High frequency cutting response to aluminium X Y Z
• Distributed vibration power and frequency cutting response across both materials and axis • Vibration is clustered in areas, peaks are not dominant • There is no significant reaction in the previously defined natural resonance frequencies, i.e. tool vibration and machine movement	

Figure 5.17 Machining: initial cut, turret vibration, frequency domain peak



Spindle	Turret
• Steel resonant frequency 1360Hz • Aluminium resonant frequency 1840Hz • Spindle Frequencies; 2340 & 4680 Hz • Steel has a higher power spindle high frequency response • Aluminium has a higher material resonance X Y	• Aluminium has a high frequency cutting axis response • Steel frequency power is dominant in the feed and radial axis

Figure 5.18 Machining: initial cut, spindle and turret vibration, frequency domain area

5.3.2 Case 2: tool wear

The previous comparison of aluminium and steel roughing cycle machining, has provided a contrasting reaction in both the time and frequency domain of the defined monitored process variables. These machining actions were undertaken specifically under the same machining parameters, in order to provide a baseline of normal reaction in tool force, spindle vibration, and turret vibration. The following tests are undertaken in order to understand the variant reaction to undesirable machining conditions, specifically tool wear. Key process indicators are sought out to identify tool wear across all process monitoring variables, in both the time and frequency domain.

Setup

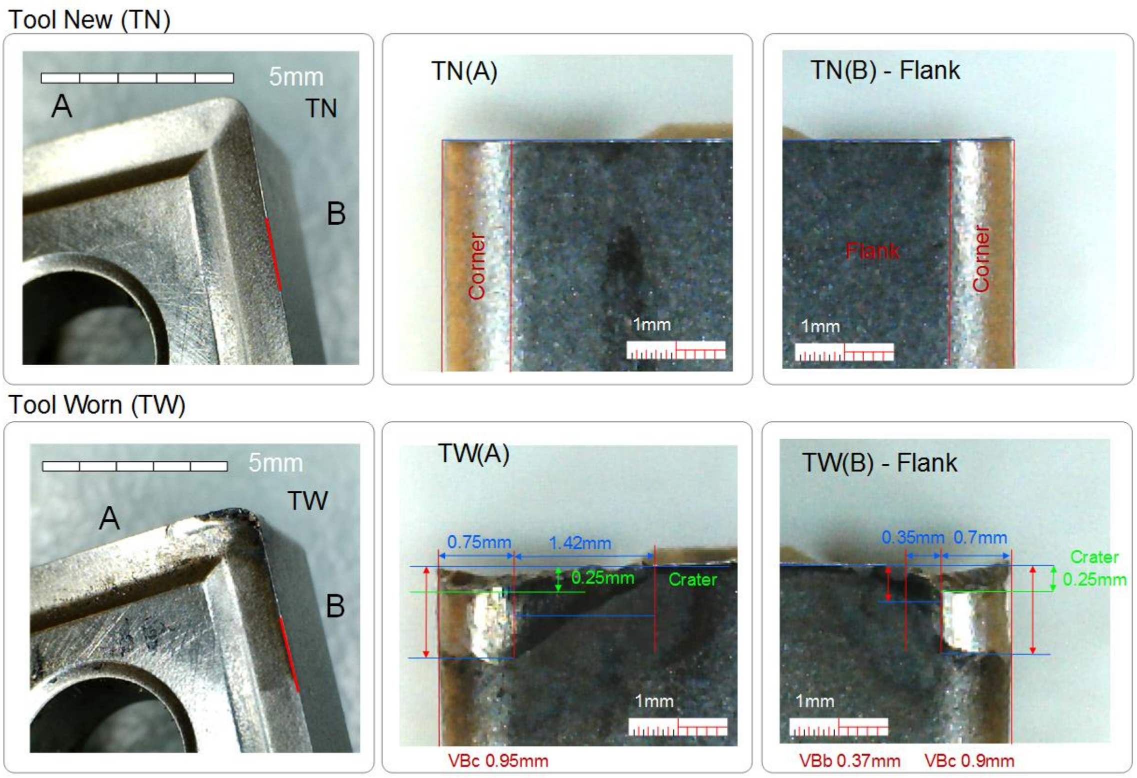
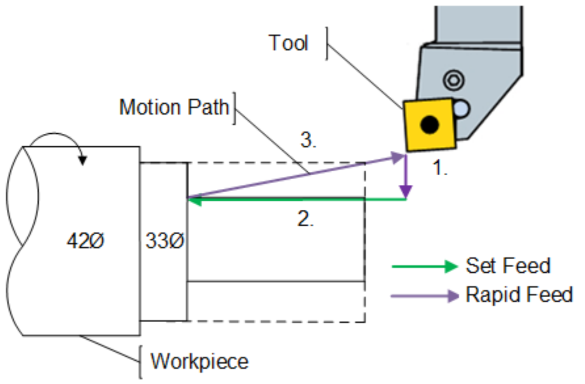


Figure 5.19 Machining: tool wear, new and worn tools

The cutting tools are identical in manufacture, however one has been worn. The wear on the tool is a mixture of both corner/flank wear and crater wear, as seen in Figure 5.19. The corner/flank wear dulls the cutting edge of the tool, and the crater wear changes the rake angle of the tool. The result is an undesirable cutting tool, which should be avoided during manufacturing production.

The machining operation and parameters are defined in Figure 5.20. Eight consecutive cutting cycles are made to obtain the average response to the cutting process. The cycle count was increased from 4 to 8 compared to the previous tests, to provide a wider scope of consecutive dry cutting machining. Once again, both Aluminium and Steel workpieces are machined to provide a comparison.



Machining Parameters

Mode	Constant Surface speed
Cutting Speed	100 m/min
Feed	0.2 mm/rev
Depth of cut	1 mm
Length of cut	30 mm
Cycles	8
Coolant	None

Other

Workpiece machining length	100mm
Tool Length	40mm
Workpiece material	Aluminium, Steel

Figure 5.20 Machining: tool wear, setup

Post machining tooling

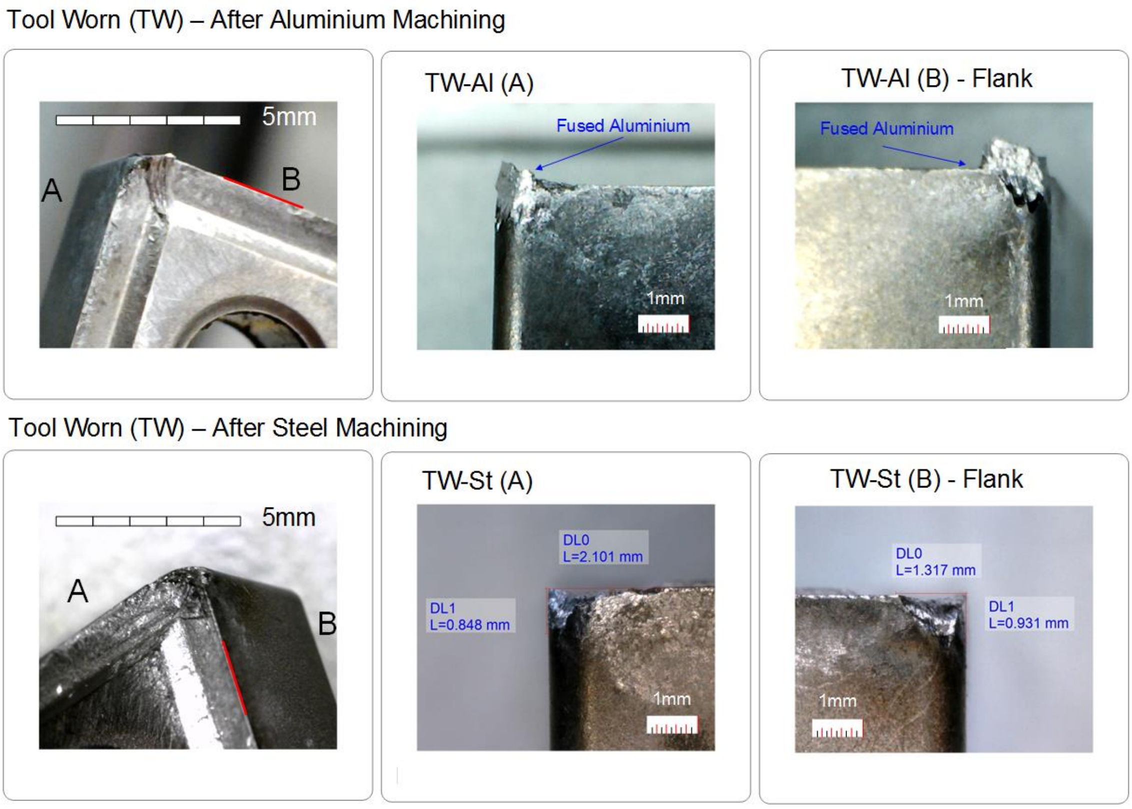


Figure 5.21 Machining: tool wear, post machining tool inspection

The machining of both materials has resulted in a significant variation in tool dimensions post machining, as seen in Figure 5.21. Aluminium has fused to the tool and created a new cutting edge. This new dimension has the potential to improve the cutting process. The crater wear has now been filled in, resulting in a new sharper cutting edge, and a smaller rake angle. In contrast, machining steel has not had the same effect. Crater and flank wear is still visible on the tools surfaces. Furthermore, scorch marks were noticeable on the tool after steel machining, indicating a high friction cutting process.

Results

The results are displayed and individually reviewed in the following; steel time domain Figure 5.22, aluminium time domain Figure 5.23, spindle vibration frequency domain area Figure 5.24, turret vibration frequency domain area Figure 5.25.

Time domain

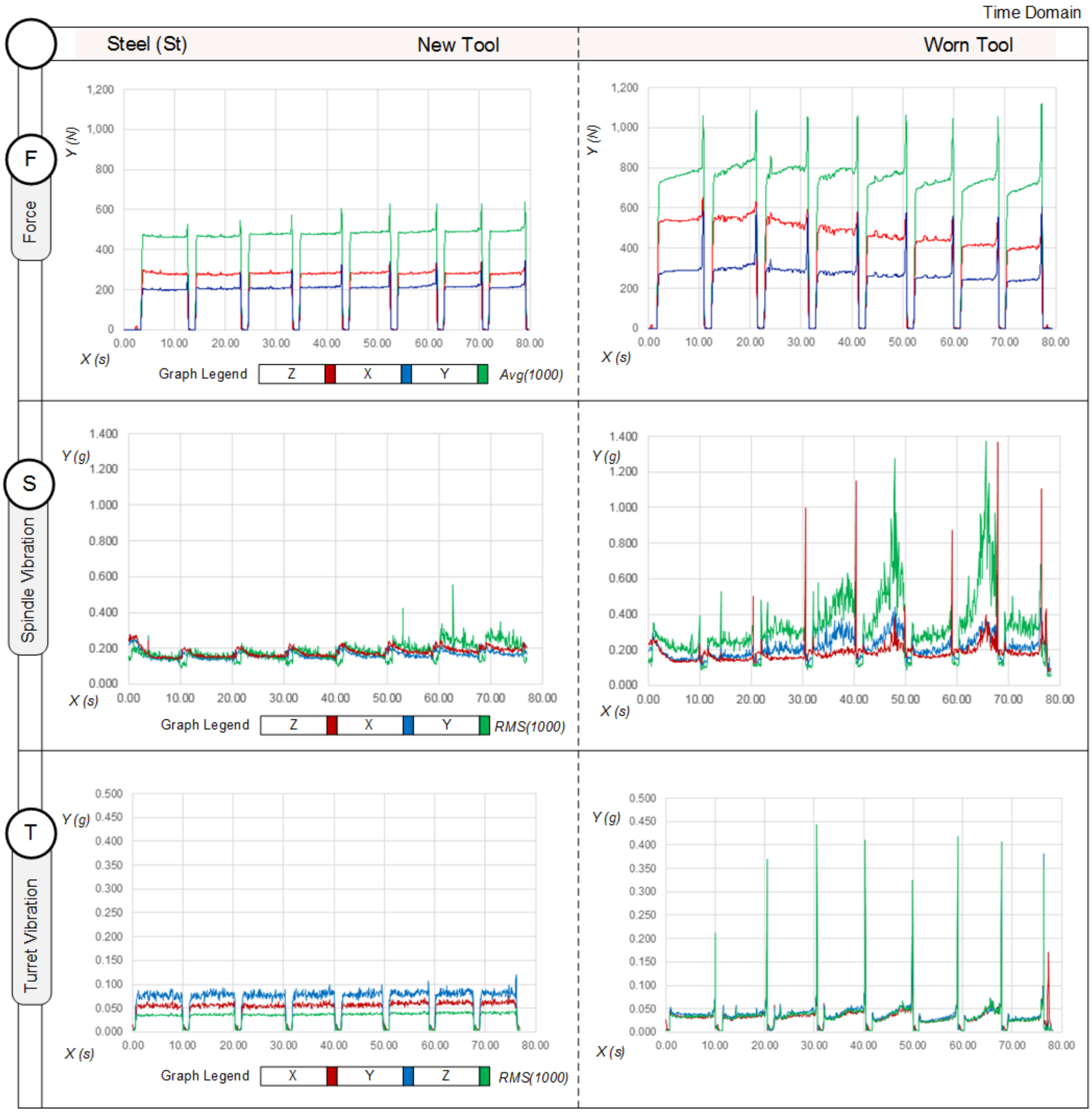
Tool wear has largely increased the tool force magnitude, signal variance, and end of cycle peak values in steel machining. Aluminium however, only has a slight increase in tool force magnitude, but a significant increase in signal variance and end of cycle peak values. Both materials identify an increase in spindle vibration amplitude, and signal variance. Steel spindle vibration is significantly more volatile with random spikes in the cutting and radial axis. Turret vibration for steel machining, has a reduction in uniform axis vibration amplitude, with reduced cutting and radial axis vibration, but extremely large cutting axis end of cycle peak values. Turning vibration for aluminium machining maintains the end of cycle peak values within normal operating conditions, but observes a decrease in these peaks during worn tool machining.

Tool wear has caused a radical change in steel time domain process variable reaction, by increasing all aspects of all signals. Tool wear for aluminium has had less of an effect, with minimal signal magnitude increase, but significant signal variance increase. The new cutting edge formed during aluminium machining has improved vibration within the cutting process, but with a less uniform response over each cutting cycle. Subsequently the occurrence of tool wear is observable through the time domain analysis, significantly in steel for magnitude and signal variance, and potentially in aluminium for signal variance.

Frequency domain

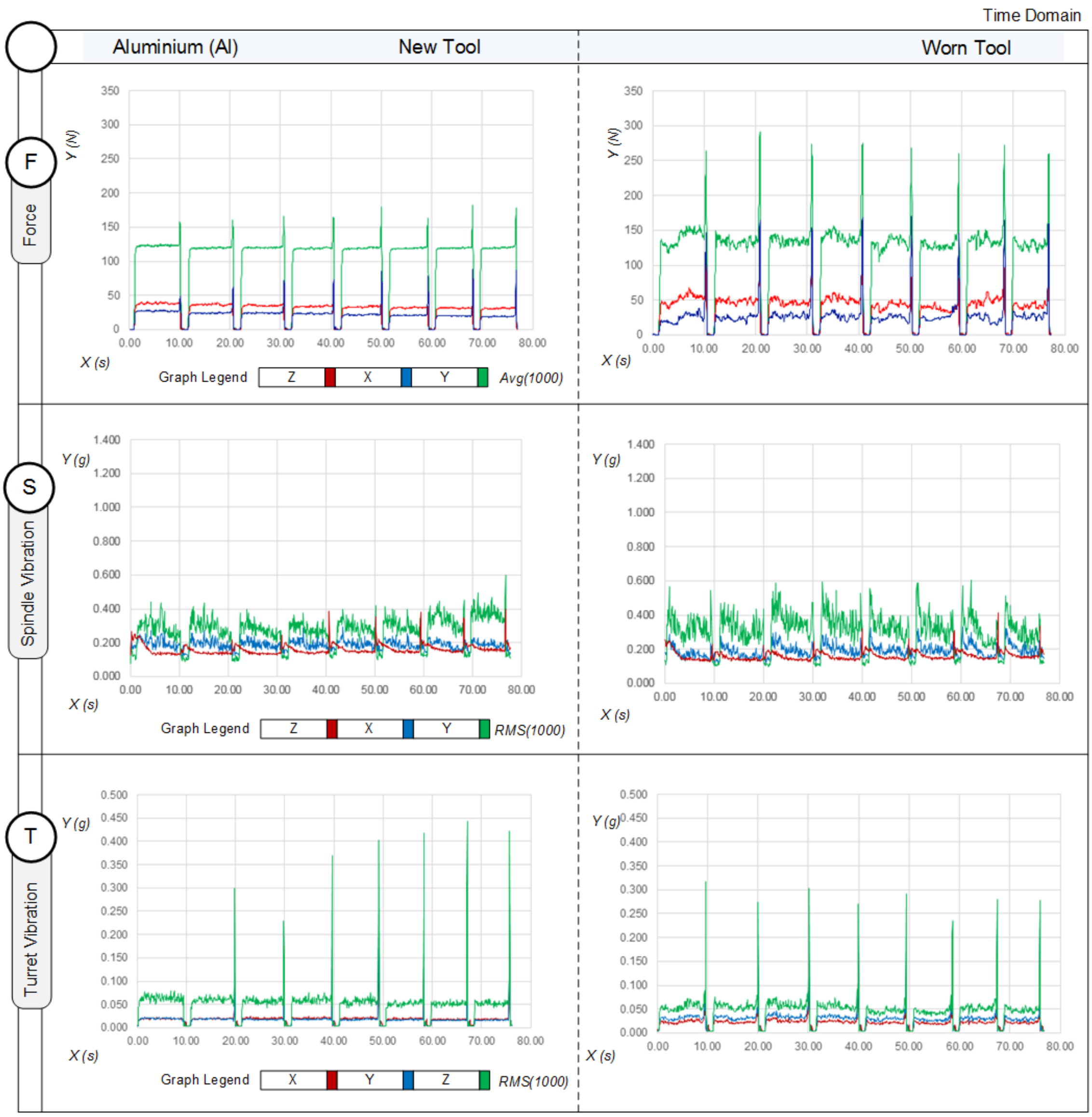
Tool wear for steel machining has provided a significant change in the material resonance in spindle vibration monitoring. There is shift in frequency response in the feed and cutting axis, and an increase in power across all axis. The signal variant response in time domain aluminium machining, is met with a more significant observation in the spindle vibration frequency domain. Similar to the steel machining, tool wear aluminium machining has a shift in frequency response in the feed and cutting axis, and an increase in power across all axis. There are similarities between both materials in the frequency domain on the cutting axis. Both materials display 2 peak areas within a band width of 1760 to 2340 Hz. However this range is a natural frequency for the new tool with aluminium machining, but with a lesser power. Additionally steels primary peak in the cutting axis, 1560 Hz, is not present during aluminium machining.

Turret vibration under worn tool machining exhibits a similar reaction in both materials. There is a high frequency response in the cutting axis, with steel having the highest peak at 5740 Hz, but both material containing two unique peaks within the frequency band 4000 – 5000 Hz. The greatest difference between materials is the high power response during aluminium machining with a new tool. However consistent and comparable key process indicators are present in both materials.



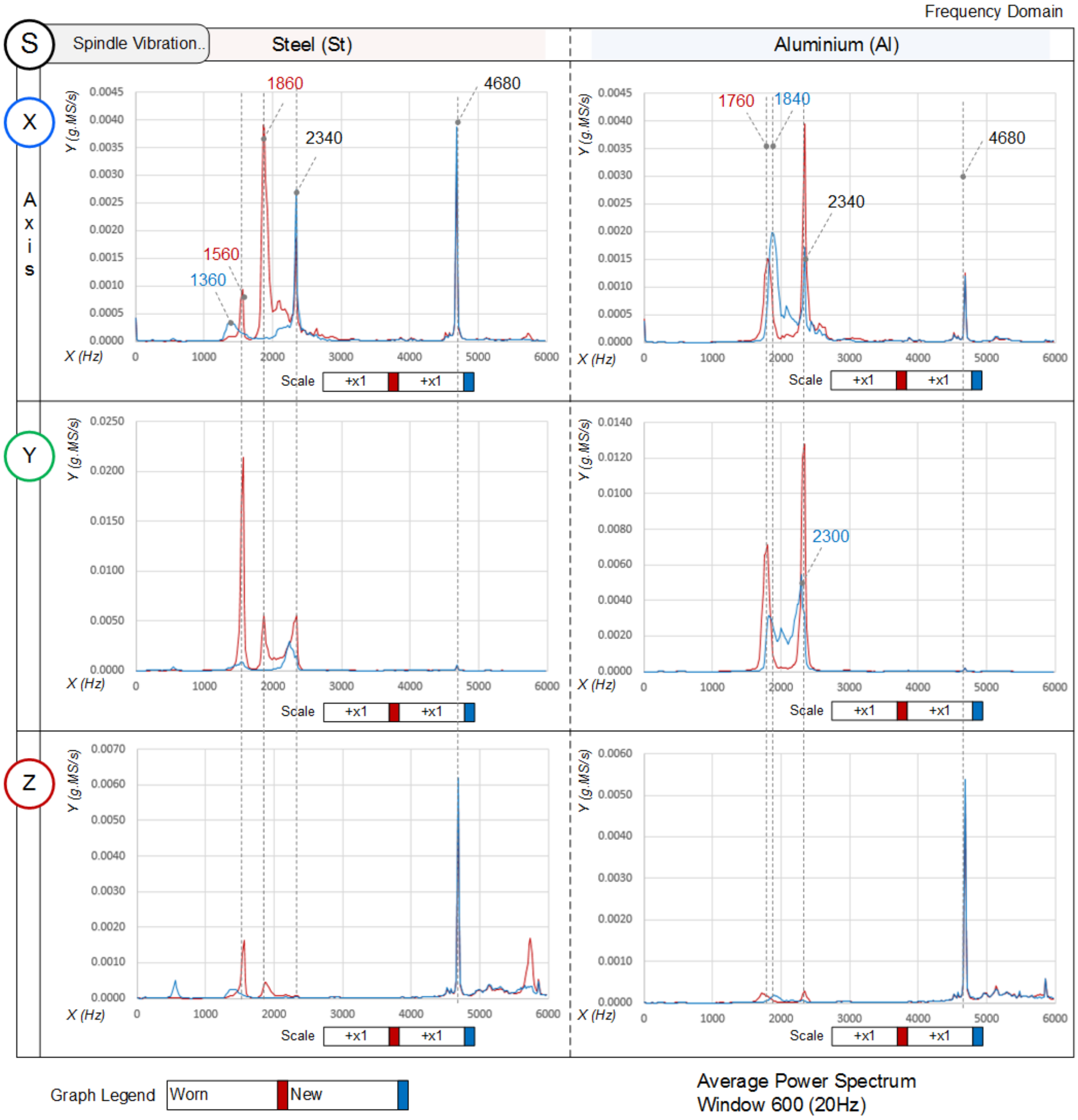
New Tool	Worn Tool
• Uniform force measurements, with minor increase in force peaks • Low spindle vibration variance, yet steadily increasing cutting axis amplitude • Uniform turret vibration measurements	• Increase in force for initial cuts, minor signal variance • Volatile spindle vibration, high signal variance and peaks • Minor turret vibration variance • High turret vibration peaks

Figure 5.22 Machining: tool wear, steel, time domain



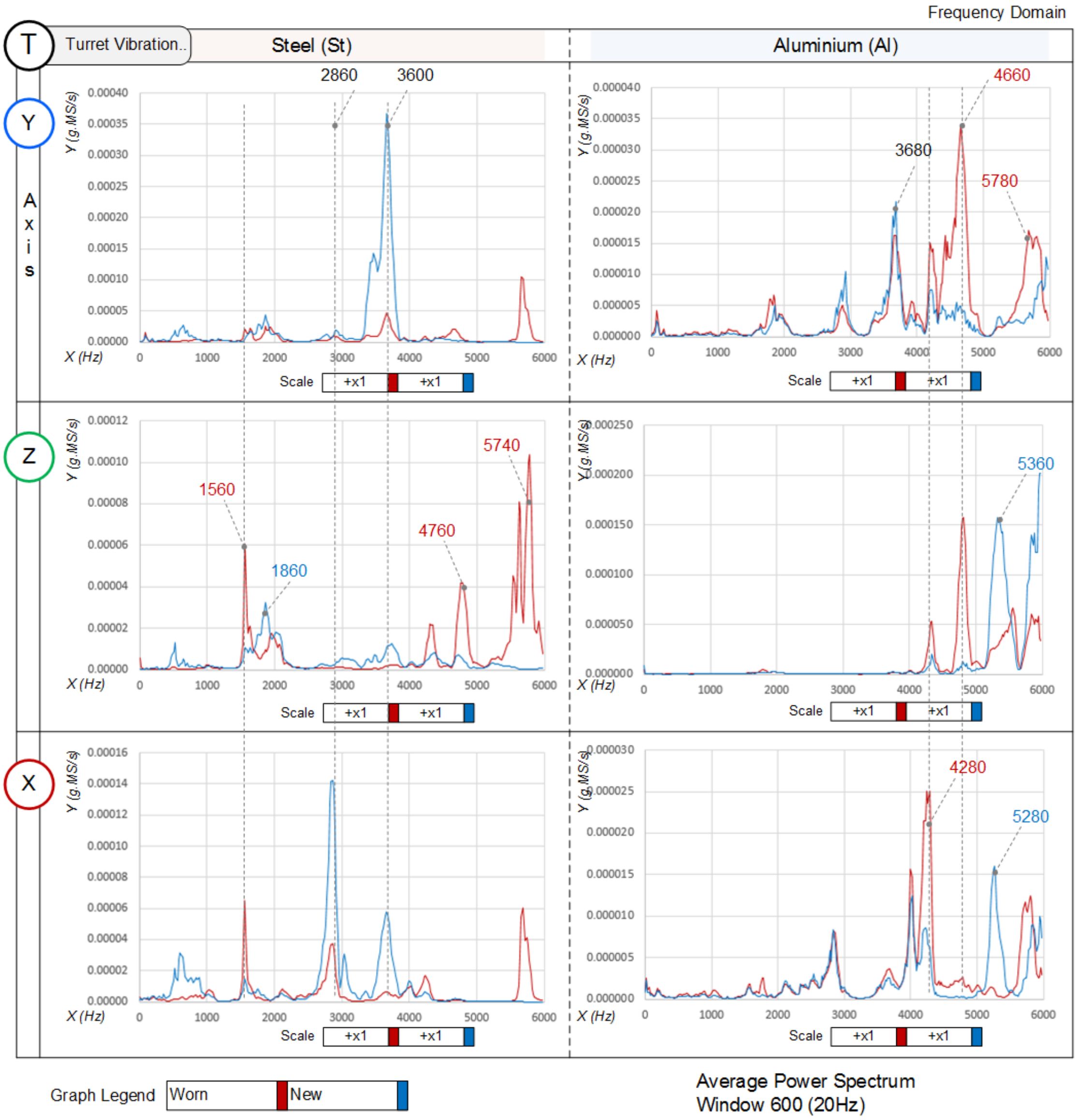
New Tool	Worn Tool
• Uniform force measurements, with minor increase in force peaks • Small sequential spindle vibration increase • High spindle vibration variance • Sequential increase in turret vibration peaks	• Variant force signal, high force peaks • High spindle vibration variance • Variant turret vibration amplitude and peaks

Figure 5.23 Machining: tool wear, aluminium, time domain



Steel	Aluminium
• Worn tool Increases in power within the defined frequency bands, Y and Z • Worn tool varies in frequency, X Y Z	• Worn tool Increases in power within a wider frequency range; 1760 – 2300 Hz X Y

Figure 5.24 Machining: tool wear, spindle vibration, frequency domain area



Steel	Aluminium
• Tool wear high frequency response; >4000 Hz X Y Z • Tool wear reduced power response 3660 Hz Y, 2860 Hz Z	• Tool wear high power response within a high frequency range; <5000 >4000 Hz X Y Z • Tool wear power reduction within a high frequency range; >5000 Hz X Z • The frequency response is reaching high levels outside the range of the accelerometer, >6000 Hz, for both the new and worn tool

Figure 5.25 Machining: tool wear, turret vibration, frequency domain area

5.3.3 Case 3: variant cutting parameters

The previous comparison of an aluminium and steel roughing cycle under normal and abnormal machining conditions, has provided a contrasting reaction in both the time and frequency domain. These machining actions were undertaken specifically under the same machining parameters to ensure the deviation in machining reactions was specifically related to the tool wear. The aim of this study is to vary the machining parameters and characterise the variance in tool force, spindle vibration, and turret vibration during dry turning roughing cycles, of both aluminium and steel workpieces. Machining parameter variation includes; feed rate, cutting speed, depth of cut, number of cutting cycles, and orientation of the tool length from the tool holder, and workpiece length from the chuck. Areas of particular interest include; identifying if machining parameter variation have key process indicators, and whether a universal key process indicator is present to qualify dynamic machining operations.

Setup

Machining Parameters	(1) Feed	(2) Speed and Depth of cut	(3) Continuous cutting	(4) Speed and Depth of cut
Mode	Constant Surface speed	Constant Surface speed	Constant Surface speed	Constant Surface speed
Cutting Speed	100 m/min	100, 125 m/min	100 m/min	100 m/min
Feed	0.1, 0.2. 0.3 mm/rev	0.2 mm/rev	0.2 mm/rev	0.2 mm/rev
Depth of cut	1 mm	1, 2 mm	1 mm	1 mm
Length of cut	30 mm	30 mm	30 mm	30 mm
Cycles	3	1	20	8
Coolant	None	None	None	None
Motion	Roughing cycle	Roughing cycle	Roughing cycle	Roughing cycle
Other				
Workpiece machining length	100mm	100mm	100mm	100, 150 mm
Tool Length	40mm	40mm	40mm	40, 100 mm
Workpiece material	Aluminium, Steel	Aluminium, Steel	Aluminium, Steel	Aluminium, Steel

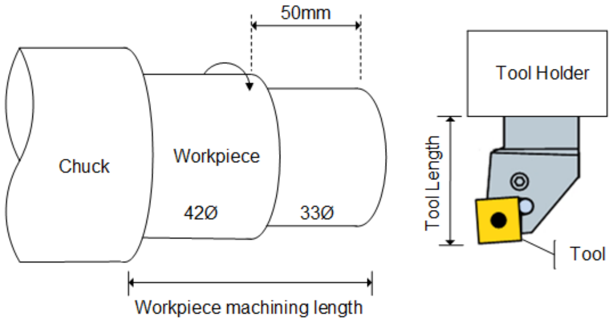


Figure 5.26 Machining: variant cutting, machining parameters

The machining parameters for each test is represented in Figure 5.26. Both the time and frequency domain of each test is examined for tool force, spindle vibration, and turret vibration. The averaging values established in the previous chapters are maintained; Time domain 6 – 12 Hz, and frequency domain area analysis 20 Hz spectral band widths.

Results

The results of the variant cutting tests are listed in Appendix C: CNC turning machining parameter variation test results. Furthermore, to review the time domain results, signal attributes were extracted from the time domain waveforms listed. The signal attributes included; average, standard deviation, and maximum value. These results were combined for review in Appendix C.6: Time domain signal analysis summary.

The conclusions from these tests are as follows:

Feed variation

Varying the feed speed increases the tool force, spindle and turret vibration magnitude and variance. The frequency response varies in power within defined frequencies. The same response is also recorded when varying the cutting speed to 125m/min.

Depth of cut

The increased depth of cut also increases the tool force, spindle and turret vibration magnitude and variance. Spindle vibration frequency response varies in both power and frequency peak in both materials. Turret vibration frequency response varies only in power within defined frequencies.

Continuous machining

Continuous machining identifies a volatile machining process, as tool force incrementally increases, and spindle and turret vibration exponential increase in magnitude and signal variance, after 12 – 15 cutting cycles. Factors influencing this occurrence include the increased temperature of the tool and workpiece, and potentially reaching the maximum limits of the OKUMA CNC turning machine. The volatile reaction in continuous cutting is more extreme in steel machining, as aluminium does display an incremental tool force increase. However the spindle and turret vibration is considerably lower in aluminium machining. Evidently the higher force requirement for steel machining is resulting in higher friction and higher machining temperature.

The frequency response in continuous machining is reactive within defined frequencies and has an increasing power response to the machining process. The severity of this power increase is once again extremely high when machining steel, and moderately high in aluminium machining. The sever change in machining variables in reaction to multiple dry cutting roughing cycles, identifies a potential incapacity to achieve a stable cutting process without coolant. This volatility also makes it difficult to achieve process monitoring, as the current sensors are reaching maximum limits.

Tool and workpiece orientation

The length of the workpiece and distance between the tool holder and tool tip should always be set to the minimal value. This ensures the workpiece and tool are held firmly and bend minimally during machining. However depending on the required machining area of the workpiece, and tool setup, these lengths can vary. The results on machining process to this variation are considerable. Tool length has a minimal effect in the time domain, but significant frequency and power response in the frequency domain. Workpiece length has an extreme effect in the time domain across all variables, with increased magnitude and signal variance. This response is matched in the frequency domain with both a power and frequency response.

5.3.4 Conclusion

Tool force is a direct cutting parameter measurement, which is highly reactive to the machining process and yields consistent results. However it is an invasive measurement method, and requires considerable modification to the CNC machine. While not implausible to utilise, the external integration of tool force monitoring for a multi-tool production line cutting is not practical. Dynamic indirect un-invasive vibration monitoring is a practical method of machining analysis. However the limitations to these systems is the inferred analysis. These systems are sensitive to a multitude of variables, and need to be controlled to produce the desired output. The comparative monitoring of vibration from two sources has provided a contrasting view of process monitoring capability. The spindle vibration was highly reactive to small changes in the process. The turret vibration was less reactive to the process yet yielded key process indicators outside of the capability of spindle monitoring. Evidently both methods could be utilised individually to achieve a range of qualitative process monitoring tasks.

The resultant machining comparison of both aluminium and steel for CNC turning, has identified a separation in reactive response, in both the time and frequency domain. This separation is justified due to the diversity in mechanical properties of both materials. Key process indicators can be extracted to identify the different materials across force, spindle vibration, and turret vibration. Specifically, the frequency domain, where utilising both peak and area frequency analysis is essential.

By recording and analysing normal operating conditions for both materials a comparative is achievable when undesired machining conditions occur. This was examined when machining with worn tools. Key process indicators in the time domain analysis of process signals include an increase in signal magnitude, variance, and peak values. Furthermore, the frequency domain has yielded significant key process indicators in the form of frequency and power changes, for both spindle and turret vibration.

Results have yielded key process indicators for identifying tool wear in both materials. These indicators are unique to the material, as a normal operating reaction in steel can be seen as a key process indicator for tool wear in aluminium. However universally both spindle and turret vibration frequency domain analysis can yield a common metric, with fixed machining parameters.

The variations in materials, setup orientations, and cutting parameters, have identified a highly diverse machining reaction in tool force, spindle and turret vibration. The capabilities of a process monitoring system to qualitatively analyse the performance of an operation depends on scaled reactions, limits, and key process indicators. The wide variety of time and frequency domain reactions to machining variations has identified an incapacity to universally monitor the turning process with varying machining properties. Subsequently, dynamic CNC turning control is not feasible through tool force, and spindle and turret vibration. These mediums are however capable in the controlled environment of batch and mass production.

5.4 Summary

Process adoption of advanced signal processing and decision support techniques is dependent on an effective framework assimilation within a specific process. Subsequently the generic building blocks present in cyber-physical production systems must be capable of forming custom solutions to real manufacturing problems. Evidently the ARC has been successfully implemented to achieve multi-source data acquisition, signal processing, and process specific analytics of a manufacturing CNC turning machining. The unique framework generated from the interconnecting virtual building blocks has provided a means for essential process characterisation inside and outside cutting operations. Furthermore, a comprehensive machining variation study has been achieved, which investigates the dry machining of both aluminium and steel, and the reactions from both tool force, spindle and turret vibration. This phase 2 investigation has yielded potential key process indicators for effectively monitoring dry roughing cycles in all three sensor sources for tool wear, for batch and mass production. The dynamic nature of the ARC will allow for any fundamental changes to the measurement or analysis chain, for future application.

Chapter 6

Summary and conclusions

6.1 Summary

This research work explores the dynamics of decentralised software architecture within field-level manufacturing process monitoring systems. The need for this understanding has been driven by the prediction that these cyber-physical systems will create the next generation of innovative intelligent machines. This research investigates the capability of decentralisation design to provide the core fundamental functionality of process monitoring systems in a new reconfigurable format. The embodiment of this investigation is the design and development of a decentralised architecture for the creation of a reconfigurable process monitoring system within field-level manufacturing.

An investigation into available data interoperability systems and field-level manufacturing process monitoring system requirements, resulted in the identification of a research opportunity. Evidently, current academic and commercial mediums could not provide for the high communication speed, high data capacity, and heterogeneous data requirements present in field-level manufacturing systems.

Through a combination of decentralised modelling, and state-of-the-art technologies and techniques, a new data interoperability architecture was developed. The resultant architecture, namely the ARC, is tested in respect to speed, capacity, and correlation accuracy. Furthermore, the ARC was adapted to monitor multiple process variables from a CNC turning machine tool, such as: tool force, spindle and axis motor current, spindle and turret vibration.

The ARC provided a platform to evaluate the migration of signal process techniques, and time and frequency domain analytics, within a decentralised architecture. Key to the success of this investigation, depended on the internal and external mechanisms required to achieve dynamic data acquisition, manipulation, and re-distribution. Furthermore, an advanced cyber-physical system was created for autonomous process performance characterisation.

In order to investigate the industrial application of the ARC, a study was undertaken into the variation in dry CNC turning machining, thereby evaluating the capability of the ARC signal processing techniques and analytics to achieve process insight. The result was a comparative of machine reactions, inside and outside of machining operations, with varying operation modes and variant cutting parameters, for dry turning machining.

6.2 Conclusions

6.2.1 Design and development of a reconfigurable process monitoring architecture

Challenges to develop a field-level manufacturing reconfigurable process monitoring system were characterised by the design requirements of; (a) open source data structuring, (b) incorporate, or be open to the integration, of state-of the art technologies and techniques, (c) meet performance criteria; (1) High data rates, > 10 kHz, (2) High communication speed, <= 1ms, (3) High accuracy correlation, <= 1ms. In order to evaluate the capability of decentralised architectures to be utilised within a manufacturing field-level environment, these design requirements needed to be satisfied.

The solution to these challenges/design requirements was achieved through the adoption of the National Instruments – Shared Variable Engine (SVE) data interoperability medium. The SVE provide the key service-oriented architecture functionalities of data distribution, data discovery, and eventing. Furthermore, the open source data structure enabled the integration of state-of-the-art binary representation for the efficient data exchange. Binary representation further facilitated a means to dynamically integrate multiple data types, sizes, and formats. The resultant data structure, namely the Binary Message Model (BMM), was produced to meet the variation present within a manufacturing process monitoring system.

The evaluation of the ARC to meet the performance criteria in a field-level manufacturing environment, was undertaken in three experiments, which quantified communication speed, data capacity, and accuracy of correlation. The ARC results include; 0.865 ms round trip time, 0.013 ms serialisation time, 0.003 ms deserealisation time, which equated to a <=1 ms average communication speed, 1 Hz to 1 MHz data capacity per variable, 1 to 10 signals per variable, 1 to 1000 samples per message or ‘package’, and a 99.8% correlation accuracy.

Therefore it can be concluded that the ARC is an effective data interoperability medium for utilisation in field-level manufacturing systems, beyond the capability of all previously reviewed systems.

6.2.2 Investigation and development of decentralised manufacturing data acquisition, signal processing and process analytic entities

In order to investigate and develop decentralised manufacturing data acquisition, signal processing and process analytic entities, a number of challenges needed to be addressed; (1) industrial application of the ARC within a manufacturing environment, (2) effective and efficient migration of signal processing techniques and analytics within a decentralised architecture, (3) collaborative configuration of decentralised tools to form a cyber-physical system.

A CNC turning industrial case-study provided the contextual basis for investigations. Multiple data-sources, including: tool force, motor current, and spindle vibration, with varying data acquisition rates, 3kHz to 12 kHz, were successfully acquired and dynamically distribution within the data cloud. The information acquired from cloud-monitoring a CNC turning machine tool, was utilised to develop and effectively migrate fundamental signal processing techniques and analytics within the ARC. The utilisation of asynchronous programming ensured effective and efficient computation of parallel data streams. Furthermore, internal and reconfigurable mechanisms enabled the dynamic customisation of these signal processing and analysis tools.

The migration of reconfigurable tools within the architecture, provided the next step in decentralised manufacturing process monitoring. Unique signal processing techniques and analytics were represented as services hosted by the cloud. This external reconfiguration capability through collaboration, identifies the transition from cloud-system to cyber-physical system. The realisation of this goal was achieved through the development of an autonomous process characterisation cyber-physical production system. The configuration of the collaborating decentralised applications, provided multi-dimensional process performance quantification.

Therefore it can be concluded that decentralised design can provide the core fundamental functionality of process monitoring systems, in a new reconfigurable format. Unique merit/novelty in this work can be seen in a first case migration of fundamental manufacturing process monitoring steps within a cyber-physical system. Furthermore, the collaborative process performance quantification system, is a high-performance realisation of Vijayaraghavan and Dornfeld's [39] proposed dynamic, event-orientated, automated system for temporal analysis of machine tools.

6.2.3 Application investigation into CNC turning characterisation and dry machining

The industrial application investigation was undertaken to; (1) evaluate the capability of decentralised signal processing techniques and analytics to achieve process insight, (2) provide a first-step investigation into the characterisation of a CNC turning machine tool, and (3) identify key process indicators for manufacturing decision support in CNC turning dry machining.

The ARC has been successfully implemented to achieve multi-scalable data acquisition, signal processing, and process performance analysis of a CNC turning machine tool. The generic building blocks present within the ARC were configured to produce unique signal feature extraction across multiple process variables. Process insight is self-evident in the multi-perspective view of machine actions, via the time and frequency domain analysis, of tool force, spindle and axis motor current, and spindle and turret vibration.

Through evaluation of scaled machine operations, a comprehensive comparative of machine actions and subsequent reactions was achieved. Evidently, vibration and motor current provide non-invasive real-time monitoring of machine operations. Both sources vary with machining parameters, i.e. feed and spindle speeds. A unique event, namely rapid movements, was identified to not vary in response to changing machining parameters. Evidently, these operations are repeatable and reliable, and can be utilised to provide state transition information, and to characterise the machining of multiple part types.

The comparative investigation into dry CNC turning machining has resulted in a mixture of time and frequency domain variation, across tool force, spindle and turret vibration. The platform developed allows for significant process insight using multiple sensor inputs, providing a detail understanding of the process and machine interaction. Similarly the platform also allows for the ranking of the measurable phenomena and its correlation to the process, the machine, and other influences. For example, in both non-invasive vibration measurement sources have been identified to individually provide a range of key process indicators, e.g. detecting tool wear. The wide variety of time and frequency domain reactions to machining variations was a potential limitation for monitoring purposes, however it also has a value in process understanding and characterisation.

Therefore it can be concluded that the developed decentralised platform has the potential to act as both a monitoring platform or as a new product introduction tool for process characterisation and optimisation.

6.3 Concluding remarks

Process monitoring systems have evolved from centralised bespoke applications to decentralised reconfigurable collectives. The resulting cyber-physical systems are made possible through the integration of collaborative communication, high power computation, and advanced analytical technology. These systems exist in this digital age due to the exponential advancement of artificial computation, and mass production within a free market.

The idea that these systems will create the next generation of innovative intelligent machines, is based on the concepts of; abstraction, simplification, and free data. Providing tools in a borderless computation collaborative space will result in new and innovative solutions. Engineers previously unable to access these resources due to high skill requirements, are now presented with reconfigurable tools, for direct utilisation, or custom modification. The power of these systems is in the hands of the users, as the environment itself is limitless in possibility.

6.4 Recommendations for future work

The areas where future work could be undertaken is categorised as follows:

1) CNC Turning investigation and real-time industrial adoption

Continuing on with the current research application, CNC turning can be further investigated in the areas of; tool wear variation, wet cutting, multi-point machining, continuous monitoring for batch/mass production, automated configuration learning, CNC controller integration, and design and development of user friendly graphical user interfaces. For industrial adoption, these research areas would need to be addressed.

2) Advancement and application of cyber physical production systems

Further development of the decentralised architecture could include; collaborative messaging between autonomous entities, production control application, multi-machine analysis and management, hard-real-time communication, and the integration of control/monitoring error handing orchestration of decentralised software applications. These research goals would provide a wider scope of industrial application, through a higher capacity and more sustainable architecture.

3) Assimilation of the ARC within other manufacturing processes

The multi-dimensional scaling of the ARC's data acquisition, signal processing, and analytic components, enables the implementation of the ARC in multiple manufacturing processes. Further work could include the reconfiguration of current systematic components to meet the requirements of other manufacturing environments, such as CNC milling.

List of publications

Conferences

- International Manufacturing Conference (2012)
  J. Morgan, J. Trostel, G. E. O'Donnell, and G. Eisenblätter,
  "Machine Tool Process Monitoring and Machine Condition Monitoring – Examining Data Acquisition Gateways for Process Adaption"
- CIRP: Conference on Innovative Manufacturing (2013)
  J. Morgan, E. O'Driscoll, and G. E. O'Donnell
  "Data Interoperability for Reconfigurable Manufacturing Process Monitoring Systems"
- CIRP: Conference on Real and Virtual Manufacturing (2014)
  J. Morgan and G. E. O'Donnell,
  "A Service Oriented Reconfigurable Process Monitoring System – Enabling Cyber Physical Systems"
- CIRP: Conference on Intelligent Computation in Manufacturing Engineering (2014)
  J. Morgan and G. E. O'Donnell,
  "The Cyber Physical Implementation of Cloud Manufacturing Monitoring Systems"

Journals

- International Journal of Computer Integrated Manufacturing (2015)
  J. Morgan and G. E. O'Donnell,
  "Enabling a ubiquitous and cloud manufacturing foundation with field-level service-oriented architecture"
  DOI: 10.1080/0951192X.2015.1032355
- Journal of Intelligent Manufacturing (2015)
  J. Morgan and G. E. O'Donnell,
  "Cyber physical process monitoring systems"
  DOI: 10.1007/s10845-015-1180-z

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[184] OKUMA, “OKUMA Industries Served.” [Online]. Available: http://www.okuma.eu/industries/. [Accessed: 01-Mar-2015].

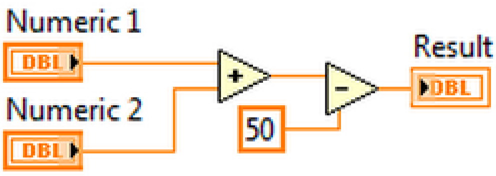
Appendix A

Software architecture

1 Labview

Reference: www.ni.com, Labview 2012 Manuals

Labview is a graphical programming language. LabVIEW follows a dataflow model for running programs or 'Virtual Instruments (VI)'. A block diagram node executes when it receives all required inputs. When a node executes, it produces output data and passes the data to the next node in the dataflow path. The movement of data through the nodes determines the execution order of the VIs and functions on the block diagram. Visual Basic, C++, JAVA, and most other text-based programming languages follow a control flow model of program execution. In control flow, the sequential order of program elements determines the execution order of a program. You transfer data among block diagram objects through wires. Each wire has a single data source, but you can wire it to many VIs and functions that read the data. Wires are different colors, styles, and thicknesses, depending on their data types.

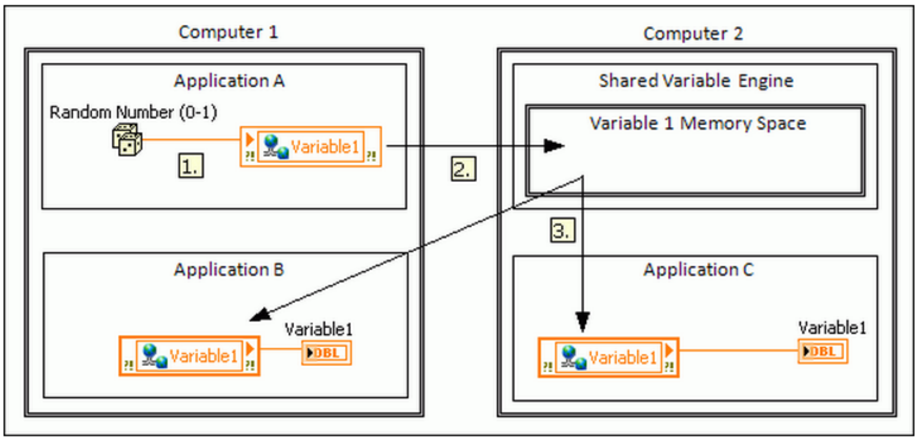


For a dataflow programming example, consider a block diagram that adds two numbers and then subtracts 50.00 from the result of the addition, as shown in the above figure. In this case, the block diagram executes from left to right, not because the objects are placed in that order, but because the Subtract function cannot execute until the Add function finishes executing and passes the data to the Subtract function. Remember that a node executes only when data is available at all of its input terminals and supplies data to the output terminals only when the node finishes execution.

2 National Instruments Shared Variable Engine

Reference: www.ni.com, Labview 2012 Manuals

Network-published shared variables publish data over a network through a software component called the Shared Variable Engine (SVE). The SVE is installed as a service on your computer when you install LabVIEW, and it manages shared variable updates using a proprietary technology called the NI Publish-Subscribe Protocol (NI-PSP). The term publish-subscribe describes a model of communication where writers, or publishers, do not send data to specific readers, or subscribers. Rather, publishers send updates to a server, in this case the SVE, and subscribers receive those updates from the server.



The following events occur in the above figure;

1. In Application A, the Random Number (0-1) function writes a random number to the Shared Variable node that corresponds to Variable 1
2. The Shared Variable node in Application A sends a request to the SVE to update the value of Variable 1
3. The SVE approves and sends the new value to the Shared Variable nodes that correspond to Variable 1 in Applications B and C.

In the above figure, although Computer 1 hosts a writer of Variable 1 in Application A and a reader of Variable 1 in Application B, Application A cannot write a new value directly to Application B. Instead, Application A must send a request to the SVE on Computer 2 to update every application that subscribes to Variable 1. Therefore, the latency involved in these updates makes shared variables ideal for publishing latest values only. To stream data continuously, use network streams.

3 Binary conversion

Reference: www.ni.com, Labview 2012 Manuals

Booleans and numeric objects

The flattened form of any numeric type and Boolean type stores the data only in big-endian format. For example, a 32-bit integer with a value of –19 is flattened to FFFF FFED. A double-precision floating-point number with a value equal to 1/4 is flattened to3FD0 0000 0000 0000. A Boolean value of TRUE is any nonzero value. A Boolean value of FALSE is 00.

The flattened form for extended-precision numbers is the 128-bit extended-precision, floating-point format. When you save extended-precision numbers to disk, LabVIEW stores them in this format.

Strings and paths

Because strings and paths have variable sizes, a flattened 32-bit integer that records the length in bytes precedes the flattened form. For example, a string type with value ABC is flattened to 0000 0003 4142 43. For strings, the flattened format is similar to the format the string takes in memory. However, paths do not have a length value preceding them when LabVIEW stores them in memory, so this value comes from the actual size of the data in memory and prefixes the value when LabVIEW flattens the data. This length is preceded by four characters: PTH0. For example, a path with value C:\File is flattened to 5054 4830 0000 000B 0000 0002 0143 0466 696C 65.

5054 4830 indicates PTH0. 0000 000B indicates 11 bytes total. 0000 is the type. 0002 is the number of components. 0143 indicates the letter C as a Pascal string. 0466 696C 65 indicates the word File as a Pascal string.

Arrays

Flattened 32-bit integers that record the size, in elements, of each of the dimensions of an array precede the data for a flattened array. The slowest varying dimension is first, followed successively by the faster varying dimensions, just as the dimension sizes are stored in memory. The flattened data follows immediately after these dimension sizes in the same order in which LabVIEW stores them in memory. The following example shows a 2D array of six 8-bit integers. { {1, 2, 3}, {4, 5, 6} } is flattened to 0000 0002 0000 0003 0102 0304 0506. The following example shows a flattened 1D array of Boolean variables. {T, F, T, T} is flattened to 0000 0004 0100 0101. The preferred value for TRUE is 01.

Clusters

A flattened cluster is the concatenation, in cluster order, of the flattened data of its elements. For example, a flattened cluster of a 16-bit integer of value 4 (decimal) and a 32-bit integer of value 12 is 0004 0000 000C. A flattened cluster of a string ABC and a 16-bit integer of value 4 is 0000 0003 4142 4300 04. A flattened cluster of a 16-bit integer of value 7, a cluster of a 16-bit integer of value 8, and a 16-bit integer of value 9 is 0007 0008 0009.

Waveforms

Waveforms are clusters.

Refnums

LabVIEW stores the majority of flattened refnums as flattened 32-bit integers, which represent an internal LabVIEW data structure. You can classify the remaining refnums by their refnum type code. Type codes 0xE, 0xF and 0x15 are refnums that store their data as a flattened string. This string contains the value of the refnum tag, and can be empty (4 bytes of zero). Type codes 0x1A, 0X1C, and 0x1D concatenate, in the following order:

- A flattened string for the name in the refnum tag. This string is empty (4 bytes of zero) if the refnum does not have a tag.
- A flattened string that contains information specific to the refnum. This string can be empty (4 bytes of zero).
- A flattened string that contains information specific to the refnum. This string can be empty (4 bytes of zero).
- A flattened 32-bit signed integer that contains information specific to the refnum.
- A flattened string that contains information specific to the refnum. This string can be empty (4 bytes of zero).

Classes

LabVIEW flattens a LabVIEW class according to the following general format:

level in hierarchy	*class name*	*version list*	*private data*

- level in hierarchy: 4-byte unsigned integer representing how many levels into the class hierarchy the class occurs. For example, if this value is 2, the class has one ancestor class between itself and LabVIEW Object. If this value is 0, the object is an instance of LabVIEW Object.
- class name: A Pascal string representing the fully qualified name of the class. This section of the flattened string includes enough pad bytes to increase the class name section to a multiple of 4 bytes.
- version list: A series of 2-byte unsigned integers that represent the version number of each class in the hierarchy. The first number in this list represents the version of class name, the second is the version of its parent, and so on. This list contains one version number for each level in hierarchy. Note If level in hierarchy is 1 and the version is 0, the flattened data represents the default data of the class.
- private data: A series of flattened clusters representing the private data of each level of the hierarchy. Unlike in the version list, the first cluster in this series corresponds to the oldest ancestor class. Each flattened cluster begins with a 4-byte signed integer that represents the number of bytes in the data that follows. If this initial number is 0, the flattened cluster represents the default data for the corresponding class in the hierarchy. Otherwise, the following data uses the standard flattened cluster representation explained earlier in this topic. Each flattened cluster ends with enough pad bytes to increase the cluster to a multiple of 4 bytes.

Appendix B

Datasheets

Appendix B

1 Sensors

1.1 Accelerometers

Acceleration

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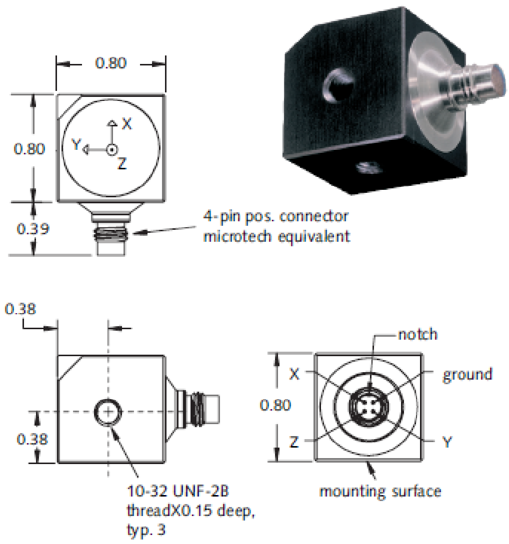
Annular Ceramic Shear Sensor

Type 8762A...

Lightweight, Voltage Mode, Triaxial Accelerometer

High sensitivity triaxial accelerometers that simultaneously measure vibration in three, mutually perpendicular axis (x, y and z). Designed primarily for modal analysis applications, the triaxial accelerometer features three tapped mounting surfaces that allow each axis to be hard mounted for calibration.

- Low impedance voltage mode
- Cube shaped, ceramic shear sensor
- Ultra low thermal transient response
- Durable hard anodized, ground isolated aluminium housing
- Conforming to CE



Description

The Type 8762A... accelerometer is a unique annular, shear sensor element that features extremely low thermal transient response, a high immunity to base strain, and transverse acceleration. An advanced hybrid charge amplifier design provides outstanding phase response, as well as a wide operating frequency range. The lightweight aluminum housing is epoxy sealed and hard anodized coated to provide ground isolation.

Each of the three sensing elements is internally connected to a microelectronic circuit that converts the charge from the ceramic piezoelectric elements into a useable high level voltage signal at a low impedance output. The Type 8762A... accelerometer series will operate directly from the internal power source found in most FFT analyzers; from several Kistler Piezotron® power supply couplers or any industry standard IEPE (Integrated Electronic Piezo-Electric) compatible power source.

Application

The lightweight Type 8762A... triaxial accelerometer series is highly desirable for measurement applications on lightweight structures where mass loading must be kept to a minimum. The accelerometers are well-suited for multi-channel measurements, modal analysis measurements on automotive bodies and aircraft structures, and general vibration measurements.

Accessing TEDS Data

Accelerometers with a "T" suffix are variants of the standard version incorporating the "Smart Sensor" design. Viewing an accelerometer's data sheet requires an Interface/Coupler such as Kistler's Type 5134B... or Type 5000M04 with TEDS Editor software. The Interface provides negative current excitation (reverse polarity) altering the operating mode of the PiezoSmart® sensor, allowing the program editor software to read or add information contained in the memory chip.

Mounting

The Type 8762A... accelerometer series can be attached to the test surface by using a 10-32 stud inserted in any one of the three threaded mounting holes. Reliable and accurate measurements require that the mounting surface be clean and flat. The instruction manual for Type 8762A... (8762A_002-233) provides detailed information regarding mounting surface preparation.

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Technical Data

Specification	Unit	Type 8762A5	Type 876A10	Type 8762A50
Acceleration range	g	±5	±10	±50
Acceleration limit	gpk	±8	±16	±80
Threshold, nom.	grms	0.0003	0.00035	0.0012
Sensitivity, ±5 %	mV/g	1,000	500	100
Resonant frequency, mounted, nom.	kHz	30	30	30
Frequency response, ±5 %	Hz	0.5 ... 6,000	0.5 ... 6,000	0.5 ... 6,000
Amplitude non-linearity	%FSO	±1	±1	±1
Time constant, nom.	s	1	1	1
Transverse sensitivity, nom.	%	<5	<5	<5
Environmental				
Base strain sensitivity @ 250 με	g/με	0.004	0.004	0.004
Shock limit (0.2 ms pulse)	gpk	5,000	7,000	7,000
Temperature coefficient of sensitivity	%/°C	–0.06	–0.02	–0.02
Operating temperature range Type 8762A...T	°C °C	–55 ... 80 –40 ... 80	–55 ... 80 –40 ... 80	–55 ... 80 –40 ... 80
Output				
Bias, nom.	VDC	11	11	11
Impedance	Ω	≤500	≤500	≤100
Voltage full scale	V	±5	±5	±5
Source				
Voltage	VDC	20 ... 30	20 ... 30	20 ... 30
Constant current	mA	2 ... 18	2 ... 18	2 ... 18
Construction				
Sensing element	type	ceramic-shear	ceramic-shear	ceramic-shear
Case/base	material	aluminum hard anodized	aluminum hard anodized	aluminum hard anodized
Degree of protection case/connector (EN 60529)		IP66	IP66	IP66
Connector	type	4-pin pos.	4-pin pos.	4-pin pos.
Ground isolated		yes	yes	yes
Mass	grams	23	23	23
Mounting (10-32 thd.x4 dp)	type	stud	stud	stud

1 g = 9.80665 m/s^2, 1 inch = 25.4 mm, 1 gram = 0.03527 oz, 1 lbf-in = 0.1129 N·m

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ACCELERATION CALIBRATION CERTIFICATE - X Axis

Type		8762A5	**Manufacturer**		Kistler
Serial Number		2109919	**Certificate ID #**		2109919-120301T0827
Time Constant	sec.	1.7	Mounted Resonant Frequency	kHz	30.0
Transverse Sensitivity	%	0.5	Mounting Torque	lbf-in	18 ± 2.0
Bias Voltage	V_{DC}	12.1		Nm	2.0 ± 0.2

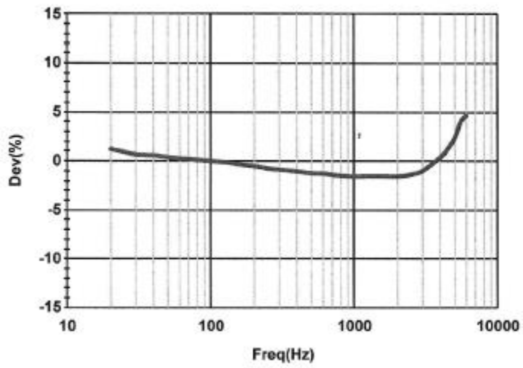
Reference Specifications

Range	g	± 5	Temp. Range, operating	°C	-54 to 80
Max Range	g	± 8	Output Impedance	Ω	≤500

Measurements

Frequency Hz	Sensitivity mV/g	Deviation % (ref=100 Hz)
20	993	1.2
50	984	0.4
100	980	0.0
200	975	-0.5
500	968	-1.3
1000	965	-1.6
2000	965	-1.6
4000	985	0.4
6000	1026	4.6

Frequency Response



Sensitivity at 100 Hz, 3.0 g rms	mV/g	980			
Sensitivity at 159 Hz, 3.0 g rms	mV/g	977		g = 9.807 m/s²	159.2 Hz = 1000 rads/sec
Environmental Temperature	°C	22 ± 4	Condition	New	
Relative Humidity	%	30 ± 30	NIST Test Report Number	681/281072-11	
Calibration Date		3/1/2012	Calibration Technician:	Mark Thomas	

This sensor was calibrated per Kistler test procedure 978-5444-701 using a comparison technique against a Kistler working standard. Kistler working standards are periodically calibrated against a primary standard system, which in turn is periodically recertified to the National Institute of Standards and Technology (NIST) or another recognized national standard. Measurements are derived from accepted values of natural physical constants according to the International System of Units (SI). This calibration meets or exceeds the requirements of MIL-STD-45662A, ISO 9001, ANSI/NCSL Z540-1 and is accredited to ISO/IEC 17025 as verified by the ANSI-ASQ National Accreditation Board/ACLASS. Refer to certificate and scope of accreditation AC-1117. Estimated uncertainty is ± 2.2% of reading with respect to the primary standard. Certificates are on file at Kistler and may be requested in writing. This certificate shall not be reproduced, except in full, without written approval of Kistler Instrument Corporation.

Reference Equipment	Manufacturer	Type	Serial Number	Reference Equipment	Manufacturer	Type	Serial Number
Accelerometer (Working Std.)	Kistler	8076K	C148323	Multimeter (Standard)	HP	34401A	3146A65537
Charge Amplifier (Working Std.)	Kistler	5020	C93919	Multimeter (Test)	HP	34401A	3146A65544
Accelerometer (Primary Std.)	Kistler	8002K	C139113	Function Generator	Wavetek	270	C6370761
Charge Amplifier (Primary Std.)	Kistler	5020	C92253	Charge Amplifier (Test)	Kistler	None	....

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ACCELERATION CALIBRATION CERTIFICATE - Y Axis

Type	8762A5	**Manufacturer**	Kistler
Serial Number	2109919	**Certificate ID #**	2109919-120301T0827
Time Constant	sec. 1.5	Mounted Resonant Frequency	kHz 30.0
Transverse Sensitivity	% 0.3	Mounting Torque	lbf-in 18 ± 2.0
Bias Voltage	V_{DC} 11.9		Nm 2.0 ± 0.2

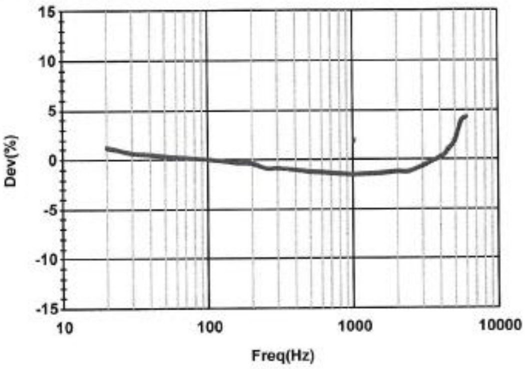
Reference Specifications

Range	g ± 5	Temp. Range, operating	°C -54 to 80
Max Range	g ± 8	Output Impedance	Ω ≤500

Measurements

Frequency Hz	Sensitivity mV/g	Deviation % (ref=100 Hz)
20	986	1.2
50	977	0.3
100	974	0.0
200	970	-0.4
500	962	-1.2
1000	960	-1.5
2000	962	-1.2
4000	977	0.3
6000	1016	4.2

Frequency Response



Sensitivity at 100 Hz, 3.0 g rms	mV/g 974			
Sensitivity at 159 Hz, 3.0 g rms	mV/g 971		$g = 9.807\ m/s^2$	159.2 Hz = 1000 rads/se
Environmental Temperature	°C 22 ± 4	Condition	New	
Relative Humidity	% 30 ± 30	NIST Test Report Number	681/281072-11	
Calibration Date	3/1/2012	Calibration Technician:	Mark Thomas	

This sensor was calibrated per Kistler test procedure 978-5444-701 using a comparison technique against a Kistler working standard. Kistler working standards are periodically calibrated against a primary standard system, which in turn is periodically recertified to the National Institute of Standards and Technology (NIST) or another recognized national standard. Measurements are derived from accepted values of natural physical constants according to the International System of Units (SI). This calibration meets or exceeds the requirements of MIL-STD-45662A, ISO 9001, ANSI/NCSL Z540-1 and is accredited to ISO/IEC 17025 as verified by the ANSI-ASQ National Accreditation Board/ACLASS. Refer to certificate and scope of accreditation AC-1117. Estimated uncertainty is ± 2.2% of reading with respect to the primary standard. Certificates are on file at Kistler and may be requested in writing. This certificate shall not be reproduced, except in full, without written approval of Kistler Instrument Corporation.

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Charge Amplifier (Working Std.)	Kistler	5020	C93919	Multimeter (Test)	HP	34401A	3146A65544
Accelerometer (Primary Std.)	Kistler	8002K	C139113	Function Generator	Wavetek	270	C6370761
Charge Amplifier (Primary Std.)	Kistler	5020	C92253	Charge Amplifier (Test)	Kistler	None	....

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ACCELERATION CALIBRATION CERTIFICATE - Z Axis

Type		8762A5	**Manufacturer**		Kistler
Serial Number		2109919	**Certificate ID #**		2109919-120301T0827
Time Constant	sec.	1.4	Mounted Resonant Frequency	kHz	30.0
Transverse Sensitivity	%	0.4	Mounting Torque	lbf-in	18 ± 2.0
Bias Voltage	V_{DC}	11.9		Nm	2.0 ± 0.2

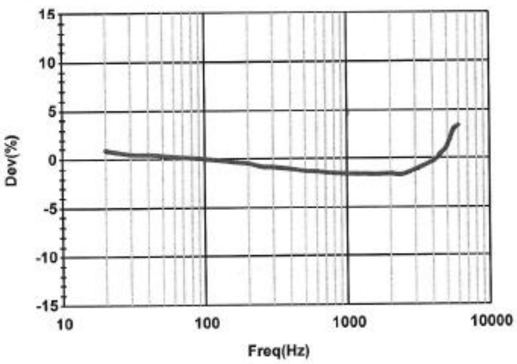
Reference Specifications

Range	g	± 5	Temp. Range, operating	°C	-54 to 80
Max Range	g	± 8	Output Impedance	Ω	≤500

Measurements

Frequency Hz	Sensitivity mV/g	Deviation % (ref=100 Hz)
20	982	0.9
50	976	0.4
100	973	0.0
200	968	-0.5
500	961	-1.3
1000	958	-1.6
2000	958	-1.6
4000	970	-0.3
6000	1005	3.3

Frequency Response



Sensitivity at 100 Hz, 3.0 g rms	mV/g	973		
Sensitivity at 159 Hz, 3.0 g rms	mV/g	970	g = 9.807 m/s²	159.2 Hz = 1000 rads/se
Environmental Temperature	°C	22 ± 4	Condition	New
Relative Humidity	%	30 ± 30	NIST Test Report Number	681/281072-11
Calibration Date		3/1/2012	Calibration Technician:	Mark Thomas

This sensor was calibrated per Kistler test procedure 978-5444-701 using a comparison technique against a Kistler working standard. Kistler working standards are periodically calibrated against a primary standard system, which in turn is periodically recertified to the National Institute of Standards and Technology (NIST) or another recognized national standard. Measurements are derived from accepted values of natural physical constants according to the International System of Units (SI). This calibration meets or exceeds the requirements of MIL-STD-45662A, ISO 9001, ANSI/NCSL Z540-1 and is accredited to ISO/IEC 17025 as verified by the ANSI-ASQ National Accreditation Board/ACLASS. Refer to certificate and scope of accreditation AC-1117. Estimated uncertainty is ± 2.2% of reading with respect to the primary standard. Certificates are on file at Kistler and may be requested in writing. This certificate shall not be reproduced, except in full, without written approval of Kistler Instrument Corporation.

Reference Equipment	Manufacturer	Type	Serial Number	Reference Equipment	Manufacturer	Type	Serial Number
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Charge Amplifier (Working Std.)	Kistler	5020	C93919	Multimeter (Test)	HP	34401A	3146A65544
Accelerometer (Primary Std.)	Kistler	8002K	C139113	Function Generator	Wavetek	270	C6370761
Charge Amplifier (Primary Std.)	Kistler	5020	C92253	Charge Amplifier (Test)	Kistler	None	....

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ACCELERATION CALIBRATION CERTIFICATE - X Axis

Type	8762A5	**Manufacturer**	Kistler
Serial Number	2100063	**Certificate ID #**	2100063-120224T0846
Time Constant	sec. 1.4	Mounted Resonant Frequency	kHz 30.0
Transverse Sensitivity	% 0.4	Mounting Torque	lbf-in 18 ± 2.0
Bias Voltage	V_{DC} 12.1		Nm 2.0 ± 0.2

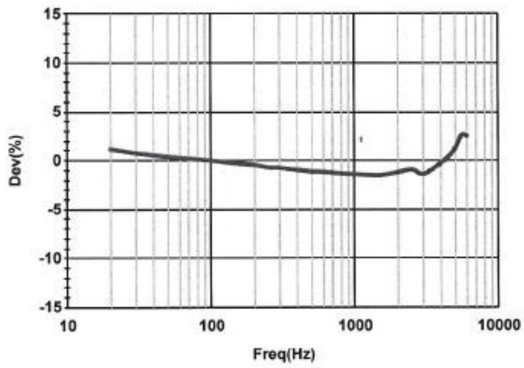
Reference Specifications

Range	g ± 5	Temp. Range, operating	°C -54 to 80
Max Range	g ± 8	Output Impedance	Ω ≤500

Measurements

Frequency Hz	Sensitivity mV/g	Deviation % (ref=100 Hz)
20	972	1.2
50	964	0.4
100	961	0.0
200	956	-0.5
500	950	-1.1
1000	947	-1.4
2000	949	-1.2
4000	959	-0.2
6000	985	2.5

Frequency Response



Sensitivity at 100 Hz, 3.0 g rms	mV/g 961		
Sensitivity at 159 Hz, 3.0 g rms	mV/g 958	g = 9.807 m/s²	159.2 Hz = 1000 rads/se
Environmental Temperature	°C 22 ± 4	Condition	New
Relative Humidity	% 30 ± 30	NIST Test Report Number	681/281072-11
Calibration Date	2/24/2012	Calibration Technician:	Mark Thomas

This sensor was calibrated per Kistler test procedure 978-5444-701 using a comparison technique against a Kistler working standard. Kistler working standards are periodically calibrated against a primary standard system, which in turn is periodically recertified to the National Institute of Standards and Technology (NIST) or another recognized national standard. Measurements are derived from accepted values of natural physical constants according to the International System of Units (SI). This calibration meets or exceeds the requirements of MIL-STD-45662A, ISO 9001, ANSI/NCSL Z540-1 and is accredited to ISO/IEC 17025 as verified by the ANSI-ASQ National Accreditation Board/ACLASS. Refer to certificate and scope of accreditation AC-1117. Estimated uncertainty is ± 2.2% of reading with respect to the primary standard. Certificates are on file at Kistler and may be requested in writing. This certificate shall not be reproduced, except in full, without written approval of Kistler Instrument Corporation.

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Charge Amplifier (Working Std.)	Kistler	5020	C93919	Multimeter (Test)	HP	34401A	3146A65544
Accelerometer (Primary Std.)	Kistler	8002K	C139113	Function Generator	Wavetek	270	C6370761
Charge Amplifier (Primary Std.)	Kistler	5020	C92253	Charge Amplifier (Test)	Kistler	ETL1026	3

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ACCELERATION CALIBRATION CERTIFICATE - Y Axis

Type		8762A5	**Manufacturer**		Kistler
Serial Number		2100063	**Certificate ID #**		2100063-120224T0846
Time Constant	sec.	1.6	Mounted Resonant Frequency	kHz	30.0
Transverse Sensitivity	%	0.7	Mounting Torque	lbf-in	18 ± 2.0
Bias Voltage	V_{DC}	12.2		Nm	2.0 ± 0.2

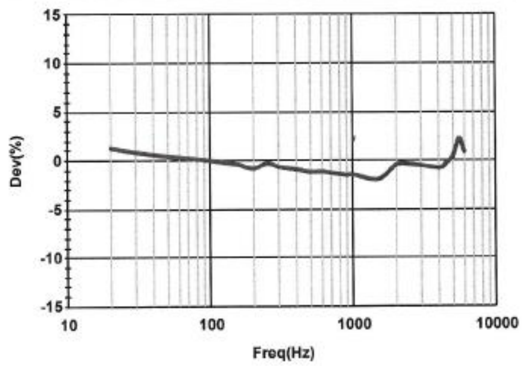
Reference Specifications

Range	g	± 5	Temp. Range, operating	°C	-54 to 80
Max Range	g	± 8	Output Impedance	Ω	≤500

Measurements

Frequency Hz	Sensitivity mV/g	Deviation % (ref=100 Hz)
20	994	1.3
50	986	0.4
100	981	0.0
200	974	-0.8
500	970	-1.2
1000	967	-1.5
2000	977	-0.5
4000	974	-0.8
6000	990	0.9

Frequency Response



Sensitivity at 100 Hz, 3.0 g rms	mV/g	981		
Sensitivity at 159 Hz, 3.0 g rms	mV/g	977	$g = 9.807\ m/s^2$	159.2 Hz = 1000 rads/se
Environmental Temperature	°C	22 ± 4	Condition	New
Relative Humidity	%	30 ± 30	NIST Test Report Number	681/281072-11
Calibration Date		2/24/2012	Calibration Technician:	Mark Thomas

This sensor was calibrated per Kistler test procedure 978-5444-701 using a comparison technique against a Kistler working standard. Kistler working standards are periodically calibrated against a primary standard system, which in turn is periodically recertified to the National Institute of Standards and Technology (NIST) or another recognized national standard. Measurements are derived from accepted values of natural physical constants according to the International System of Units (SI). This calibration meets or exceeds the requirements of MIL-STD-45662A, ISO 9001, ANSI/NCSL Z540-1 and is accredited to ISO/IEC 17025 as verified by the ANSI-ASQ National Accreditation Board/ACLASS. Refer to certificate and scope of accreditation AC-1117. Estimated uncertainty is ± 2.2% of reading with respect to the primary standard. Certificates are on file at Kistler and may be requested in writing. This certificate shall not be reproduced, except in full, without written approval of Kistler Instrument Corporation.

Reference Equipment	Manufacturer	Type	Serial Number	Reference Equipment	Manufacturer	Type	Serial Number
Accelerometer (Working Std.)	Kistler	8076K	C148323	Multimeter (Standard)	HP	34401A	3146A65537
Charge Amplifier (Working Std.)	Kistler	5020	C93919	Multimeter (Test)	HP	34401A	3146A65544
Accelerometer (Primary Std.)	Kistler	8002K	C139113	Function Generator	Wavetek	270	C6370761
Charge Amplifier (Primary Std.)	Kistler	5020	C92253	Charge Amplifier (Test)	Kistler	ETL1026	3

Kistler Instrument Corp.
75 John Glenn Drive
Amherst, NY 14228-2171

Tel 1-888-KISTLER
Fax 1-716-691-5226
info.us@kistler.com

ISO 9001 Certified Quality System
ISO 17025 Accredited Calibration Laboratory
026-5007-001 Rev B - Page 3 of 4

www.kistler.com

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ACCELERATION CALIBRATION CERTIFICATE - Z Axis

Type	**8762A5**	**Manufacturer**	**Kistler**
Serial Number	**2100063**	**Certificate ID #**	**2100063-120224T0846**
Time Constant	sec 1.3	Mounted Resonant Frequency	kHz 30.0
Transverse Sensitivity	% 0.6	Mounting Torque	lbf-in 18 ± 2.0
Bias Voltage	V_{DC} 12.0		Nm 2.0 ± 0.2

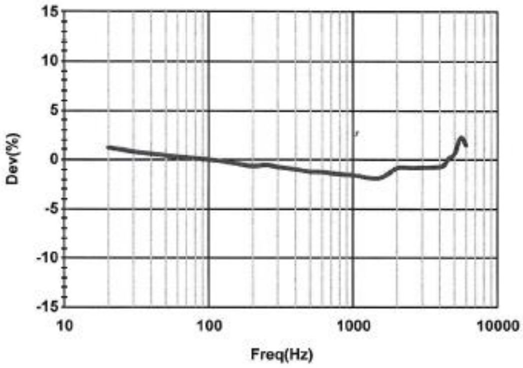
Reference Specifications

Range	g ± 5	Temp. Range, operating	°C -54 to 80
Max Range	g ± 8	Output Impedance	Ω ≤500

Measurements

Frequency Hz	Sensitivity mV/g	Deviation % (ref=100 Hz)
20	1025	1.3
50	1017	0.4
100	1013	0.0
200	1006	-0.7
500	1000	-1.2
1000	997	-1.6
2000	1004	-0.9
4000	1005	-0.7
6000	1028	1.5

Frequency Response



Sensitivity at 100 Hz, 3.0 g rms	mV/g 1013		
Sensitivity at 159 Hz, 3.0 g rms	mV/g 1008	g = 9.807 m/s²	159.2 Hz = 1000 rads/sec
Environmental Temperature	°C 22 ± 4	Condition	New
Relative Humidity	% 30 ± 30	NIST Test Report Number	681/281072-11
Calibration Date	2/24/2012	Calibration Technician:	Mark Thomas

This sensor was calibrated per Kistler test procedure 978-5444-701 using a comparison technique against a Kistler working standard. Kistler working standards are periodically calibrated against a primary standard system, which in turn is periodically recertified to the National Institute of Standards and Technology (NIST) or another recognized national standard. Measurements are derived from accepted values of natural physical constants according to the International System of Units (SI). This calibration meets or exceeds the requirements of MIL-STD-45662A, ISO 9001, ANSI/NCSL Z540-1 and is accredited to ISO/IEC 17025 as verified by the ANSI-ASQ National Accreditation Board/ACLASS. Refer to certificate and scope of accreditation AC-1117. Estimated uncertainty is ± 2.2% of reading with respect to the primary standard. Certificates are on file at Kistler and may be requested in writing. This certificate shall not be reproduced, except in full, without written approval of Kistler Instrument Corporation.

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1.2 Dynamometer

KISTLER

3-KOMPONENTEN-DYNAMOMETER
3-COMPONENT DYNAMOMETER

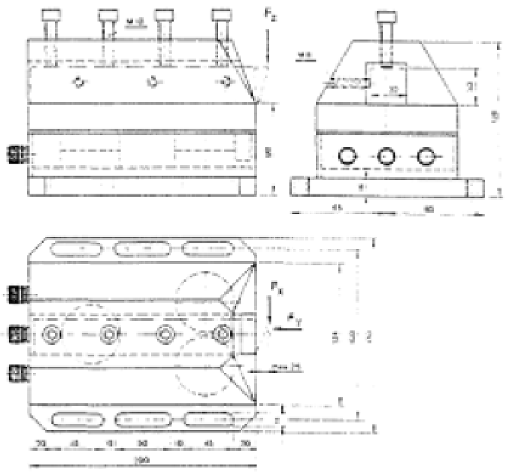
9263 6. 3.72 1
9263de

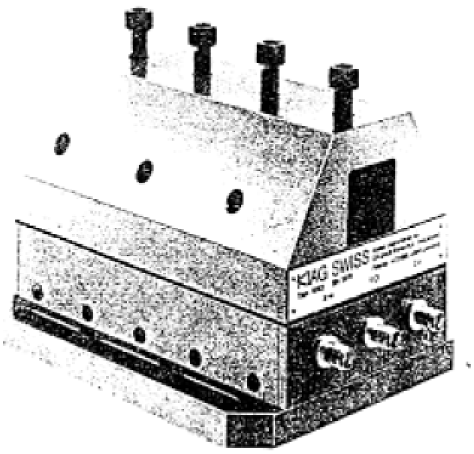
VORLAEUFIGE DATEN

Quarzkristall 3-Komponenten-Dynamometer für Drehstähle bis 32 x 32 mm² Schaftquerschnitt, zur Messung einer Kraft in drei orthogonalen Komponenten. Höchste Auflösung, grosse Steifheit, minimale Messwege, kompakte Konstruktion.

TENTATIVE DATA

Piezo-electric three component dynamometer for cutting tools with up to 32 x 32 mm² shank cross section. It measures a force in three orthogonal components and offers highest resolution, high rigidity, minimal deflection, compact design.





TECHNISCHE DATEN / TECHNICAL DATA

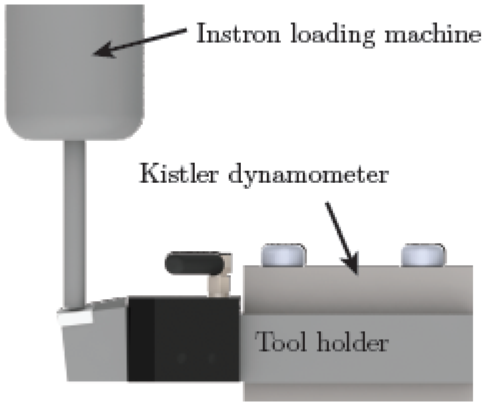
TECHNISCHE DATEN	TECHNICAL DATA		
max. Messbereiche: F_x, F_y	max. measuring ranges: F_x, F_y	kN	±10
F_z	F_z	kN	0 ... 20
Ueberlastbarkeit	overload capacity	%	50
Ansprechschwelle	resolution	N	0,01
Empfindlichkeit	sensitivity	pC/N	-3,8
Linearität	linearity	%FSO	≤ ±1
Hysterese	hysteresis	%FSO	≤ 1
Uebersprechen: $F_x \rightleftarrows F_y$	crosstalk: $F_x \rightleftarrows F_y$	%	≤ ±2
$F_{x,y} \rightarrow F_z$	$F_{x,y} \rightarrow F_z$	%	≤ ±5
$F_z \rightarrow F_{x,y}$	$F_z \rightarrow F_{x,y}$	%	≤ ±1
Eigenfrequenz (niedrigste)	resonant frequency (lowest)	kHz	> 2,5
Steifheiten: x- und y-Richtung	rigidities: x- and y-direction	kN/µm	~ 2
z-Richtung	z-direction	kN/µm	~ 5
Isolationswiderstände	insulation resistance	Ω	$>10^{13}$
Kapazität	capacitance	pF	< 1200
Temperaturkoeffizient der Empfindl.	temperature coefficient of sens.	%/°C	-0,02
Betriebstemperaturbereich	working temperature range	°C	0 ... 70
Gewicht ohne/mit Kiste	weight without/with case	kg	18/22

1 N (Newton) = 1 kg · m · s^{-2} = 0,1019 ... kp = 0,2248 ... lbf; 1 kg = 2,204 ... lb; 1 in = 25,4 mm

KIAG SWISS® Kistler Instrumente AG, CH-8402 Winterthur/Schweiz

Calibration setup:

- Instron machine simulating cutting force
- Stepped calibration loading profile [0 - 1KN]
- SAWR sensor and Kistler signals analysed
- RF interference assessed
- Interrogator position considerations
- Signal to noise ratio of SAWR demonstrated
- Piezo vs SAWR technology comparison



- Schematic of the loading setup carried out during the system calibration.

Sensor	*Ssen(V/200N)*	*Hyster*	R^2	*STD (V)*	*SNR*
9232A strain sensor	0.065	4.2%	0.997	0.0003	205
9263 Dynamometer F_c	0.334	0.32%	0.999	0.0011	296
MGRHR single SAWR	0.0155	1.2%	0.996	0.0026	5.9

Reference: “Surface acoustic wave strain sensor technology for machine monitoring applications in cnc turning”, Phd Thesis, Trinity College Dublin, Rory Stoney, 8/2013

1.3 Current transformers

MAGNELAB

Split-Core AC Current Sensor SCT-0400

0.40" Opening With Ratings Up To 75 Amps

Description:

Magnelab's SCT-0400 Series split-core current sensors "sense" AC current up to 75 Amps passing through the center conductor. Split-core transformers are ideal for installation on existing electrical wiring by snapping around the conductor. The SCT series have a self-locking mechanism guaranteed for 500 opening-closing cycles. Custom outputs and other parameters are available at customer request.

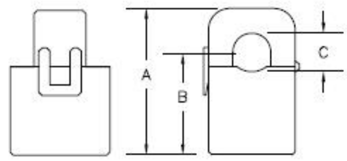
Features:

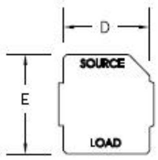
- Rated input up to 75 Amp
- Output 0.333 Volt AC at rated current
- Linearity accuracy ± 1%
- Accuracy at 10% to 130% of rated current
- Phase angle < 2 degrees (valid for 20A or higher)
- Operates from 50 Hz to 1,000 Hz
- 8 ft. twisted-pair lead
- Maximum Voltage: 600 V (on bare conductor)
- Hinge guaranteed for 500 opening-closing cycles.
- UL Recognized, CE, and RoHS compliant

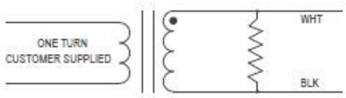
PART NUMBER AND RATING	
SCT-0400-000	No Burden Resistor*
SCT-0400-005	5 Amp
SCT-0400-010	10 Amp
SCT-0400-015	15 Amp
SCT-0400-020	20 Amp
SCT-0400-025	25 Amp
SCT-0400-030	30 Amp
SCT-0400-040	40 Amp
SCT-0400-050	50 Amp
SCT-0400-060	60 Amp
SCT-0400-075	75 Amp

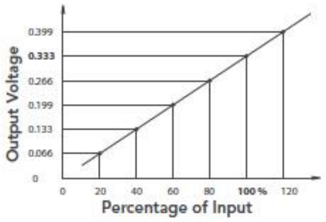
* Zener diode limits the output voltage to 22 V

DIMENSION	INCH	MM
A	1.560	39.62
B	1.000	25.40
C	0.400	10.16
D	1.000	25.40
E	1.000	25.40





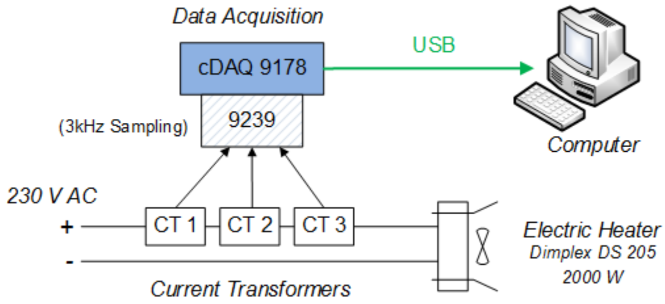


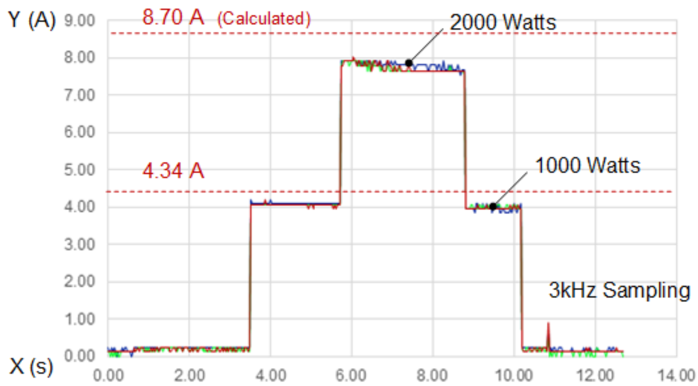


CE RoHS UL ISO 9100:2000

Rev. B

Magnelab.com





Graph Legend

Type	Scale
Current Transformer 1	+x1
Current Transformer 2	+x1
Current Transformer 3	+x1

(Current Peak to Peak / 2)*100 = 10% error

Scaling factor: 110

1.4 Force hammer

Impulse Force Hammer; Low Force Range, Type 9722A...

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Technical Data

Type	**Units**	**9722A500**	**9722A2000**
Force Range	lbf	0 ... 100	0 ... 500
Maximum Force	lbf	500	2500
Sensitivity nom.	mV/lbf	50	10
Resonant Frequency	kHz	27	27
Frequency Range with steel impact tip (-10 dB)	Hz	8200	9300
Time Constant nom	s	500	500
Rigidity	lbf/µin	4.8	4.8
Temperature Range Operating	°F	-5 ... 160	-5 ... 160
Output:			
Voltage F.S.	V	±5	±5
Bias nom.	VDC	11	11
Impedance	Ω	<100	<100
Source:			
Voltage	V	20 ... 30	20 ... 30
Constant current	mA	2 ... 20	2 ... 20
Hammer head dimensions:			
Diameter	in	0.69	0.69
Length	in	2.4	2.4
Weight	gram	100	100
Length of handle	in	7.4	7.4
Connector	type	BNC neg.	BNC neg.

1 N = 0.2248lb, 1 g = 9.80665 m/s2, 1 inch = 25.4 mm, 1 gram = 0.03527 oz

2 Data acquisition

2.1 Analogue input

NI 9234

±5 V, IEPE and AC/DC Analog Input, 51.2 kS/s/ch, 4 Ch Module

- 51.2 kS/s per channel maximum sampling rate; ±5 V input
- 24-bit resolution; 102 dB dynamic range; anti-aliasing filters
- Software-selectable AC/DC coupling; AC-coupled (0.5 Hz)
- Software-selectable IEPE signal conditioning (0 or 2 mA)
- Smart TEDS sensor compatibility
- -40 °C to 70 °C operating range, 5 g vibration, 50 g shock

Reference: www.ni.com

NI 9239

±10 V, Simultaneous Analog Input, 50 kS/s, 4 Ch Module

- 4 differential channels, 50 kS/s per channel sample rate
- ±10 V measurement range, 24-bit resolution
- Antialias filter
- 250 Vrms ch-ch, CAT II (screw terminal), or 60 VDC ch-ch, CAT I (BNC) isolation
- Screw-terminal or BNC connectivity
- -40 °C to 70 °C operating, 5 g vibration, 50 g shock

Reference: www.ni.com

2.2 Data acquisition

NI cDAQ-9178

NI CompactDAQ 8-Slot USB Chassis

- Choose from more than 50 hot-swappable I/O modules with integrated signal conditioning
- Four general-purpose 32-bit counter/timers built into chassis (access through digital module)
- Run up to 7 hardware-timed analog I/O, digital I/O, or counter/timer operations simultaneously
- Stream continuous waveform measurements with patented NI Signal Streaming technology
- Built-in BNC connections for external clocks and triggers (up to 1 MHz)
- Measure in minutes with NI-DAQmx software and automatic code generation using the DAQ Assistant

Reference: www.ni.com

NI cDAQ-9171

NI CompactDAQ 1-Slot USB Chassis

- Choose from more than 50 hot-swappable I/O modules with integrated signal conditioning
- Four general-purpose 32-bit counter/timers built into chassis (access through digital module)
- Stream continuous waveform measurements with patented NI Signal Streaming technology
- Measure in minutes with NI-DAQmx software and automatic code generation using the DAQ Assistant

Reference: www.ni.com

NI cDAQ-9191

NI CompactDAQ 1-Slot Ethernet and 802.11 Wi-Fi Chassis

- Send data to a host PC over Ethernet or IEEE 802.11 Wi-Fi
- Use 4 general-purpose 32-bit counter/timers built into the chassis (access through digital module)
- Stream continuous waveform measurements with patented NI Signal Streaming technology
- Measure in minutes with NI-DAQmx software and automatic code generation using the DAQ Assistant
- Choose from more than 50 NI C Series hot-swappable I/O modules with integrated signal conditioning

Reference: www.ni.com

3 Peripheral equipment

3.1 Next Unit of Computing (NUC)

Processor	5th generation Intel® Core™ i5-5250U processor (1.6 GHz up to 2.7 GHz Turbo, dual core, 3 MB cache, 15 W TDP)
Memory	Dual-channel DDR3L SODIMMs 1.35V, 1333/1600 MHz, 16 GB maximum
Graphics	Intel® HD Graphics 6000 1x Mini HDMI* 1.4a 1x Mini DisplayPort* 1.2
Audio	Up to 7.1 surround audio via Mini HDMI and Mini DisplayPort Headphone/microphone jack on the front panel
Peripheral connectivity	2x USB 3.0 ports on the back panel 2x USB 3.0 ports on the front panel (1x charging capable) 2x internal USB 2.0 via header Consumer Infrared sensor on the front panel
Storage	Internal support for M.2 Key Type M SSD card (22x42, 22x60, or 22x80)
Networking	Intel® 10/100/1000 Mbps Network Connection Intel® Wireless-AC 7265 M.2 soldered-down, wireless antennas (IEEE 802.11ac, Bluetooth* 4, Intel® Wireless Display)

Reference: www.intel.com

3.2 Ethernet router

Product Description	NETGEAR ProSafe GS108 8-port Gigabit Desktop Switch 10/100/1000 Mbps - switch - 8 ports - desktop
Device Type	Switch - 8 ports
Enclosure Type	Desktop
Ports	8 x 10/100/1000
MAC Address Table Size	8K entries
Features	Full duplex capability, auto-sensing per device, auto-uplink (auto MDI/MDI-X)
Compliant Standards	IEEE 802.3u, IEEE 802.3i, IEEE 802.3ab
Dimensions (WxDxH)	28.7 cm x 10 cm x 2.5 cm
Weight	0.9 kg
System Requirements	Apple MacOS, Novell NetWare, Microsoft Windows
Manufacturer Warranty	NETGEAR lifetime warranty

Reference: www.netgear.ie

3.3 Charge amplifier

Industrial Charge Amplifier – Robust Construction (IP67), Type 5038A...

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Technical Data

Charge Amplifier		
Measuring ranges		
(Adjustable with slide switches and exchangeable potentiometers)		
Range I	pC	100 … 1 000
Range II	pC	1 000 … 10 000
Range III	pC	10 000 … 100 000
Setting tolerance	%	<0,1
Drift (r.F. <50 %, with opened cover)		
25 °C typical	pC/s	<0,03
25 °C maximum	pC/s	<0,05
60 °C	pC/s	<0,3
Reset/Operate transition	pC	<±1
Output voltage	V	0 … ±5
Output current	mA	0 … ±2
Output impedance	Ω	100
Output interference signal	mV_{pp}	<3
Zero point error (Reset)	mV	<±15
Frequency limit		
–5 %	kHz	0 … >4
–3 dB	kHz	0 … >10

Control Inputs for Reset/Operate (All Channels)		
Operate		
(Control connection Operate/Reset for TTL levels)		
Operate		Connection to GND or <0,8 V
Reset		Input open or >2,4 V
Input impedance on +7,5 V		
1 channel	kΩ	215
2 channels	kΩ	107
3 channels	kΩ	70
Operate +/Operate –		
Control connection Operate/Reset electrically isolated by optocouplers		
Control voltage	VDC	5 … 45
Current consumption	mA	0,4 … 4,4
Operate-Reset time (Residual charge <0,5 % FS)		
Range <5 000 pC	ms	<6
Range <100 000 pC	ms	<40

Power Supply		
Supply voltage	VDC	15 … 30
Current consumption (without load)		
1 channel	mA	<18
2 channels	mA	<25
3 channels	mA	<32

General Data		
Temperature range		
for specifications	°C	0 … 60
for function	°C	–10 … 60
Housing material		Aluminium
Degree of protection		
with connection for protection hose and armouring Type 1409	EN60529	IP67
with conduit gland Type 1411A	EN60529	IP67
with TNC gland Type 1900A1	EN60529	IP65*
with DIN round pin plug Type 1500A59	EN60529	IP65*
with BNC gland Type 1900A3	EN60529	IP60*
with Fischer connector Type 1900A11	EN60529	IP60*
Vibration resistance	g_p	10
Test conditions: 20 … 2 000 Hz continuous in 2 min., 8x within 16 min.		
Shock resistance during 1 ms	g	200
Connections optional (see accessories)		
Weight	g	ca. 550
Dimensions		
LxWxH	mm	150x64x34,5
with insulation plate	mm	172x64x42,5

* counts only with connected cable

Dimensions

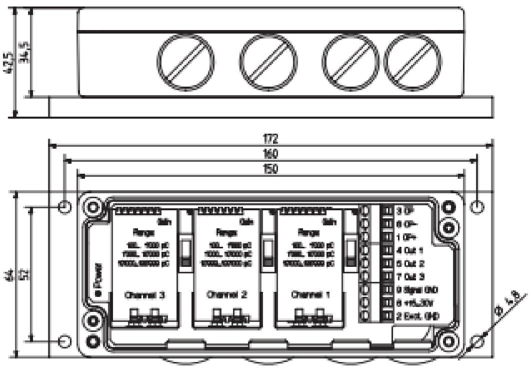
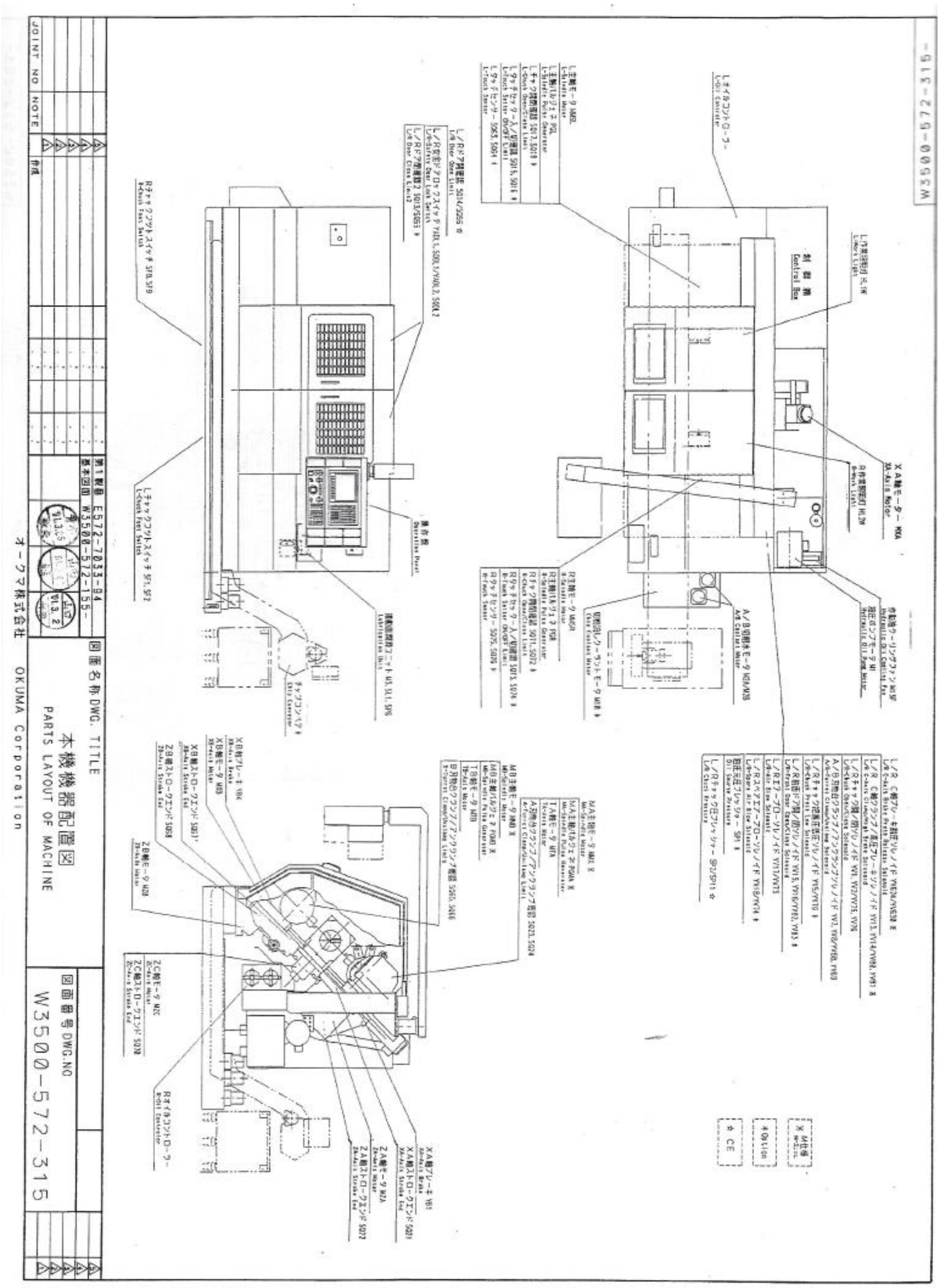


Fig. 1: Dimensions of industrial charge amplifier Type 5038A...

4 Machine tools

4.1 OKUMA CNC turning machine



4.2 Cutting tool

SNMG 12 04 12 H13A
T-Max® P insert for turning

Insert | Tool item (6) | My calculation (1)

Product information

Ordering code

ISO	SNMG 12 04 12 H13A
ANSI	SNMG 433 H13A
Material ID	5750044
Bar code	10110343

Product Description
T-Max® P insert for turning

Price and availability

Log in for more information about price and availability

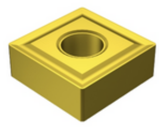
Buy

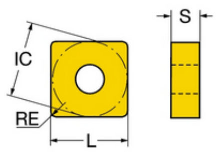
SSCM	insert seat size code	12
SSCN	insert seat size code	1/2
CTPT	operation type	Medium
L	cutting edge length	12.7 mm
S	insert thickness	4.7625 mm
IC	inscribed circle diameter	12.7 mm
LE	cutting edge effective length	11.5 mm
RE	Corner radius	1.1906 mm
D1	fixing hole diameter	5.156 mm
HAND	hand	N
TSYC	tool style code	SNMG
GRADE	grade	H13A

+ Show additional product data

S ap: 3 mm(1.5-6) fn: 0.35 mm/r(0.35-0.6) vc: 25 m/min(15-25)

Pictures shown describe a group of similar products and may not be an exact illustration of the product presented





PSBNL 2525M 12
T-Max® P shank tool for turning

Tool item | Inserts (475) | Products - Machine direction (37) | Spare/included parts (7) | My calculation (1)

Product information

Ordering code

ISO	PSBNL 2525M 12
ANSI	PSBNL 2525M 12
Material ID	5738841
Bar code	10402372

Product Description
T-Max® P shank tool for turning

Spare parts
Spare/included parts

Download:
CAD Drawing (.dxf)
3D Model (.stp)

Price and availability

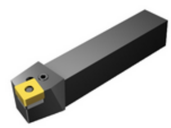
Log in for more information about price and availability

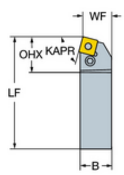
Buy

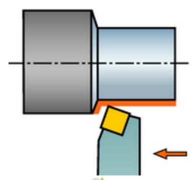
SSCM	insert seat size code	12
SSCN	insert seat size code	1/2
ADINTMS	adaptive interface machine direction	Rectangular shank -metric: 25 x 25
CZC	connection size code	25 x 25
KAPR	tool cutting edge angle	75 deg
PSIR	tool lead angle	15 deg
RMPX	maximum ramping angle	10 deg
OHX	maximum overhang	27.5 mm
LF	functional length	150 mm
WF	functional width	22 mm
HF	functional height	25 mm
WT	weight of item	0.756 kg

+ Show additional product data

Pictures shown describe a group of similar products and may not be an exact illustration of the product presented







Reference: http://www.sandvik.coromant.com

4.3 Recommended cutting parameters

Cutting speed recommendations, metric values

The recommendations are valid for use with cutting fluid.

ISO P MC No.	CMC No.	Steel Material	Specific cutting force k_{c1} N/mm²	Hardness Brinell HB	<<<< WEAR RESISTANCE CT5005	CT5015	GC1525	GC15
					h_{ex}, mm ≈ feed f_n, mm/r			
					0.05-0.1-0.2	0.05-0.1-0.2	0.05-0.1-0.2	0.1-0.2-0.3
					Cutting speed (v_c), m/min			
		Unalloyed steel						
P1.1.Z.AN	01.1	C = 0.1–0.25%	1500	125	730-590-485	650-540-440	560-465-380	300-250-215
P1.2.Z.AN	01.2	C = 0.25–0.55%	1600	150	650-530-420	570-480-385	495-415-335	275-225-195
P1.3.Z.AN	01.3	C = 0.55–0.80%	1700	170	-	510-425-340	430-365-295	260-215-185
		Low-alloy steel (alloying elements ≤5%)						
P2.1.Z.AN	02.1	Non-hardened	1700	180	530-450-360	480-400-320	375-320-255	220-175-150
P2.1.Z.AN	02.12	Ball bearing steel	1800	210	-	-	-	190-155-135
P2.5.Z.HT	02.2	Hardened and tempered	1850	275	395-325-250	285-235-190	200-165-135	140-115-100
P2.5.Z.HT	02.2	Hardened and tempered	2050	350	320-260-200	230-190-150	160-135-110	110-95-80
		High-alloy steel (alloying elements >5%)						
P3.0.Z.AN	03.11	Annealed	1950	200	-	395-330-250	260-215-175	-
P3.0.Z.HT	03.21	Hardened tool steel	3000	325	-	195-165-130	145-115-90	-
		Steel castings						
P1.5.C.UT	06.1	Unalloyed	1550	180	-	260-215-175	225-185-145	-
P2.6.C.UT	06.2	Low-alloy (alloying elements ≤5%)	1600	200	-	270-225-170	175-145-105	-
P3.0.C.UT	06.3	High-alloy (alloying elements >5%)	2050	225	-	200-165-125	140-115-85	-

Cutting data GENERAL TURNING

Cutting speed recommendations, metric values

GC1515	GC1125	GC3005	GC4205	GC4215	GC4225	GC2015	GC4235	GC30	GC2025	TOUGHNESS >>>>
0.1-0.2-0.3	0.1-0.2-0.3	0.1-0.3-0.5	0.1-0.4-0.8	0.1-0.4-0.8	0.1-0.4-0.8	0.1-0.4-0.8	0.1-0.4-0.8	0.15-0.25-0.4	0.1-0.4-0.8	
310-290-255	310-290-255	520-415-340	620-450-330	570-405-300	510-345-245	440-300-210	425-275-200	305-260-215	295-200-145	
280-255-245	280-255-225	470-370-305	560-405-295	510-365-265	455-305-215	400-270-190	380-245-180	275-235-195	265-180-130	
285-260-230	260-235-210	445-355-290	530-385-275	460-330-240	425-290-205	370-250-175	365-235-170	260-220-185	250-170-120	
295-200-125	-	500-375-300	610-410-285	560-370-260	460-305-215	395-265-190	300-185-135	215-180-150	220-145-100	
-	-	-	530-350-250	460-305-215	395-265-190	350-230-160	250-155-110	190-160-130	195-125-85	
195-100-40	-	275-215-175	330-230-175	300-210-155	255-180-140	260-180-140	185-120-85	135-115-95	145-95-65	
160-80-34	-	225-170-140	265-185-140	240-170-125	205-145-110	210-145-115	150-95-70	110-95-80	115-75-50	
	-	370-275-225	445-295-215	405-270-200	300-205-150	260-180-130	240-155-105		185-125-85	
	-	180-130-105	220-140-105	200-130-95	135-95-75	115-85-65	110-70-50		85-55-38	
	-	275-220-185	335-235-185	300-215-170	240-180-130	210-155-110	185-140-100		140-105-80	
	-	270-200-170	290-205-155	260-185-140	210-140-100	180-120-85	165-100-70		125-80-55	
	-	205-155-130	225-150-115	205-135-105	185-125-90	160-110-75	145-95-65		110-75-50	

Reference: Sandvik Turning tools 2012

Cutting speed recommendations, metric values

The recommendations are valid for use with cutting fluid.

ISO N MC No.	CMC No.	Non-ferrous metals Material	Specific cutting force k_{c1} N/mm²	Hardness Brinell HB	<<<< WEAR RESISTANCE CD10	 CD1810	 H10
					h_{ex}, mm ≈ feed f_n, mm/r		
					0.05-0.4	0.15-0.8	0.15-0.8
					Cutting speed (v_c), m/min		
		Aluminium alloys					
N1.2.Z.UT	30.11	Wrought or wrought and coldworked, non-aging	400	60	2 000 (2500-250)[1)]	2 000 (2500-250)[1)]	2 000 (2500-250)[1)]
N1.2.Z.AG	30.12	Wrought or wrought and aged	650	100	2 000 (2500-250)[1)]	2 000 (2500-250)[1)]	2 000 (2500-250)[1)]
		Aluminium alloys					
N1.3.C.UT	30.21	Cast, non-aging	600	75	2 000 (2500-250)[1)]	2 000 (2500-250)[1)]	2 000 (2500-250)[1)]
N1.3.C.AG	30.22	Cast or cast and aged	700	90	2 000 (2500-250)[1)]	2 000 (2500-250)[1)]	2 000 (2500-250)[1)]
		Aluminium alloys					
	30.41	Cast, 13–15% Si	700	130	1 550 (1950-195)[1)]	770 (960-95)[1)]	450 (560-55)[1)]
N1.4.C.NS	30.42	Cast, 16–22% Si	700	130	770 (960-95)[1)]	510 (640-65)[1)]	300 (375-38)[1)]
		Copper and copper alloys					
N3.3.U.UT	33.1	Free cutting alloys, ≥1% Pb	550	110	500 (630-65)[1)]	500 (630-65)[1)]	500 (630-65)[1)]
N3.2.C.UT	33.2	Brass, leaded bronzes, ≤1% Pb	550	90	500 (630-65)[1)]	500 (630-65)[1)]	500 (630-65)[1)]
N3.1.U.UT	33.3	Bronze and non-leadad copper incl. electrolytic copper	1350	100	300 (375-38)[1)]	300 (375-38)[1)]	300 (375-38)[1)]

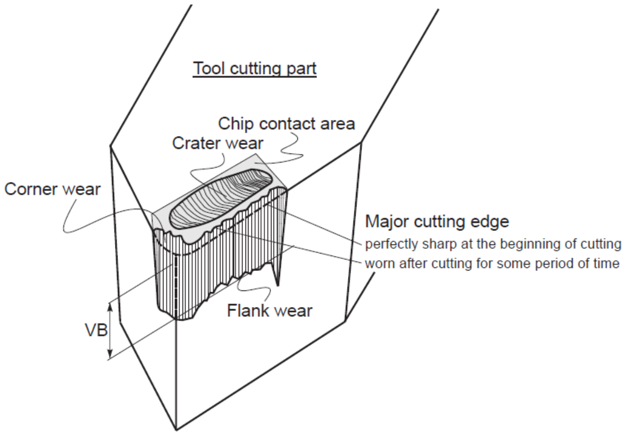
Cutting data GENERAL TURNING

Cutting speed recommendations, metric values

							TOUGHNESS >>>>
H13A	GC1115	GC15	GC1025	GC1125			
0.15-0.8	0.15-0.8	0.15-0.8	0.15-0.8	0.15-0.8			
1 900 (2400-240)[1)]	810 (1000-100)[1)]	810 (1000-100)1)	770 (960-95)[1)]	770 (960-95)[1)]			
1 900 (2400-240)[1)]	315 (395-39)[1)]	315 (395-39)1)	300 (375-38)[1)]	300 (375-38)[1)]			
1 900 (2400-240)[1)]	810 (1000-100)[1)]	810 (1000-100)1)	770 (960-95)[1)]	770 (960-95)[1)]			
1 900 (2400-240)[1)]	540 (680-70)[1)]	540 (680-70)1)	510 (640-65)[1)]	510 (640-65)[1)]			
400 (500-50)[1)]	315 (395-39)[1)]	315 (395-39)1)	300 (375-38)[1)]	300 (375-38)[1)]			
250 (315-31)[1)]	220 (275-28)[1)]	220 (275-28)1)	210 (265-26)[1)]	210 (265-26)[1)]			
450 (560-55)[1)]	210 (265-26)[1)]	210 (265-26)1)	200 (250-25)[1)]	200 (250-25)[1)]			
450 (560-55)[1)]	125 (155-16)[1)]	125 (155-16)1)	120 (150-15)[1)]	120 (150-15)[1)]			
270 (340-34)[1)]	90 (115-11)[1)]	90 (115-11)1)	85 (105-11)[1)]	85 (105-11)[1)]			

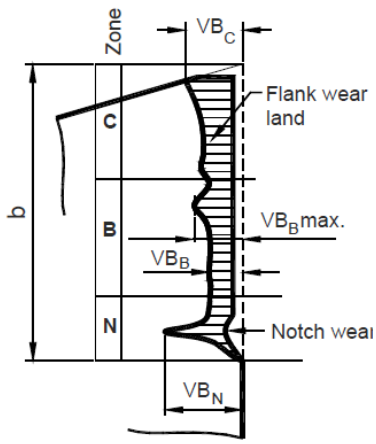
Reference: Sandvik Turning tools 2012

4.4 Tool wear

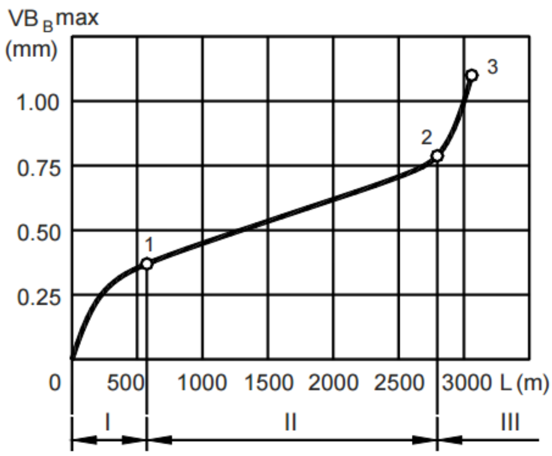


Reference: V. Marinov, "Manufactuirng Technology." Eastern Mediterranean University

Types of wear observed in cutting tools



Single point tool wear ISO 3685:1993



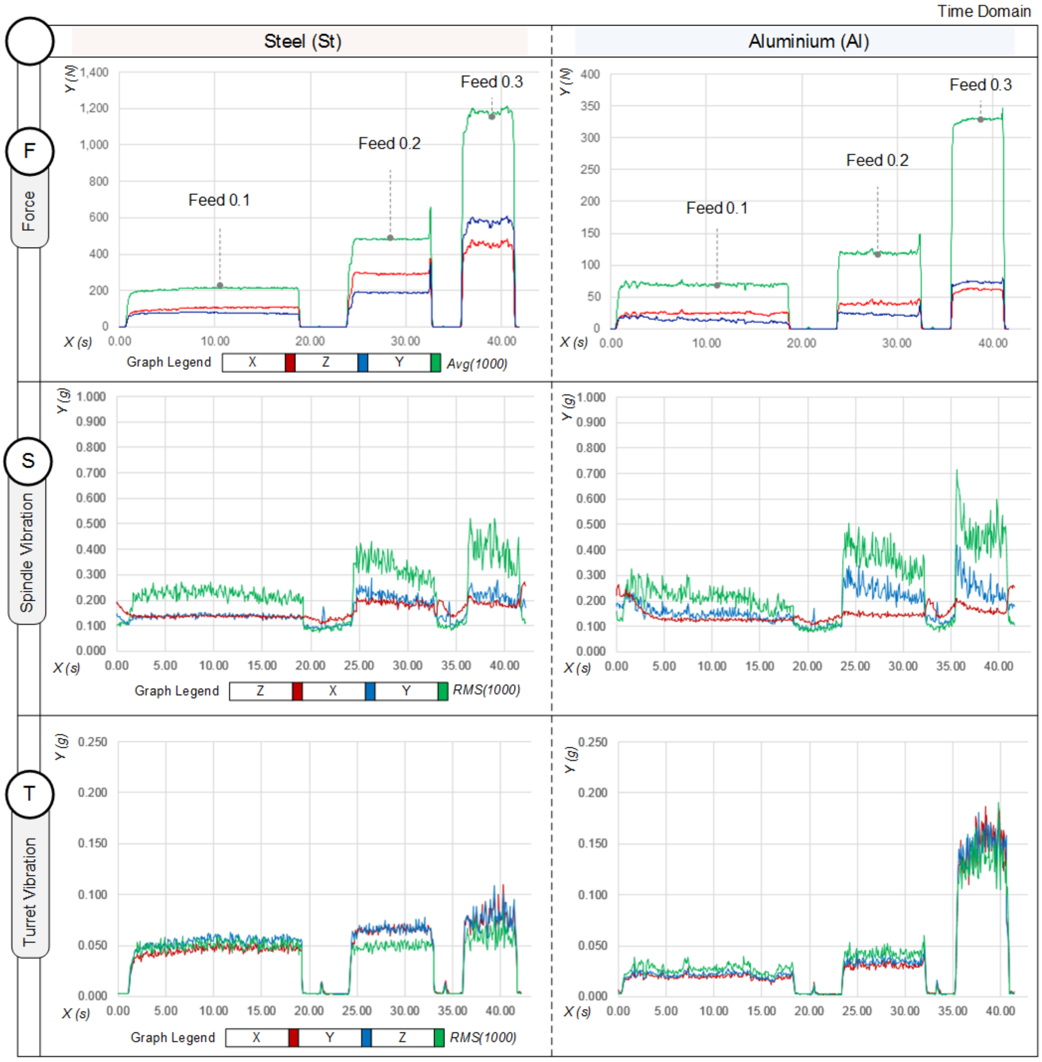
Reference: V. P. Astakhov and J. P. Davim, "Tools (Geometry and Material) and Tool Wear," in *Machining SE - 2*, Springer London, 2008, pp. 29–57.

Flank-wear curve, VB vs cutting path length

Appendix C

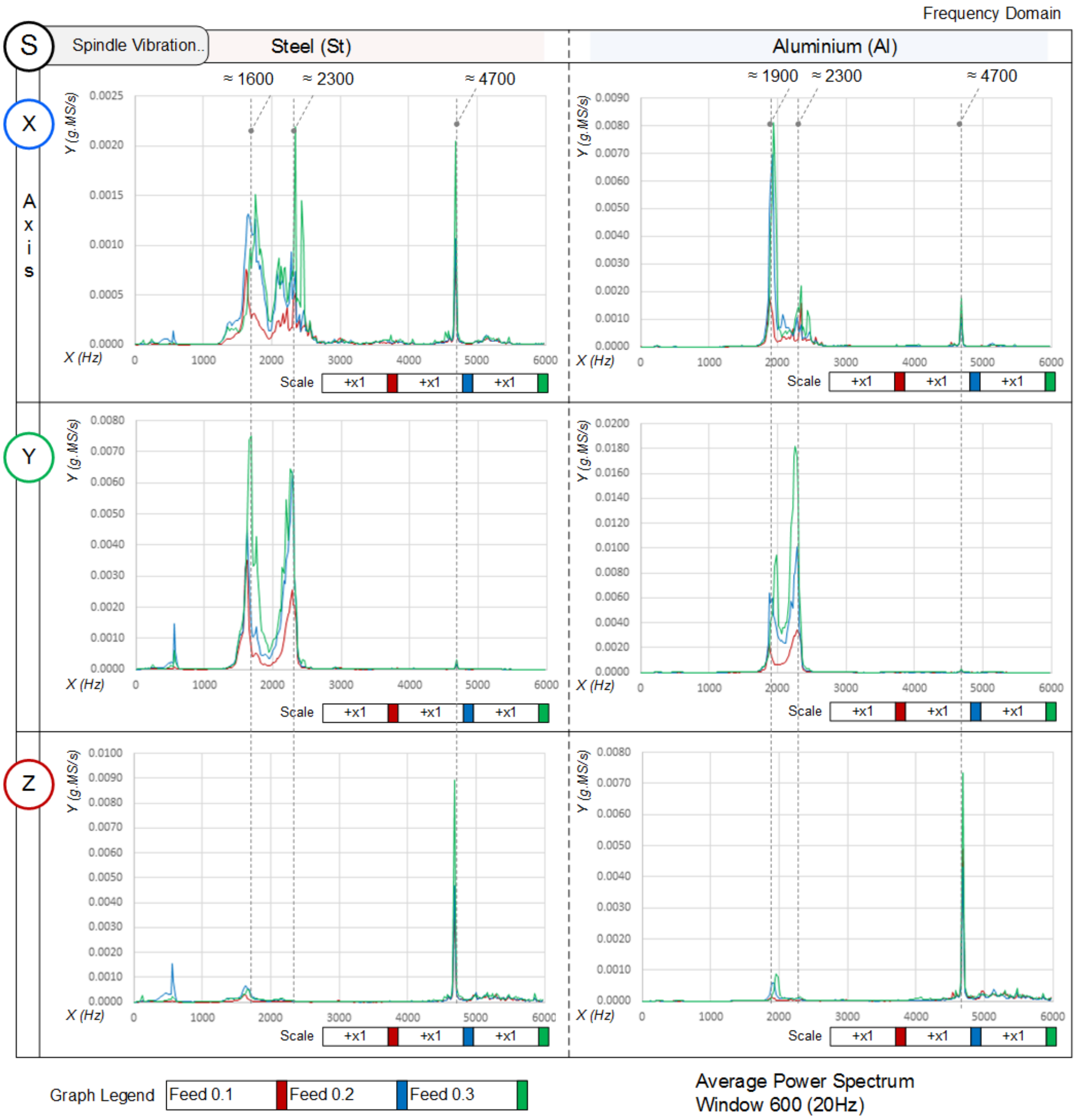
CNC turning machining parameter variation test results

1 Machining feed variation



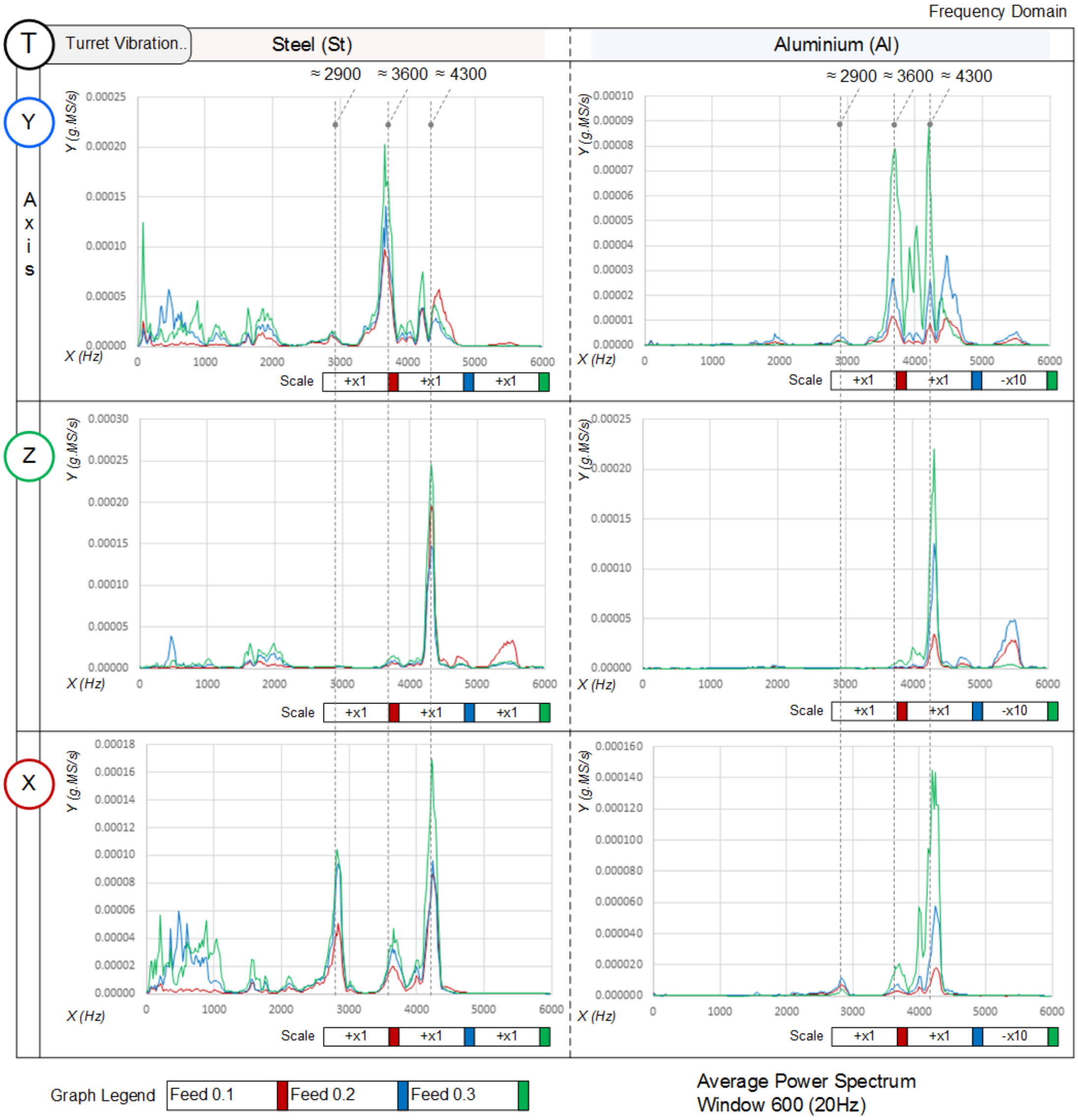
Steel	Aluminium
• Force, spindle and turret vibration magnitude and variance increases with feed rate • Feed force becomes greater than radial force during feed 0.3 • Turret vibration is marginally higher in amplitude in the radial and feed axis in feed 0.2 and 0.3	• Force, spindle and turret vibration increases with feed rate • Force and Turret vibration at feed 0.3 identifies a significant force increase, with the radial and feed axis become greater than cutting axis in turret vibration • Vibration variance is increased with feed rate
• Significantly higher force required for steel machining. • Spindle vibration is greater during aluminium machining.	

Figure 7.1 Machining: feed variation, time domain



Steel	Aluminium
• 3 peak frequencies are identified; 1600 (Material), 2350 (Spindle), and 4700 (Spindle) Hz • Feed rate varies the power in set frequencies	• 3 peak frequencies are identified; 1900 (Material), 2300 (Spindle), and 4700 (Spindle) Hz • Feed rate varies the power in set frequencies
Similar frequency response between materials, however steel has a wider frequency gap between peaks, 1600 – 2300 = 700Hz, and aluminium has a narrower gap, 1900 – 2300 = 400Hz. Aluminium has a significantly larger peak power in the feed and cutting axis.	

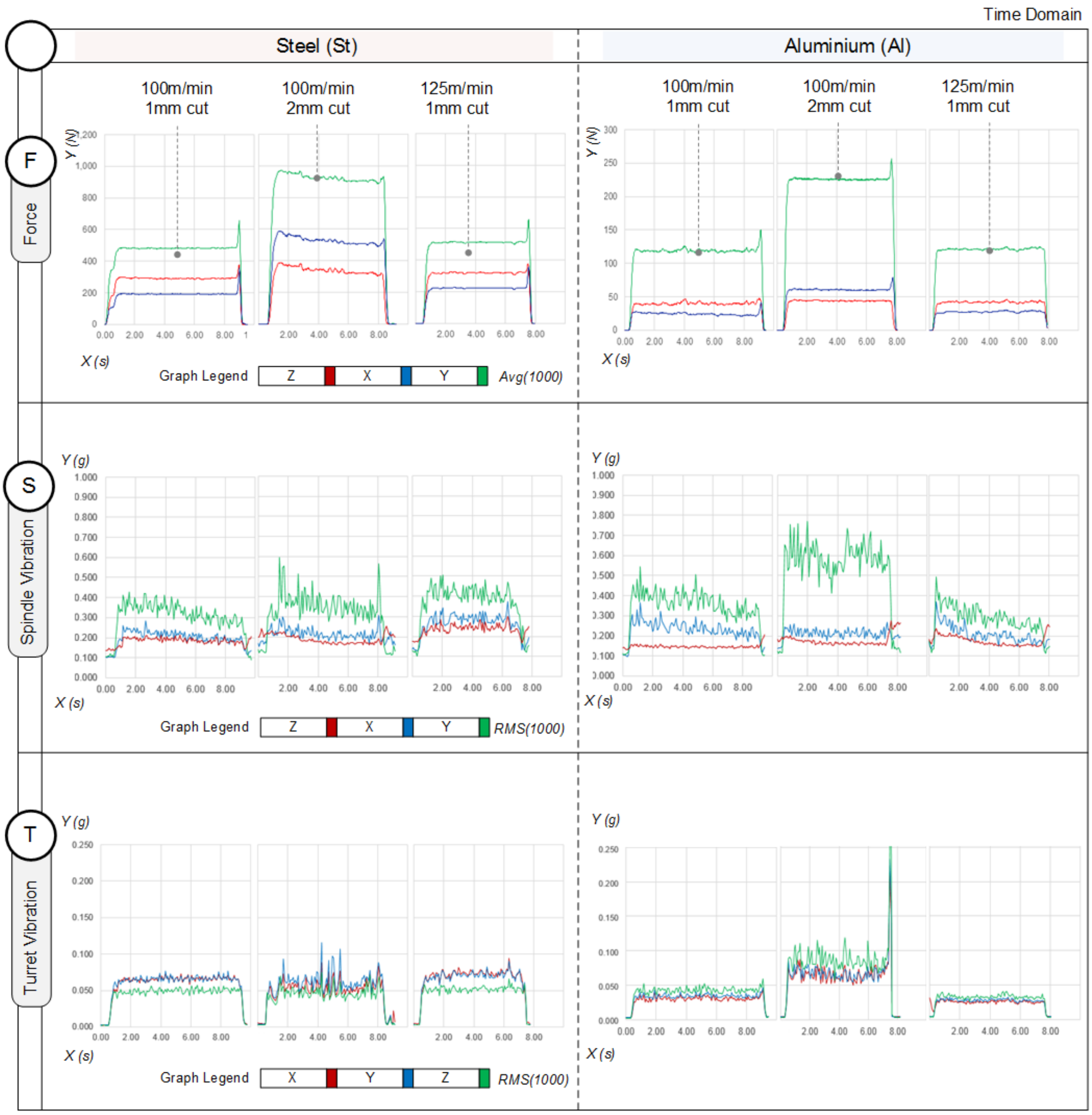
Figure 7.2 Machining: feed variation, spindle vibration, frequency domain



Steel	Aluminium
• 3 peak frequencies are identified; 2900, 3600, and 4300 Hz • Feed rate varies the power in set frequencies	• 3 peak frequencies are identified; 2900, 3600, and 4300 Hz • Feed rate varies the power in set frequencies • Turret vibration power during feed 0.3 is scaled, due to a significantly large power
Diverse frequency response between materials, significant increase in power and frequency of lower frequencies, <3000Hz, during steel machining (Tool vibration <1000)	

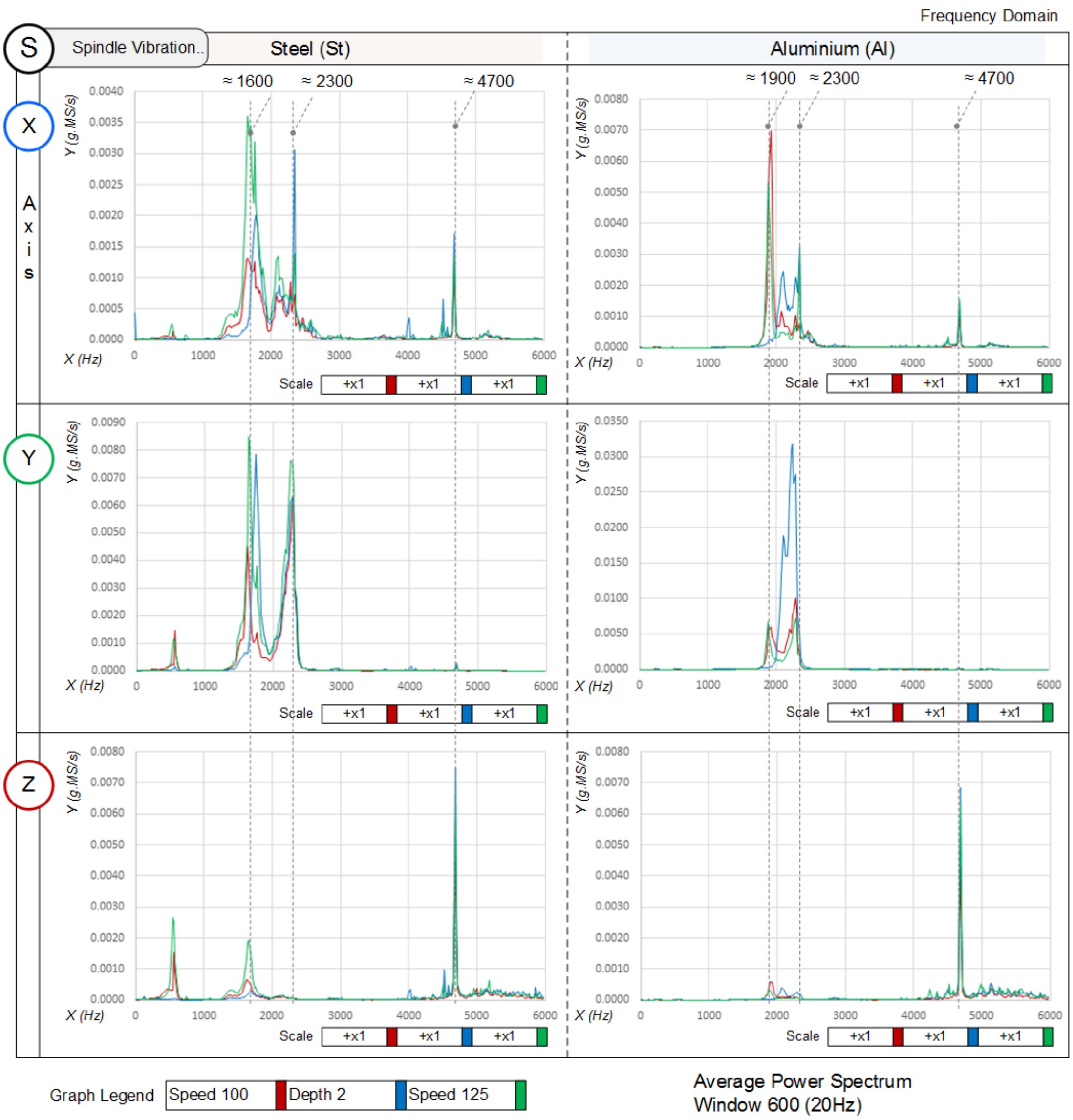
Figure 7.3 Machining: feed variation, turret vibration, frequency domain

2 Machining speed and depth of cut



Steel	Aluminium
• Force and spindle vibration increase with increased depth of cut and cutting speed • No increase in turret vibration, only an increase in variance for 2mm cut	• Force, spindle and turret vibration increase with increased depth of cut. • Increased spindle speed reduces force, spindle and turret vibration • Increased vibration variance and peak during 2mm cut
N/A	

Figure 7.4 Machining: speed and depth, time domain



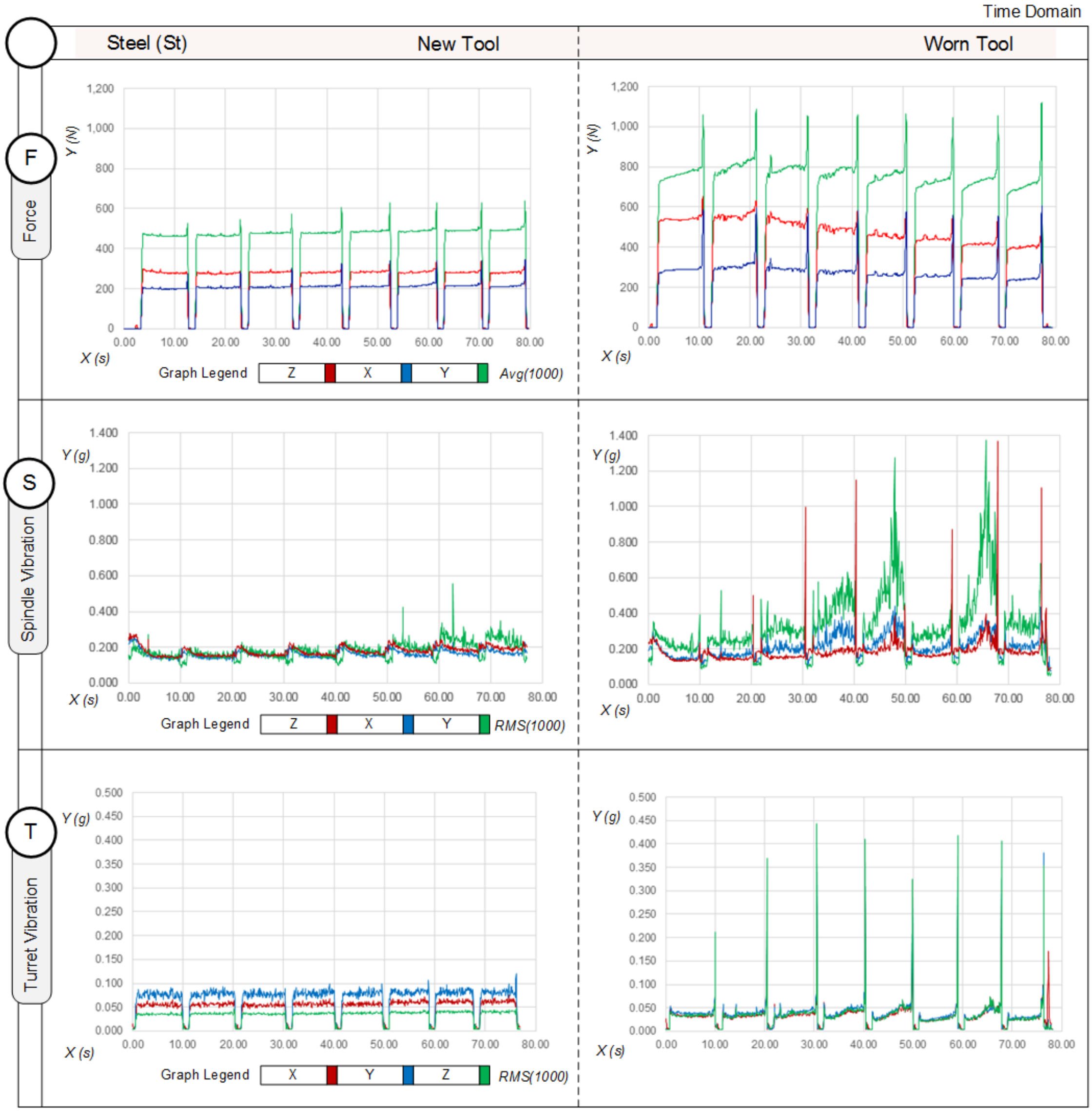
Steel	Aluminium
• Increase in power within the defined frequency bands, between cutting variations	• Increase in power within the defined frequency bands, between cutting variations • Frequency change during 2mm cut; 2100 – 2200 Hz Y
N/A	

Figure 7.5 Machining: speed and depth, spindle vibration, frequency domain

Steel	Aluminium
• Increase/Decrease in power within the frequency bands, between cutting variations • Increased speed has increased the tool vibration <1000 Hz	• Increase/Decrease in power within the frequency bands, between cutting variations
N/A	

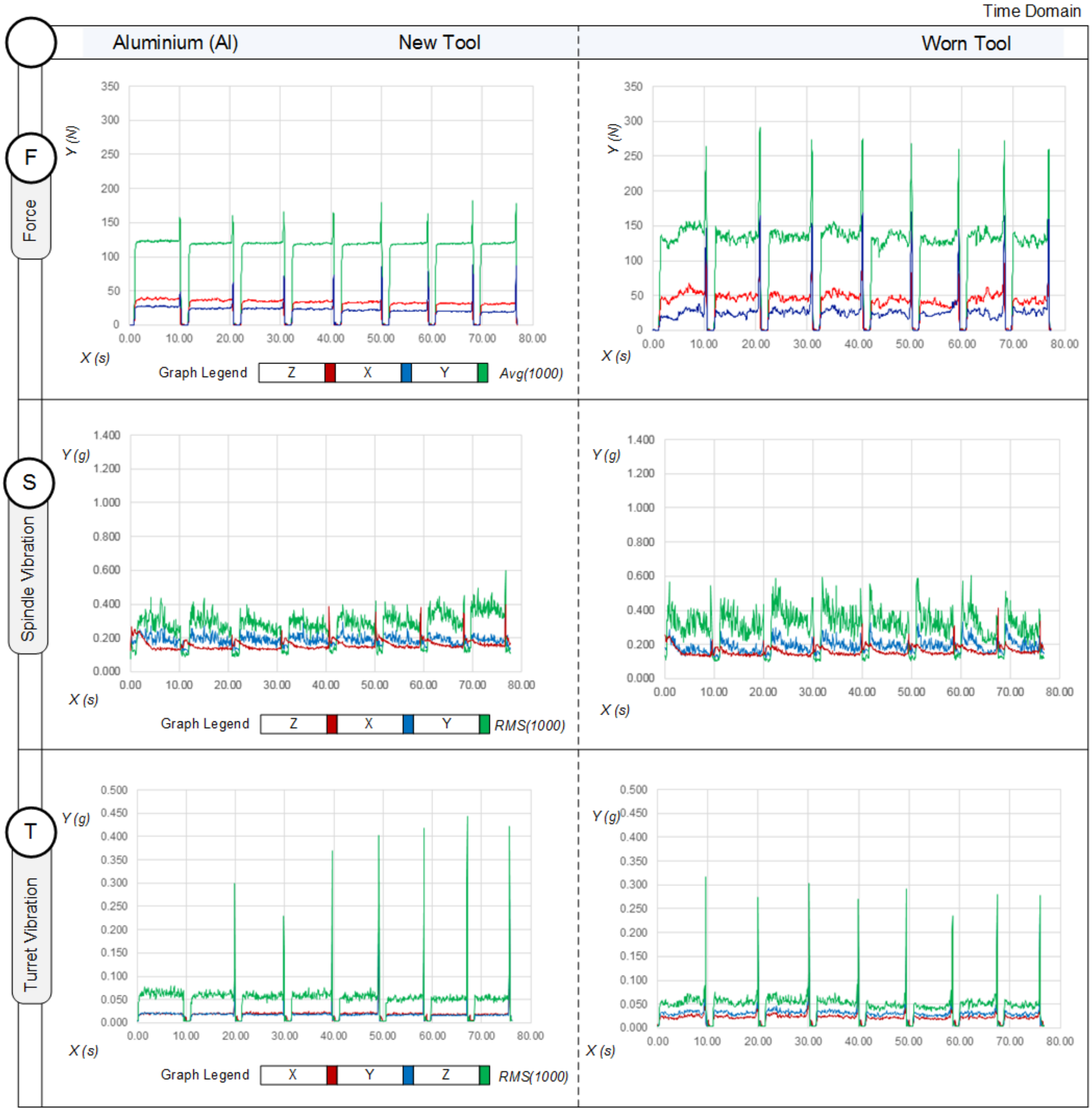
Figure 7.6 Machining: speed and depth, turret vibration, frequency domain

3 Machining tool wear



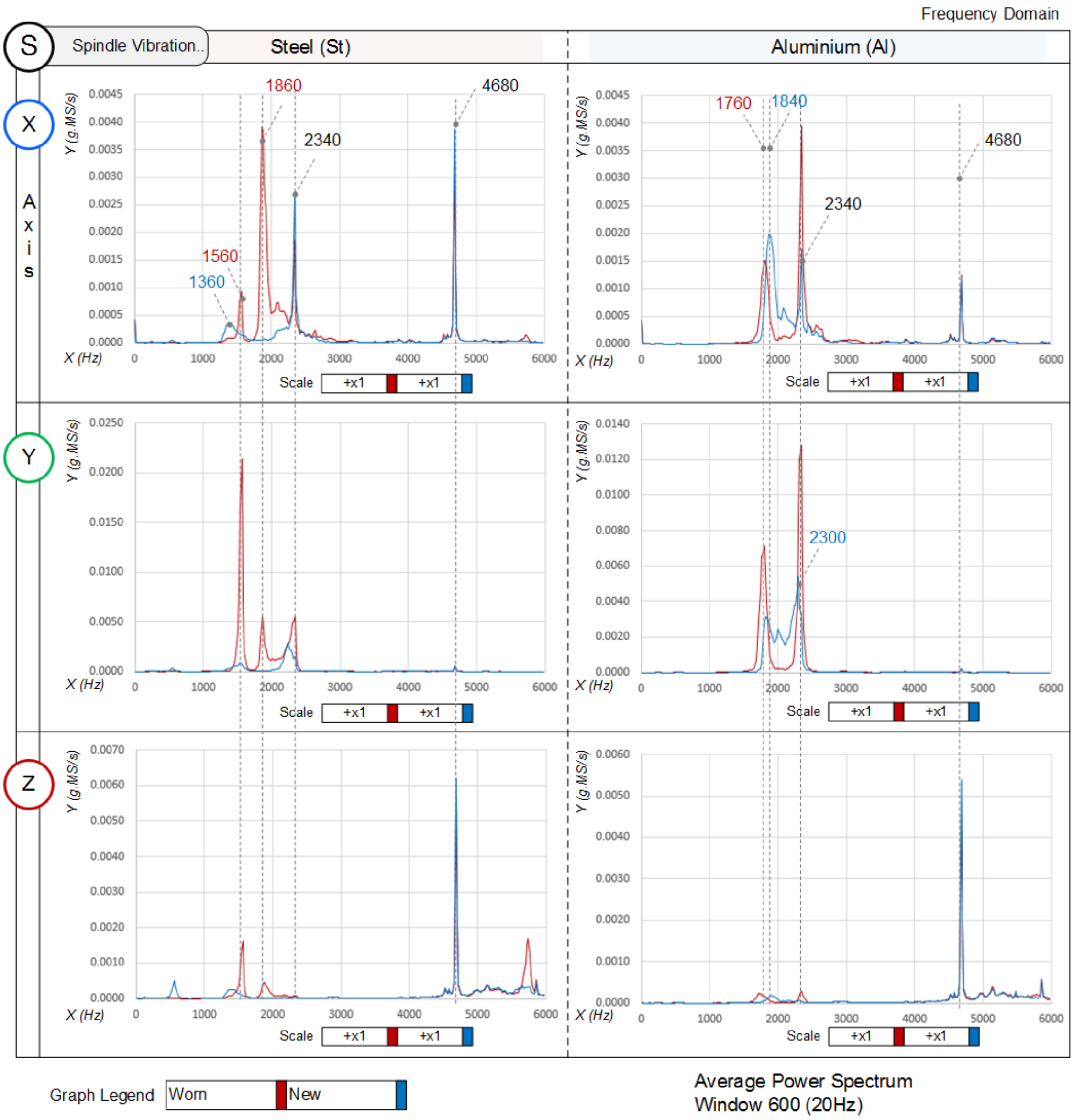
New Tool	Worn Tool
• Uniform force measurements, with minor increase in force peaks • Low spindle vibration variance, yet steadily increasing cutting axis amplitude • Uniform turret vibration measurements	• Increase in force for initial cuts, minor signal variance • Volatile spindle vibration, high signal variance and peaks • Minor turret vibration variance • High turret vibration peaks

Figure 7.7 Machining: tool wear, steel, time domain



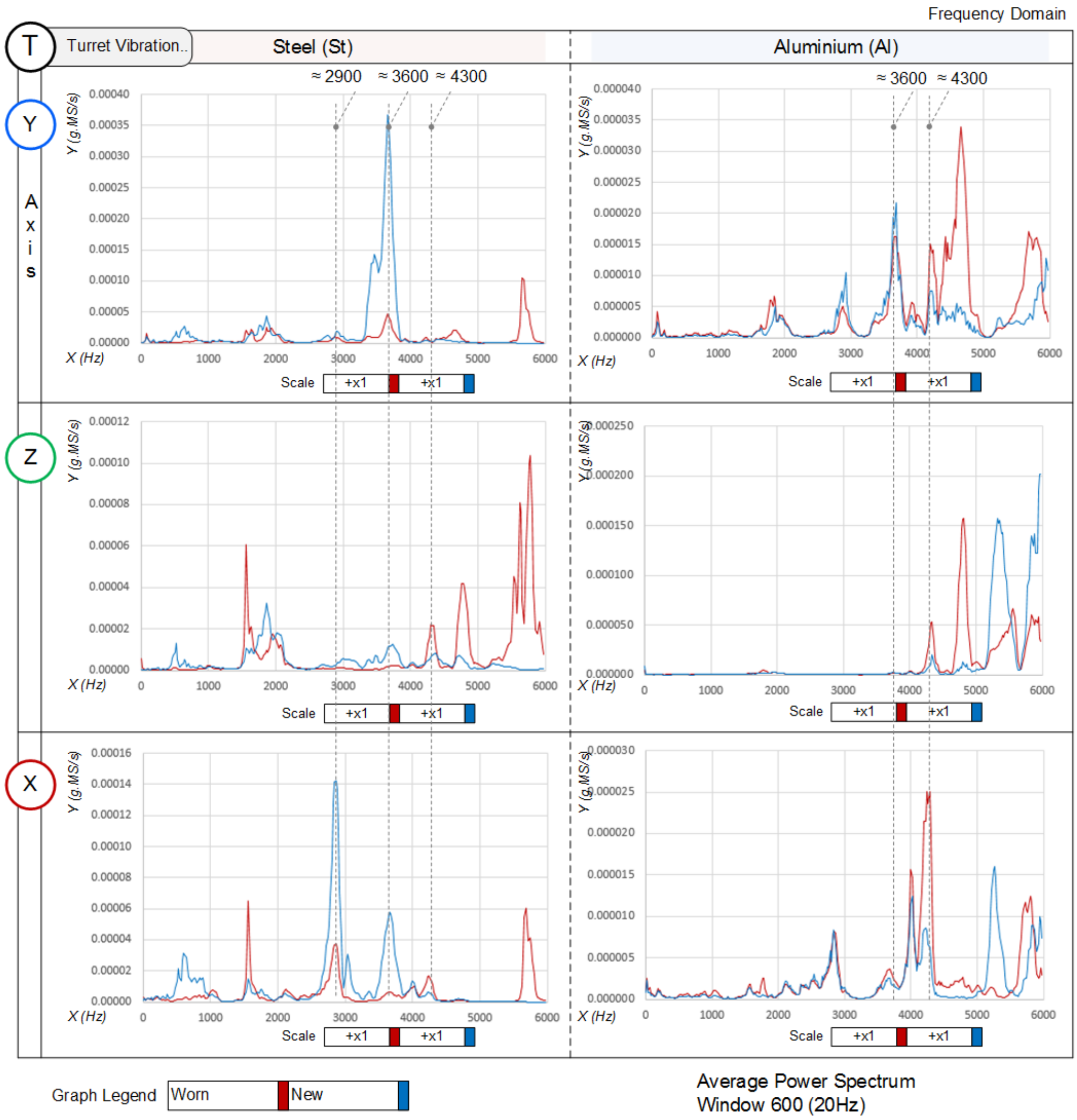
New Tool	Worn Tool
• Uniform force measurements, with minor increase in force peaks • Small sequential spindle vibration increase • High spindle vibration variance • Sequential increase in turret vibration peaks	• Variant force signal, high force peaks • High spindle vibration variance • Variant turret vibration amplitude and peaks

Figure 7.8 Machining: tool wear, aluminium, time domain



Steel	Aluminium
• Worn tool Increases in power within the defined frequency bands, Y and Z • Worn too varies in frequency, X Y Z	• Worn tool Increases in power within a wider frequency range; 1760 – 2300 Hz

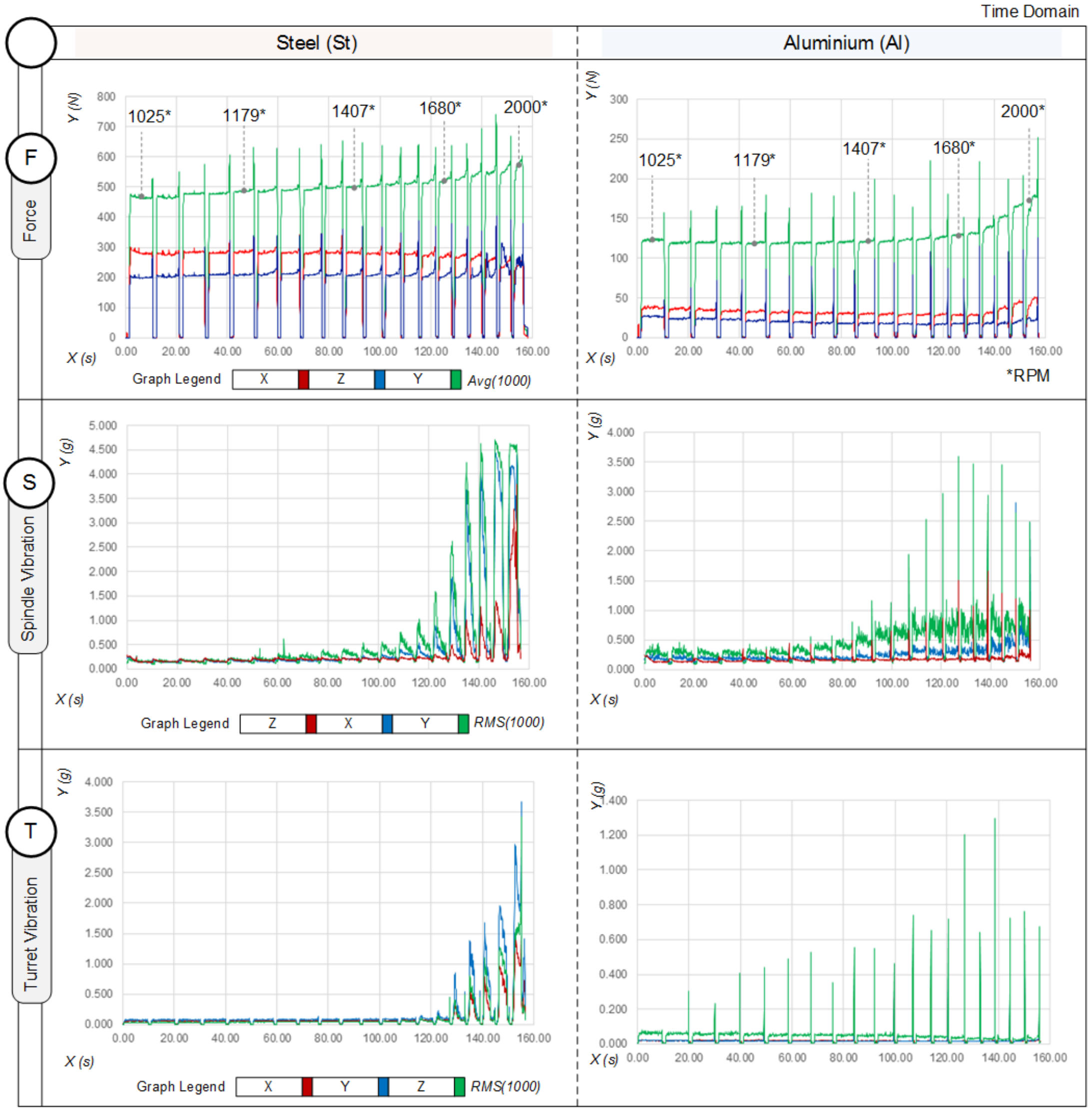
Figure 7.9 Machining: tool wear, spindle vibration, frequency domain



Steel	Aluminium
• Tool wear high frequency response; >4000 Hz X Y Z • Tool wear reduced power response 3660 Hz Y, 2860 Hz Z	• Tool wear high power response within a high frequency range; <5000 >4000 Hz X Y Z • Tool wear power reduction within a high frequency range; >5000 Hz X Z • The frequency response is reaching high levels outside the range of the accelerometer, >6000 Hz, for both the new and worn tool

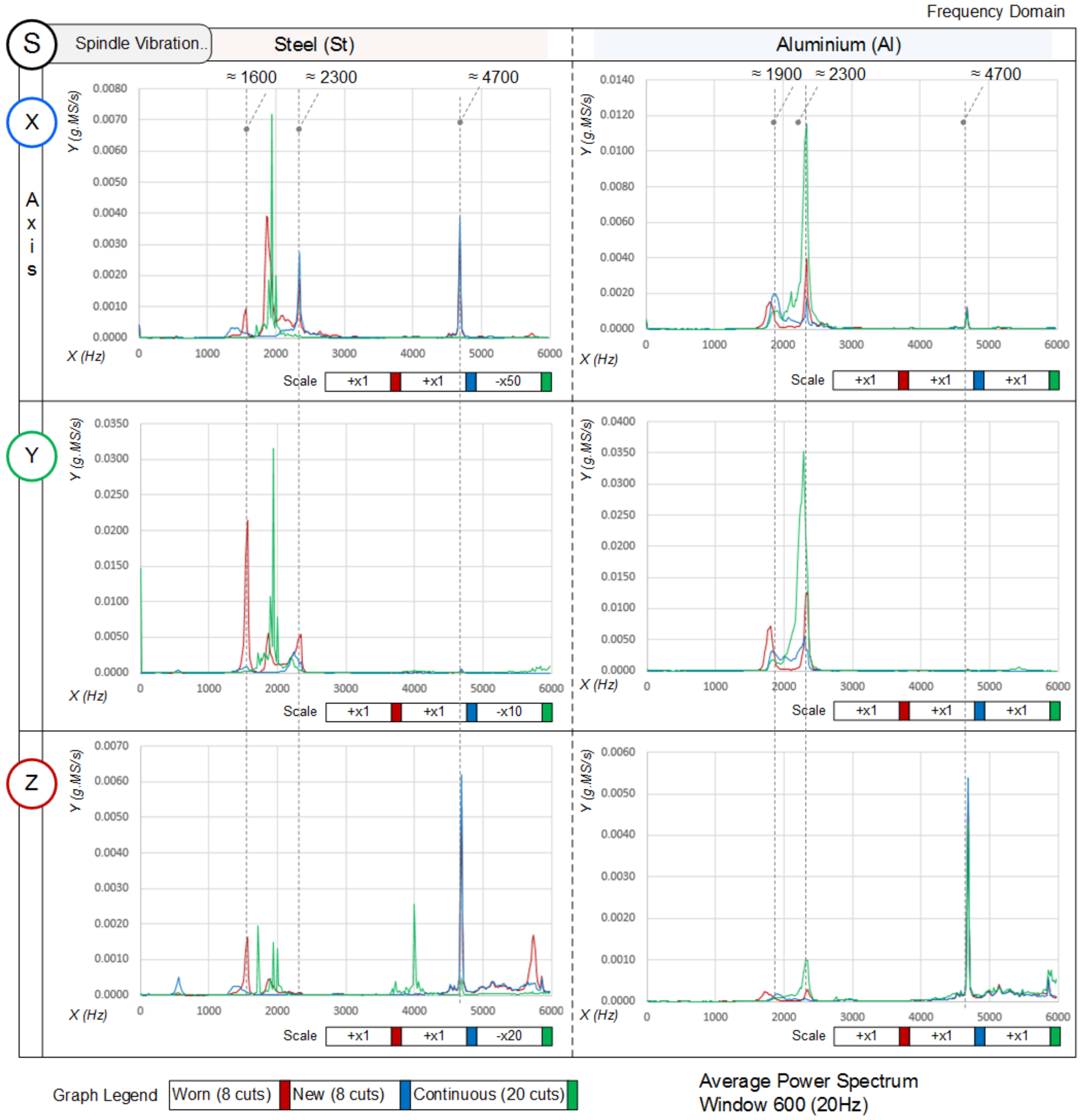
Figure 7.10 Machining: tool wear, turret vibration, frequency domain

4 Continuous Machining



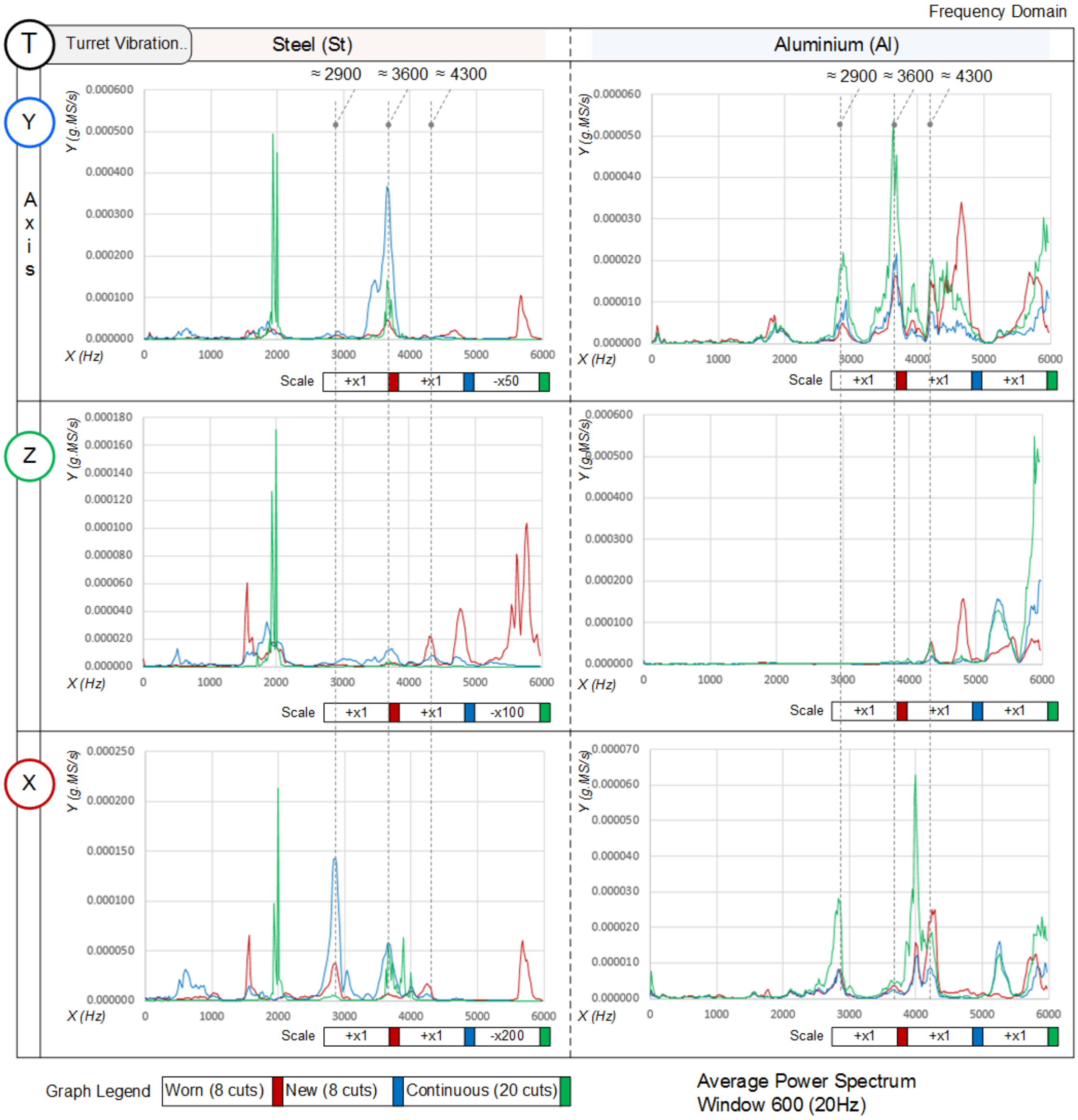
Steel	Aluminium
• Increasing cutting force on every cutting cycle • Spindle vibration increases in amplitude on every cycle, and reaches a point of exponential growth; after cut 14 • Turret vibration exponential growth observed after cut 14, where the feed axis becomes higher than cutting axis	• Increasing cutting force after cut 10 • Increase in spindle vibration amplitude, variance and peak after cut 10 • Slow decrease in turret cutting vibration, however significant peak variance and magnitude
• Extreme heat induced during continuous dry cutting could be the cause of the increase in force and vibration	

Figure 7.11 Machining: continuous, time domain



Steel	Aluminium
• X: Significant power increase across all frequencies, continuous machining is overpowering • Y Z: Significant power increase from frequencies >1600, however frequency 1600 is unique for tool wear • Continuous cutting causes high material resonance 1900 Hz	• X Y Z: large power increase in spindle frequency band 2300, however unique tool wear identifier at 1760

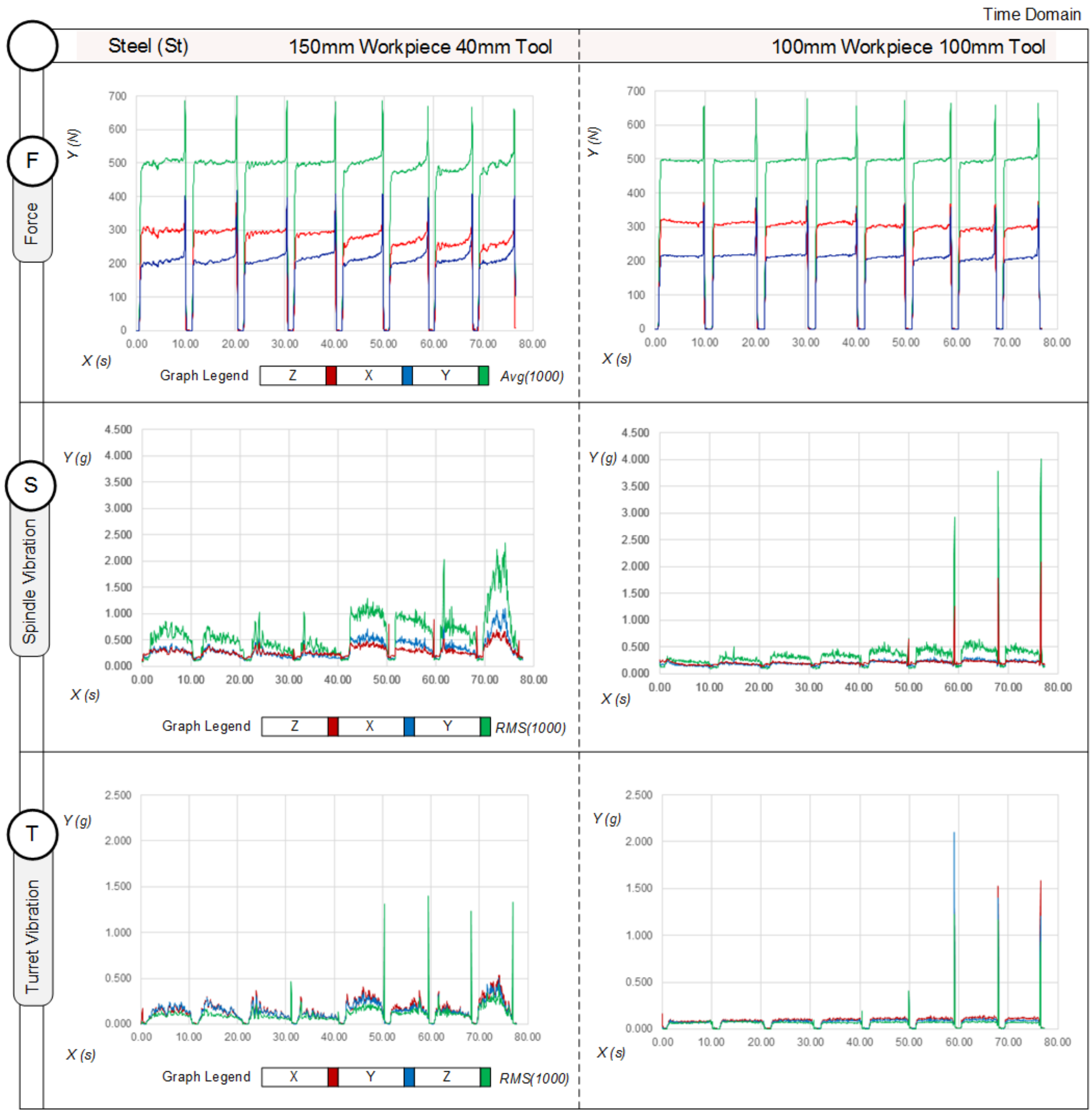
Figure 7.12 Machining: continuous, spindle vibration, frequency domain



Steel	Aluminium
• X Y Z: Continuous cuts overpower all frequencies below 5000, however unique tool wear frequency observable >5000	• Y Z: Overwhelming power increase across all frequencies, however Unique tool wear identifier at 4800

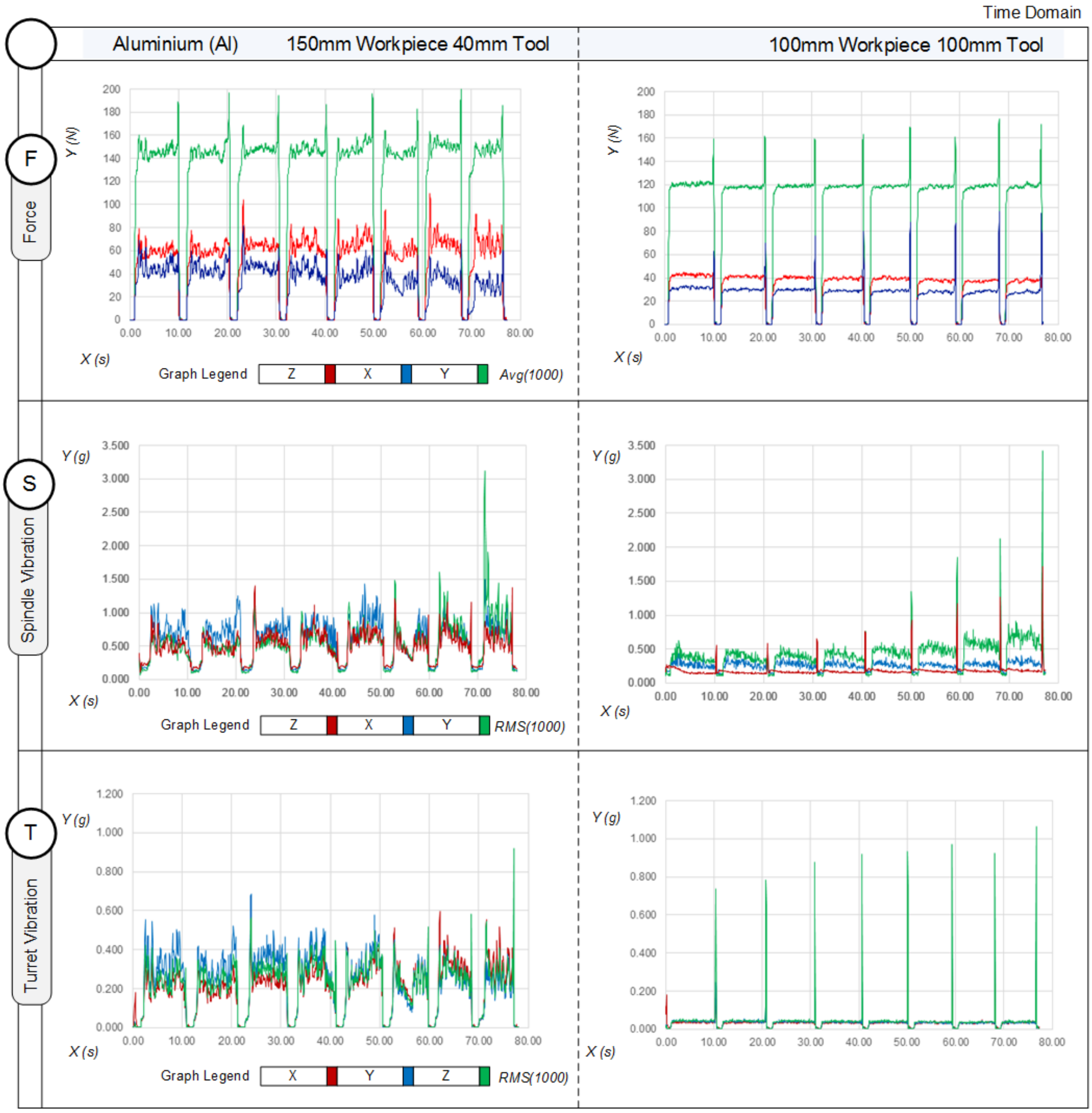
Figure 7.13 Machining: continuous, turret vibration, frequency domain

5 Machining workpiece and tool orientation



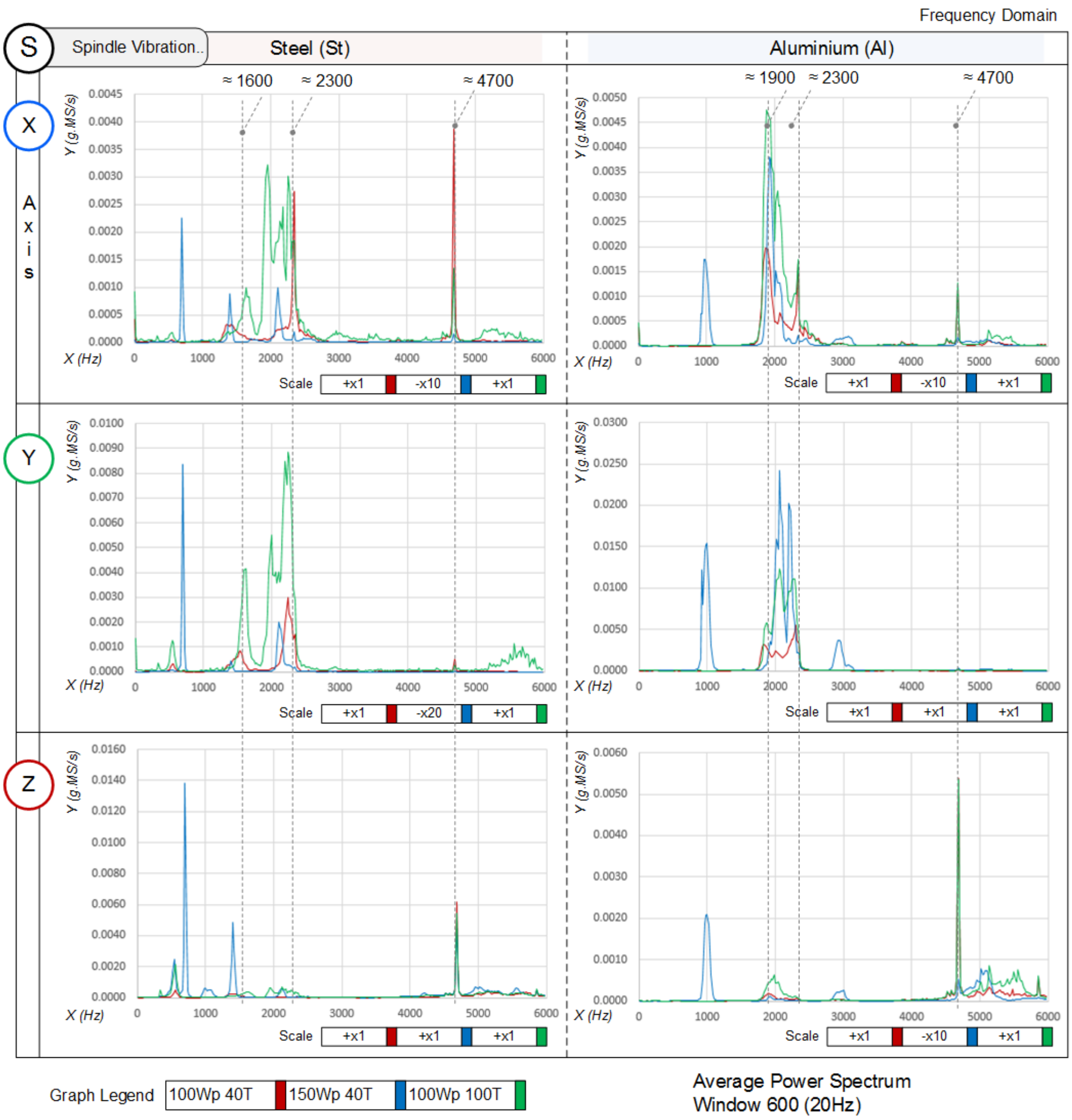
150 mm Workpiece 40 mm Tool	100 mm Workpiece 100 mm Tool
• Increase in force variance • Volatile spindle and turret cutting axis vibration	• Consistent tool cutting force • Increasing spindle vibration and peak values • Increasing turret peak values

Figure 7.14 Machining: orientation, steel, time domain



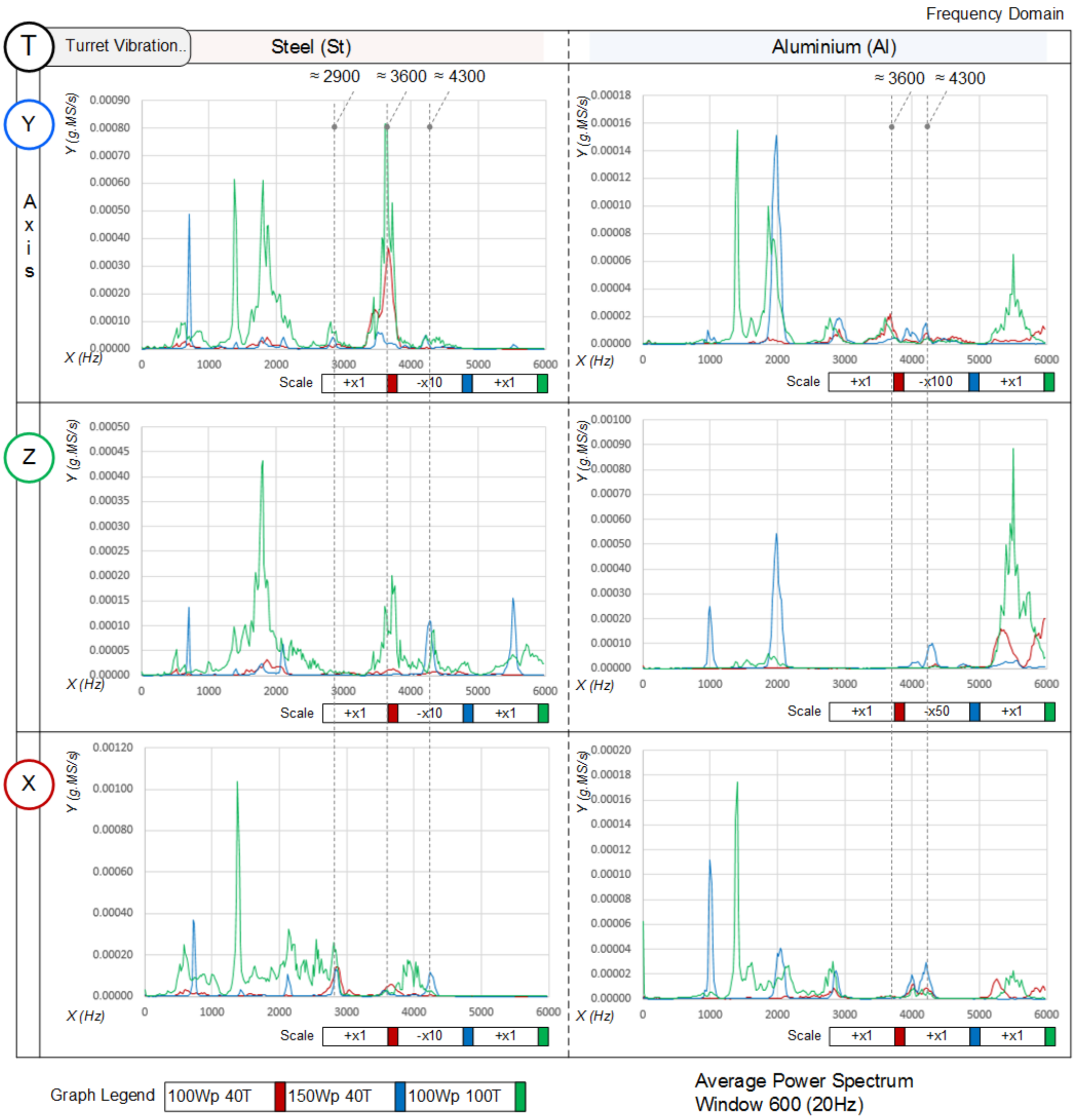
150 mm Workpiece 40 mm Tool	100 mm Workpiece 100 mm Tool
• Extremely high tool force variance, and feed and radial magnitude • Extremely high spindle and turret vibration variance, feed axis greater than cutting axis	• Uniform cutting force • Increasing spindle vibration on the cutting axis • Increasing turret peak vibration

Figure 7.15 Machining: orientation, aluminium, time domain



Steel	Aluminium
• Frequency variation on the feed axis x • Diverse power variation on cutting axis Y	• Power variation on the feed and cutting axis
• High power response for the 150mm work piece	

Figure 7.16 Machining: orientation, spindle vibration, frequency domain



Steel	Aluminium
• High frequency and power variation between orientations	• High frequency and power variation between orientations
• High frequency and power response for the 150mm work piece	

Figure 7.17 Machining: orientation, spindle vibration, frequency domain

6 Time domain signal analysis summary

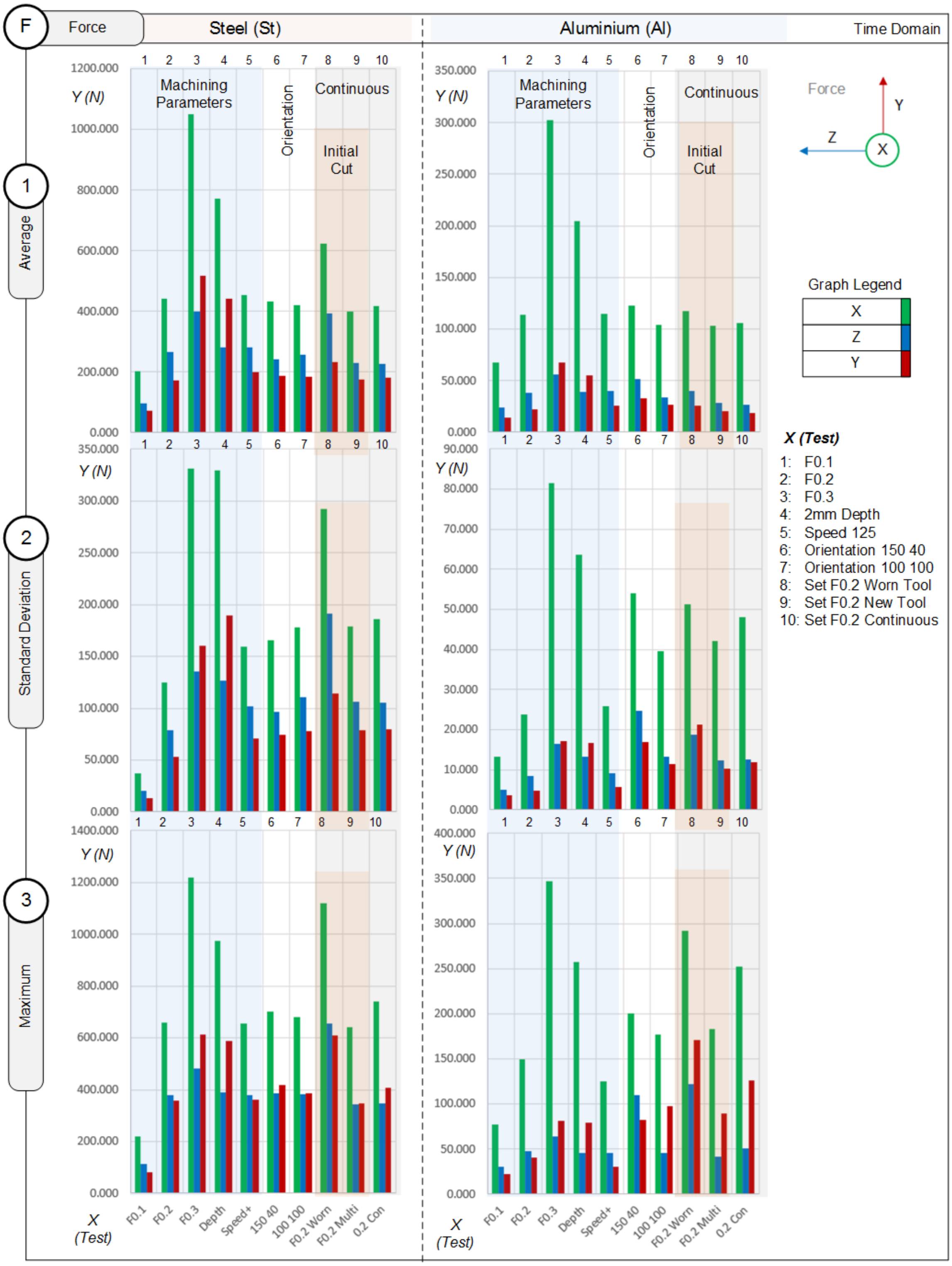


Figure 7.18 Machining, time domain analysis, tool force summary

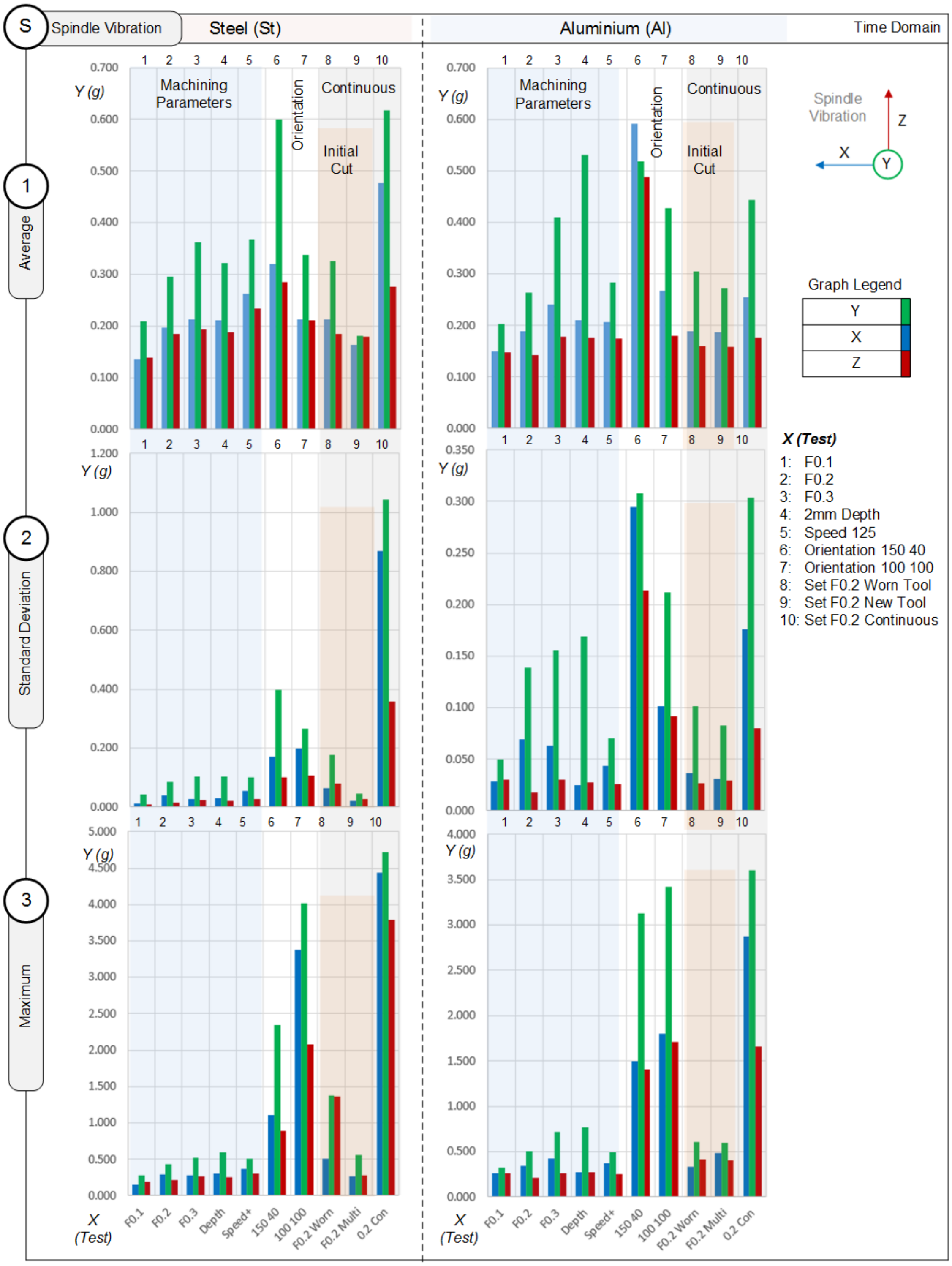


Figure 7.19 Machining, time domain analysis, spindle vibration summary

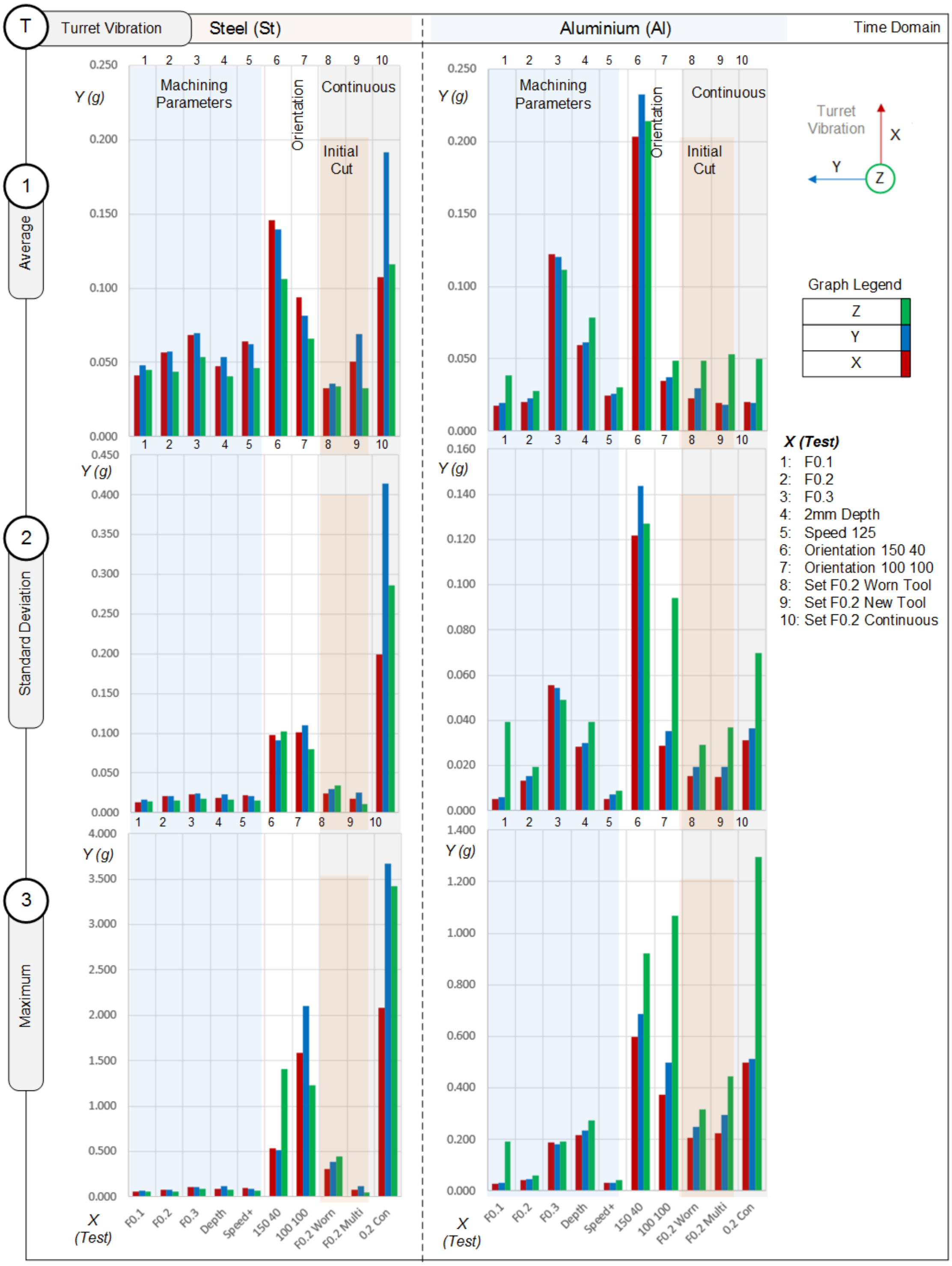


Figure 7.20 Machining, time domain analysis, turret vibration summary