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Performance Estimation, Testing, and Control of Cyber-Physical Systems Employing Non-Ideal Communications Networks

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Abstract:

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Dedication

The author would like express his gratitude to his beautiful daughter, Erin, for all of her generous support, kindness, and care, and her countless hours as a child accompanying me in my laboratory. I hope that she remembers fondly those weekends listening to her Avengers movies while I ran factory simulators and troubleshooted robots.

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Lastly, I thank God for all of his many blessings through hardships, successes, triumphs, and failures!

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1

INTRODUCTION

Some text about this chapter [151]

1.1/ INDUSTRIAL REVOLUTIONS

Major advances in manufacturing of goods for the betterment of humanity have occurred many times in the last two hundred and fifty years in the history of humanity. These advancements occurred of science and technology occurred as revolutionary events at different times. The first revolution occurred at the edge of the eightieth century primarily in England but also in France, Germany, and the United States with the applicant of automatic mechanization of large machines using coal powered steam engines. These machines were mainly used for the processing of cotton, wool, and silks in the production of textiles for export throughout the world. Advancements during this period included uses of coal to produce steam power, the production of iron, steel, and other rudimentary alloys, and, very importantly, the engineering advancements of tool making. The advancements of the first industrial revolution paved the way for the centralization and mass production of goods.

The next century was marked by the development of scientific and engineering advancements in chemistry, physics, and engineering. Experimentation with electricity and the production thereof led to the eventual explosion of industrial machinery, tooling, electrification, chemical manufacture, petroleum refinement, rail and marine transportation, the automobile, agriculture, and telecommunications by wire over long distances. This period of discovery culminated with rapid expansion of industrialization through the world, especially in North America and Japan up until the beginning of World War I.

The third industrial revolution began in the tears immediately following the second world war with the rapid advancement of pure and applied sciences. These advancements were driven primarily by the cold war and the space race between the United States and the USSR. This period of advancement was marked by many discoveries and scientific applications such as the development of telecommunications theories (Claude Shannon), advancement of radio and wired communications, the discovery of the transistor, and the rapid expansion of computers and information technology in business and defense. Also during these years, arrived the application of computing within manufacturing and process control settings. Computers slowly began to replace the basic relay circuit in control systems. By utilizing the programmable logic controller (PLC), manufacturers gained the ability to develop control their processes more easily and develop control strategies that were once more difficult to implement in the past with dedicated, specialized equipment. PLCs offered both the ability to more easily adapt processes to information gathered directly from the factory operation as well as slowly collect and store information electronically. However, electronic storage of this information was still both difficult and expensive as telecommunications technology was yet relatively slow and storage expensive. Over the years following through the 1980's until today, computers have followed closely Moore's "Law" which states according to the the perception of Intel Corporation founder, Gordon E. Moore, that the number of transistors on a microchip doubles every two years. This paradigm of exponential growth in digital computing technology in terms of computing speed, storage, and efficiency has created a world in which computers and computing devices have become ubiquitous, surrounding practically every aspect of human endeavours and leading to the latest installment of industrial advancement, the 4th Industrial Revolution, also known as the *Information Revolution* which is currently ongoing.

The Information Revolution is defined by a culture that is highly interconnected and data depended. Clearly, the modern world is dominated by the Internet, high-performance computers, and personal mobile communications devices such as cell phones developed over the last several decades. Within the hands of each individual one may find a smartphone capable of performing computing and communications tasks not even imaginable fifty years ago. Indeed, within each of these devices resides a powerful microprocessor capable of clocking speeds in the gigahertz, offline storage spanning gigabytes, at-least one high-resolution camera, and communication components enabling high-speed connectivity capable. These personal devices are smart and easily re-programmable by downloading of new applications, i.e., *apps* enabling users to produce and consume information rapidly. Users enjoy the ability to speak at any moment, send brief messages using apps such as WhatsApp™, download videos, play games, store documents, music, photographs, and videos within "the cloud." Within office and business enterprises, a personal computer is within reach of every employee and is the tool used for information production. The data produced is stored within the cloud and usually produced and maintained locally, although the services of data production are quickly shifting to the cloud as well depending on the needs the end user.

These capabilities have also been permeating industrial environments although at a slower rate given the inherent conservatism of industrial establishments. Industrial environments include aerospace and automotive manufacturing, electrical power production, food processing, petroleum and chemical production. That is not to say that industrial establishments are not open to technological change, but that established production system can be difficult or risky to modify once they are operational. While industrial operations have distinctly different requirements than office businesses; analogues may be made between the computing constructs found within the personal/business computing domains and those constructs founds within the industrial computing domains. For example, within a factory production enterprise, the Internet itself exists as an outside entity providing global connectivity, hosting, storage, computing resource, and analysis tools. These services are often replicated within the business enterprise of the factory operation and extended into the factory environment to some degree from the factory management system to the factory floor.

In addition, with the explosiveness of ubiquitous, low-cost computing devices,

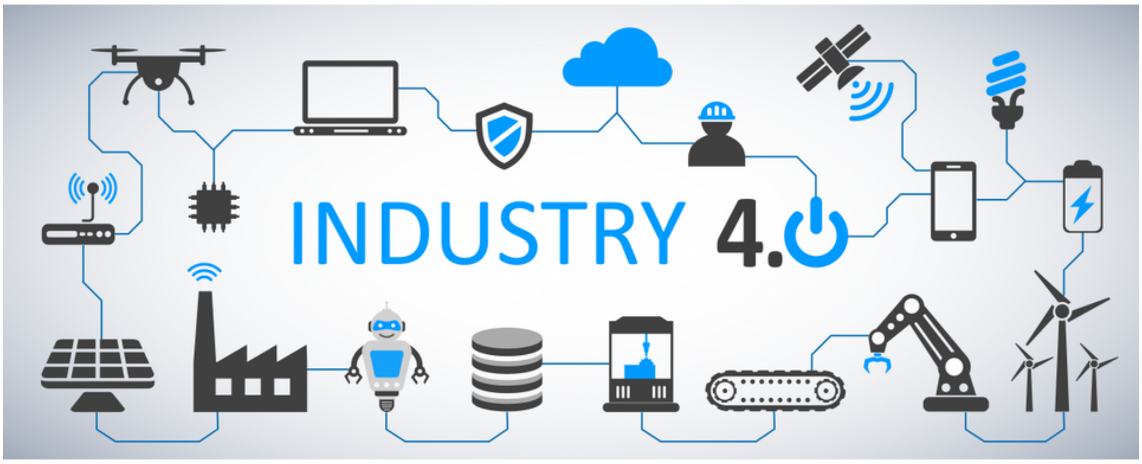


Figure 1.1: Industry 4.0: Incorporating the benefits of machine learning, massive data, mobility, and autonomy within the modern factory.

the modern factory operation is changing to include more intelligence and adaptability at the factory edge. This includes discrete devices such as sensors and actuators, collaborative robots, autonomous gantry systems, intelligent vehicular systems, tracking and inventory systems, and the like. These systems coupled with the plethora of computing resources have the potential to create an enormous amount of information as well as the opportunities for greater control over the factory enterprise. It is just a matter of tapping the information within the factory and bringing that information to a useful purpose. Where the third industrial revolution brought computing and automation to the factory, the fourth industrial revolution will improve upon the automation found within the factory by adding intelligence, autonomy, and machine learning powered by data. This defines Industry 4.0.

1.2/ Industry 4.0

Industry 4.0 also known as ”smart manufacturing” was officially launch by President Barack Obama of the United States and Chancellor Angela Merkel of Germany at the Hannover Messe industry show on April 24, 2016 [151]. Smart manufacturing is a term used to described the ongoing efforts within academia, government, and private industry to improve upon existing and future factory operations by incorating

Industry 4.0 is a term used to describe the latest evolution trend in global industrialization with respect to manufacturing. It is marked by the ambitious end goal of a completely automated and data-driven factory enterprise. The concept of Industry 4.0 is centered around the smart factory in which .

Computer

“Industry 4.0” is an abstract and complex term consisting of many components when looking closely into our society and current digital trends. To understand how extensive these components are, here are some contributing digital technologies as examples:[25]

Mobile devices Internet of Things (IoT) platforms Location detection technologies Advanced human-machine interfaces Authentication and fraud detection 3D printing Smart sensors Big data analytics and advanced algorithms Multilevel customer interaction and customer profiling Augmented reality/ wearables Fog, Edge and Cloud computing Data visualization and triggered ”real-time” training Mainly these technologies can be summarized into four major components, defining the term “Industry 4.0” or “smart factory”:[25]

Cyber-physical systems IoT Cloud computing Cognitive computing

1.3/ Manufacturing Enterprise

ISA-95 model of distributed hierarachical: Batch production, Job production, Flow production Modern paradigms: Edge computing, AI/ML

Unlike the MESA model, which focused on business process, the ISA-95 model focuses on information architecture. The ISA-95 model divides production systems into 5 levels, based on the Purdue Enterprise Reference Architecture (PERA) model.

In this way, the ISA-95 standard helps define boundaries between systems. Intelligent devices, such as sensors, belong to Level 1. Control systems such as PLCs ,

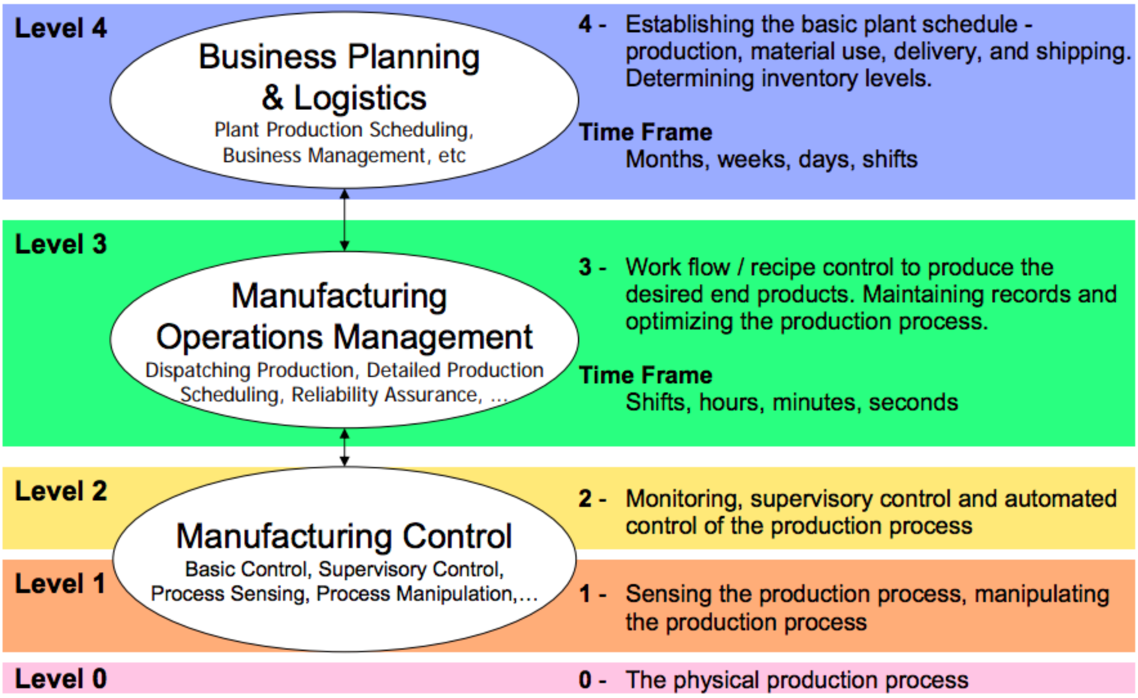


Figure 1.2: The ISA-95 model: Legacy enterprise model developed by the ISA which divides production systems into 5 distinct levels based on the Purdue Enterprise Reference Architecture (PERA).

DCS, OCS, belong to Level 2. MES, belong to Level 3. ERP to level 4.

By situating MES on Level 3, ISA-95 implies that MES connect production with enterprise systems, manage workflows to produce end products, maintain records of production, and optimize the production process.

The goal was to develop a standard that would enable efficient interfacing and integration between an ERP system and an MES. This would facilitate effective communication between stakeholders, lowering the total cost of ownership and enabling error-free integration.

1.4/ The Importance of Wireless in Automation

The fourth industrial revolution, commonly referred to as Smart Manufacturing in the U.S. and Industry 4.0 in Europe, promises unparalleled productivity and capability advances in the manufacturing. Propelled by economic pressure toward greater efficiency, factory agility, and product customization, future factories will have the technological ability to adapt to customer demands quickly, modify manufacturing processes automatically based on quality feedback, and fabricate products with a reduced environmental impact. Technological advances required for smart manufacturing to be truly successful include a collaborative and mobile robotics, distributed machine autonomy based on artificial intelligence, and a high degree of interconnectivity of among the automation resources. Robots will work together and with people to accomplish complex tasks. Robots will have the ability to roam between work-cells within a factory, learn its role quickly, become aware of edge devices, and communicate with other actors within the work-cell to accomplish its goals. Current manufacturing architectures use wired connectivity through field bus and industrialized Ethernet for sensing and real-time control.

Indeed, through advances in time-sensitive networking, many of the promises of smart manufacturing are being realized; however, the true goals of smart manufacturing require a large deployment of sensing and actuation devices and untethered (i.e. mobile), autonomous robotics actors. The use of wires precludes mobility and makes deployment of edge devices more expensive as each devices requires power, wires, and conduit for communication. By adopting wireless for both sensing and control of machines within the work-cell, a lower-cost, untethered operation is achievable. once wireless is adopted as the primary mode of communication, questions arise as to the required latency, reliability, and scale of the wireless network especially when the network is used for the control of machines and the assurance of safety.

Latency is defined as the data time-of-flight between two applications, e.g. when an event is acquired at a sensor to the point it is made available at a programmable logic controller (PLC). Reliability is defined as the data loss probability between two applications. Scale is defined as the number of stations accessing the wireless network. The requirements of reliability, latency, and scale directly relate to the complexity and cost of the wireless network; therefore, a rigorous analysis, validated by physics and untainted by market hype, is necessary to define realistic, achievable, and cost effective performance parameters of the wireless network. In this paper, we investigate the validity of commonly advertised requirements of wireless networks used for industrial control systems whiling providing a validated perspective on those requirements making realization of such networks more achievable using existing technologies. We begin with a close examination of existing wireless network requirements for factory automation. We follow with an architectural analysis of the future collaborative work-cell. This architectural analysis drives a cyberphysical system simulation to determine limits of reliability, latency, and scale constraints of wireless stations within the work-cell. We then conclude with recommendations for reliability, latency, and scale constraints that will accommodate most industrial automation applications and are realizable with devices that are based on ubiquitous standards.

1.5/ Challenges in Industrial Wireless Networks

1.5.1/ Avoiding the Hype: Understand the Requirements

1.5.2/ Interference

1.5.3/ Multi-path Propagation

1.5.4/ Reliability

1.5.5/ Latency in Time-sensitive Applications

1.5.6/ Energy Efficiency Application for Battery-powered Devices

1.5.7/ Trading Reliability, Latency, Scale, and Power

1.5.8/ Trade-space for Requirements

Insert special graph showing the competing requirements

1.6/ Industrial Wireless Use Cases

1.7/ Plethora of Wireless Technologies

Explain the plethora of wireless tech available, difficulty understanding which if any tech is applicable to a particular use case

Show the resilience week paper

Show

1.8/ Need for Evaluation Methods

Explain how testing the communication network is not sufficient. need to test the impact of network on the physical system. Need methods by which to do this. Start with requirements, proceed to design of the system, and then verification of performance of network AND physical system, and then feedback into design/requirements.

Need to show the architecture

L'objectif principal de votre thèse peut être mis en avant à l'aide de l'environnement ci-dessous:

Proposer un modèle qui fait quelque chose!

2

Thesis Summary

2.1/ Thesis Objectives

2.2/ Thesis Organization

We are going to provide a visual map of how it all fits together: flow chart of activities, papers, and data outputs

3

SURVEY: INDUSTRIAL WIRELESS TECHNOLOGY

The use of wireless technologies within factories demands a comprehensive understanding of the problems and potential solutions associated with the rigors of the manufacturing environment. A clearly defined problem space would significantly ease the selection and deployment of appropriate wireless solutions to connected factory systems. A mapping of potential technologies to classes of use cases within the problem space will be useful to factory operators, system integrators, and wireless systems manufacturers. Identification of use cases, not addressed by existing technologies, may be used to spur targeted innovation where reliability, resilience, latency, and scalability are joint concerns. Motivated by the industry need for independent practical guidelines and solutions to difficult wireless control problems, this paper provides a classification of the problem categories where networking technologies may be deployed. It then maps specific technologies that may serve as interim or terminal solutions for those use cases identified within the problem space taxonomy.

3.1/ Introduction

3.1.1/ Purpose

Industrial wireless is a key enabling technology for the Industrial Internet of Things (IIoT). The IIoT promises lower costs of deployment, increased mobility of factory assets, massive interconnectivity, improved situational awareness, increased efficiency of the operation, and improved operations analytics. IIoT and advanced manufacturing technology seek to improve competitiveness, productivity, and responsiveness to customer needs. However, it is often stated that where wireless is deployed, factory enhancements fail to meet expectations typically in areas of reliability, resilience, and scalability. Moreover, transmission security is often cited as an area of concern. Risk averse organizations will establish policies that preclude wireless to be deployed for specific types of applications such as feedback control or safety. Yet, factory operators are increasingly demanding that wireless be deployed for critical and sometimes perceivably dangerous applications. For this reason, the National Institute of Standards and Technology (NIST) is developing best practice guidelines to help factory operators select appropriate wireless systems for their particular use case and then deploy that solution effectively. Such a mission requires participation by factory operators, system integrators, and device manufacturers. A comprehensive taxonomy of the existing problem space within industry and a survey of existing and missing technologies are necessary to the success of such a mission. This paper provides our classification of industrial wireless cases and links current technologies to those use cases if applicable.

3.1.2/ Related Work

The use of industrial wireless networks has been studied in many works in the literature. However, no comprehensive survey of the whole problem space of industrial communications has been performed.

In [45], the authors have introduced a comparison between the commercial and industrial communications networks where an industrial network has been divided to five different levels. These levels include field equipment, controller level, application, supervisory, and external networks. The differences in requirements between different levels are discussed. Moreover, three types of information are considered which are control, diagnostic, and safety information as described in [20]. However all these levels of industrial networks are mentioned in [45], the article focuses only on the manufacturing and instrumentation communications and does not consider other types of communications networks that exist in industrial environments. Also, in [6], three levels of communications are considered which are device, control, and information levels. Moreover, the current wired industrial technologies for these levels are discussed briefly.

More works focused on the communications at the field devices level where sensing and control information is transfered. In [59], the communication between field devices has been studied where the requirements for a large number of nodes may not be achieved. The use of fieldbus solutions limit the scalability and resilience and hence industrial Ethernet capabilities are introduced in this article. Moreover, in [2], the communication for monitoring and control operations is discussed. A comparison between fieldbus technologies, industrial Ethernet, and wireless solutions is performed. The author has discussed the use of Wi-Fi, Bluetooth, ZigBee, and WirelessHART technologies in industrial applications. Similarly, the authors of [27] considered the industrial communications networks requirements in process automation specifically at field devices level. Finally, in [3], many case-studies are discussed for communication networks in industrial scenarios. Moreover, the design steps for these solutions are briefly discussed.

3.1.3/ Paper Organization

The rest of the paper is organized as follows. The problem space for employing wireless networks is presented in Section II. Then, the technical considerations while designing industrial wireless networks are discussed briefly in Section III. In Section IV, a mapping between the problem space and the current technology space is provided. Finally in Section V, future directions and conclusions are presented.

3.2/ Problem Space

3.2.1/ Introduction and Success Considerations

Implementing a factory enhancement program requires economic and technical planning, and justification. Wireless technologies by themselves are interesting and can provide value; however, it is incumbent upon plant leadership to fully assess the potential risks and benefits of the enhancement before proceeding with deployment. Wireless technologies are often deployed as a means to monitor or control factory process. They have the potential to unlock improved observability and control. By understanding the problem space and the risks and benefits of potential wireless solutions, factory operators can assess if the rewards outweigh the risks. In navigating the risk/reward question, we assert that any wireless program must address one or more of the following success criteria before embarking on an enhancement involving wireless communications.

Reliability Wireless systems can be deployed to add redundancy or replace faulty wired solutions with a more reliable wireless solution for particularly harsh industrial environments where temperature, pressure, vibration, radiation, and chemistry may make wired communication unreliable.

Safety Wireless systems may be used to detect or prevent injury to humans. They may be used as backup to wired systems or serve as the primary communication system.

Production Cost Wireless systems can increase observability and the resulting data may be used for precise optimization of the factory operations, machine scheduling, and maintenance.

Quality Various measurements are possible to improve quality of the factory output. Using wireless solutions may make deployment of sensors and inspection equipment more practical.

Environment Wireless sensors and control mechanisms may be used to detect toxic conditions and prevent environmental accidents from occurring. Wireless actuation devices may serve to improve reliability and address environmental mitigation control.

Regulations In some scenarios, government regulations may require specific sensor instrumentation to be deployed for certain scenarios. Wireless solutions could make regulatory compliance practical or cost effective in some cases.

3.2.2/ Use Cases

Once a plant upgrade enhancement program is initiated, and some type of wireless technology is anticipated, the first step in realizing the program is defining and understanding the problem space where wireless technologies will be used. To support this assessment, we provide a taxonomy of industrial use cases to which wireless communication may be employed. The industrial wireless landscape is diverse, and a classification of those technologies can be helpful in mapping particular technologies to an application. Our classification is shown in Fig. 3.1 and includes instrumentation, safety, and back-haul connectivity, among others. Each class of the problem space is explained in the following subsections.

3.2.2.1/ Manufacturing Instrumentation

Manufacturing instrumentation includes devices commonly known as sensors and actuators. Sensors transmit measured variables from the physical process. Actuators receive manipulation variables from a controller and apply changes to the physical process. This class of application demands typically a very low latency and high reliability communication channel.

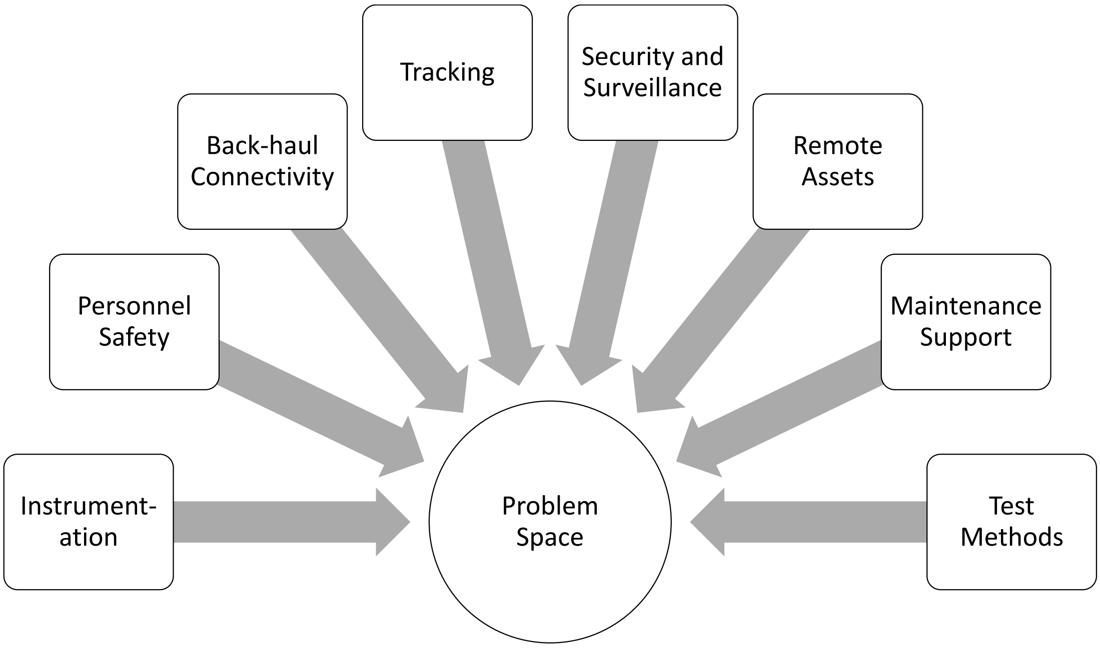


Figure 3.1: Industrial wireless technologies are applicable across most aspects of an industrial operation.

3.2.2.2/ Personnel Safety

Industrial settings can be hazardous to both humans and machines. For humans, conditions may arise that pose a substantial risk for injury or death. For machines, conditions may develop that cause substantial damage requiring extensive repair or replacement. Prevention of industrial accidents is therefore of paramount importance within factories [125]. Slips, trips, and falls on the same level are commonly cited as lead causes of injury [86]. Falls from higher levels are of great concern to the aerospace industry [104] as inspection teams must work on elevated levels where falls prove fatal. Within the oil and gas industry, safety concerns include air toxicity and combustibility in both open and confined spaces where reliable monitoring and reporting save lives. Wireless gas leak detection and leak localization provide important and effective safety enhancements to such systems [88]. Within smart manufacturing systems where humans and robots work closely and even within traditional robot environments, safety systems provide an added layer of protection to prevent human injury [115], [99]. Within these human-robot environments, it is clear that reliable, low-latency communication is an important aspect of safety implementation, and, as mobility of robots within the factory increases, reliable low-latency wireless networks will become increasingly important to safety implementation.

3.2.2.3/ Back-haul Connectivity

The back-haul is generally defined as the network that connects a lower level network to a higher level network [91]. Back-haul connectivity is usually characterized by large amounts of transfered data. In industrial environments, various types of back-haul scenarios are needed to be deployed for the operation of industrial communication networks. We can divide the back-haul problem space into three partitions which are i) nearby or indoor back-hauls, ii) distant back-hauls, and iii) geographically remote back-hauls. This categorization is based on the distance over which data is transfered.

First, the indoor back-haul networks are used in factory floors or process plants for data transfer between the control level networks to data centers, and higher level application layer networks. Second, the distant back-hauls are used for information transfer between various buildings in a plant where the two ends may have a line of sight (LOS) or need a non-LOS (NLOS) technology [7]. Finally, the geographically remote back-hauls are used for information transfer between sites in different cities or even countries such as data transfer to headquarters. Various technologies which are currently used for back-haul networks are discussed in [7].

3.2.2.4/ Tracking

Tracking in industrial environments is employed to follow the states of inventory, personnel, and tools which help in process control and factory management [93]. The focus of this class of the problem space is the set of transmissions related to the tracking process itself and not the recovered data transmissions back to higher levels. We categorize the tracking wireless systems to the following divisions based on various requirements: i) materials tracking, ii) personnel tracking, iii) tools tracking, iv) inventory management, v) localization, and vi) identification.

Materials, personnel, and tools tracking is focused on following the state and the location of the tracked item. The selection of the used technology will depend on the tracked item characteristics including its speed, required accuracy level, and scalability [1]. Inventory management includes the decisions related to the change of inventory status over time. Identification and localization are required for the determination of the position and identity of a person or an item at a specific situation or time. It can be important in safety and security related applications.

The characteristics and applications of various tracking, localization, and identification technologies are discussed in [93]. These technologies include the use of specific wireless communications technologies like the global positioning system (GPS), and the radio-frequency identification (RFID) or deploying the general-purpose technologies like Wi-Fi, Bluetooth, and the cellular-based technologies. Moreover, examples of the existing products for assets tracking and their performance are compared in [1].

3.2.2.5/ Security and Surveillance

Industrial installations require protection of the physical grounds, the operation, and the data produced from the installation. This protection requires surveillance of the property and implementation of network security controls. Guidance on selecting which controls are applicable to a specific risk level may be found in [82]. Assessment of the security robustness of specific wireless technologies is outside the scope of this paper; however, the implementation of physical security controls such as personnel authorization and grounds protection requires transmission of varying amounts of data. Transmission of such data includes voice traffic, video, and status information. In some installations, security and surveillance transmissions will coexist with factory instrumentation. This is sometimes the case with IEEE 802.11 mesh networks carrying voice, video, and instrumentation traffic.

3.2.2.6/ Remote Assets

Remote monitoring and control extend the range of the management to remote sites, especially in the process industry. Industrial remote communications provide access to widely distributed assets such as well head and pipeline monitoring [4]. The main goals of employing remote monitoring and control are minimizing labor cost, improved operations of remote sites, and prevention of unplanned failures [159].

The use of wireless networks in remote monitoring and control reduces the installation and maintenance cost significantly. However, the main challenge for industrial wireless remote monitoring and control is security and hence encryption and authentication protocols are deployed. Examples of remote assets communications are discussed in [4].

3.2.2.7/ Maintenance Support

Factories require maintenance teams to keep machinery operating efficiently. Machines may be instrumented with sensors that measure machine health data such as vibration levels or current calibration values. Using this information, machines can be scheduled for maintenance prior to failure thereby allowing the factory to operate without unexpected interruption. Maintenance of the factory may also include automation of the building and infrastructure for climate control. Heating, ventilation, and air conditioning (HVAC) systems can be automated such that the ambient conditions are controlled. Augmented reality is an emerging technology that promises to bring knowledge to the factory floor allowing maintenance personnel to gain access to information during uncertain situations [62]. Augmented reality is a high-bandwidth application that requires high-reliability, high-throughput wireless connectivity within the factory.

3.2.2.8/ Test Methods

Industrial control systems are often intolerant of communication faults and network latency, and often require very high transmission reliability [56]. Depending on the purpose of the wireless network (monitoring, supervisory control, feedback control, or safety monitoring), understanding the system performance of the network may be critical. For feedback control and safety monitoring systems, understanding the performance of the network from the perspective of the industrial controller or safety alarm system is essential. Factory operators, system integrators, and control systems designers are rarely experts in wireless communications systems. Considerations such as electromagnetic propagation, antenna efficiency, path loss exponents, packet error rates, and medium access are often foreign concepts to factory engineers. If factory engineers are expert in wireless theory and design practice, the information that they need to make educated decisions are usually unavailable. When available, link quality metrics such as packet loss ratios are informative but can be difficult to understand with complex mesh architectures and routing algorithms.

Moreover, it is generally difficult to measure these quantities for operational networks. The control system designer will only need to know the statistical distribution of latency and reliability of information through the network to design a controller that is robust. Therefore, practical methods for characterizing the performance of the wireless network that do not require an in-depth understanding of wireless communications or electromagnetic wave propagation are needed.

3.3/ Technical Considerations

3.3.1/ Radio Frequency (RF) Environment

Using wireless communications in industrial environments requires the knowledge of the RF environment characteristics and their behavior under the added wireless networks. The first step is obtaining and modeling field data in industrial environments. In [106], the

RF environments of multiple examples of industrial scenarios were studied where models and characterization parameters have been derived. Moreover, theoretical models are proposed to model the RF channel such as the IEEE802.15.4a model including its channel impulse response [14]. In characterizing the RF environments, various parameters should be included, such as the multi-path, the interference sources, the mobility, and shadowing effects. Moreover, the operating frequency band can play an important role based on the required performance and the nature of RF activity in a certain environment.

3.3.2/ Device Characteristics

Another important aspect while deploying wireless networks in industrial environments is the used devices characteristics. Typically, the harsh industrial environments in many applications require higher ratings of the used devices. The considered device characteristics include size, weight, power, cost, safety, and ingress protection (IP) ratings. Based on the application requirements and the physical environments, these device requirements are determined.

3.3.3/ Network Characteristics

Table 3.1 lists requirements typically expected of a network based on its intended purpose and problem domain. Industrial networks will have three basic characteristics: reliability, latency, and scale. These characteristics are described in the following subsections. The numbers listed in the table are based on existing applications. It is difficult to provide a standard metric for all use cases as each will impose different requirements on the network. In some cases, the control algorithm can be designed to adapt to information loss and delay, thereby improving the performance of the physical system.

3.3.3.1/ Latency

is a measure of the delay that information takes to arrive at its destination. We define latency, l, as the measured delay from the time of an event to the time in which knowledge of that event is made available to an application. Using the Open Systems Interconnection (OSI) model as a guide, latency would be measured at the application layer. In a packaging system, an example of measured latency would be the time between a proximity event and the time knowledge of that event is received by a programmable logic controller.

3.3.3.2/ Reliability

is a measure of the likelihood of data loss within the industrial network. We define reliability, r, as the probability that a block of transmitted data is delayed long enough to become obsolete or lost due to noise. Similar to latency, we measure reliability at the application layer thereby ignoring technology-specific issues such as data segmentation and retries similar to the approach taken in the developing 5G cellular networks for machine-to-machine communications [90].

3.3.3.3/ Scale

is a measure of the number of devices that may be deployed within a network without sacrificing reliability or latency. The network size will often dictate the maximum bandwidth allotted to any one node. The larger the network, the less bandwidth is alloted for transmissions between nodes. The complexity of a fully interconnect mesh will theoretically exhibit factorial growth in network interconnections. In practice, signal-to-noise ratios between nodes, programming within the governing network controller, and provisioned constraints will limit the number of interconnections. Most wireless sensor network specifications such as WirelessHART, ISA100.11a, and Zigbee provide support for large scale deployments; however, in such deployments, the network infrastructure must support the throughput load of the network and the scan rate requirements of the factory

Table 3.1: Industrial control latency, error rate, and scalability considerations for wireless deployments.

	Latency, l ms	Pr. Loss, r	Scale, s
Monitoring	$l < 1000$	$r < 10^{-5}$	$s < 10,000$
Supervisory Control			
Flow-based	$l < 1000$	$r < 10^{-6}$	$s < 30$
Job-based	$l < 100$	$r < 10^{-7}$	$s < 10$
Feedback Control			
Flow-based	$l < 1000$	$r < 10^{-6}$	$s < 100$
Job-based	$l < 10$	$r < 10^{-7}$	$s < 10$
Safety	$l < 10$	$r < 10^{-7}$	$s < 10$

application [97]. The ISA100.11a standard provides support for distributed access points, prescribed routing, and a partitioned architecture to allow for large-scale deployments.

3.3.3.4/ Interoperability

In a factory application, easy integration of devices is essential to the flow of data through a network. While many wireless standards exist, making physical layer integration of devices within the wireless domain easier, most industrial networks fail to address the application layer well. WirelessHART describes an application layer interface, while ISA100.11a provides the constructs for such an interface. ZigBee and Wi-Fi provide neither the interface nor the constructs for an application layer protocol. On the back-haul side of wireless networks which usually begins at a wireless gateway and ends at an automation server, many protocols such as Open Platform Communications (OPC) and Modbus make integration easier; however, again, they fail to specify the interface but instead provide the constructs. The authors assert that a standardization of the automation interface (gateway to automation server) is needed to provide such interoperability.

3.3.3.5/ Security

Prescribing security controls within an automation system requires understanding of the risk of not implementing these controls and the impacts of them on the physical process.

Work is being undertaken to measure the impacts of cybersecurity controls on the physical process as explained in [68] and [67]. In addition, the work is being undertaken to assess the impacts of stealthy attacks as described in [95]. NIST Special Publication 800-82 and IEC-62443 provide best practice guidelines for the implementation of a cybersecurity program in an automation system.

3.4/ Wireless Technology Applicability

Many existing wireless technologies could be applied to the use cases in Section II. Others may be applicable with limitations, and others are not applicable entirely. Table 3.2 captures mapping of technologies to applicable use cases. This table represents assertions by the authors of applicability of wireless technologies to industrial control systems problem domains based on industry practice and original intent of the technology. The authors assert that the problem domains and wireless technologies included within this table represent the majority of problems found within industry and the existing technologies that may be applied. Technologies were evaluated based on original design intent, latency, reliability, energy, and practicality. Modifications may be made to the listed technologies resulting in applicability to a specified problem; however, possible modifications were not considered. Very low bit rate (VLBR) wide area networks (WAN) are assumed to have an infrastructure-based topology and support a bit rate of under 600bps.

3.5/ Conclusions

This work represents a step toward employing wireless technologies in industrial environments where all classes of problems which wireless technologies can be used to solve have been comprehensively and collectively discussed. The success criteria and the technical aspects for employing wireless technologies in various scenarios have been considered briefly. More work is needed where success criteria are to be quantified and prioritized for various industrial scenarios. More detailed discussion is needed regarding technical considerations while employing wireless networking, including the physical environmental aspects such as the factory floor parameters, obstructions, data models, and interaction between various items within the factory floor. Finally, we have introduced a mapping between technologies and the discussed problem classes to highlight various industrial problems which can be solved or need more work while employing wireless technologies. Multiple comparisons between the current technologies exist in the literature. However, this work initiates consideration of the problem space where wireless technologies are employed. NIST has introduced this work while continuing to develop its capabilities as described in [67] to explore applicability of wireless technologies to specific industrial scenarios capable of replication within a laboratory space. An RF channel emulator is used to simulate the RF environment to include fading and multipath. A technical working group was created to directly address the needs of the wireless users employing wireless within their factories.

Table 3.2: Asserted applicability of wireless technologies.

		Flow-based					Job-based						Safety			
		Process Monitoring	Supervisory Control	Feedback Control	Alarm Conditions	In-situ Inspection	Factory Monitoring	Assembly: Sensing	Assembly: Actuation	Robots: Supervision	Robots: Feedback Control	Quality Inspection	Fall Prevention	Confined Spaces	Critical Event Detection	Human-Machine Colocation
Home/Office	IEEE 802.11	●	●	◐	◐	-	●	◐	◐	◐	◐	◐	○	○	◐	○
	IEEE 802.15.1	○	○	○	○	○	○	◐	◐	◐	○	●	○	◐	○	○
Industrial	IEEE 802.15.4 TDMA	●	●	◐	◐	-	●	◷	◷	◷	◷	◐	◷	◐	◐	○
	IEEE 802.15.4 CSMA	◐	◐	○	○	-	●	◷	◷	◷	◷	◐	◷	◐	◐	○
	IEEE 802.11 TDMA	⚹	⚹	⚹	⚹	-	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹
	VLBR WAN	●	●	○	◐	-	●	◷	◷	◷	◷	◷	◷	○	○	○
Satellite	Geostationary	◐	◐	○	○	○	○	○	○	○	○	○	○	○	○	○
	Low-earth Orbit	◐	◐	○	○	○	○	○	○	○	○	○	○	○	○	○
	VLBR WAN	◐	◐	○	◐	○	◷	◷	◷	◷	◷	◷	◷	○	○	○
Tracking	RFID	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Optical	Indoor Dispersive	⚹	⚹	⚹	⚹	○	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹
	Free-space	◐	◐	◐	◐	○	○	○	○	○	○	○	○	○	○	○
Cellular	Legacy	◐	◐	○	○	-	○	○	○	○	○	○	◷	◷	◷	◷
	4G	◐	◐	○	◷	-	○	○	○	○	○	○	◷	◷	◷	◷
	5G	⚹	⚹	⚹	⚹	-	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹
Land-mobile	All types	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Specialty	Leaky Coax	◐	◐	-	◐	◐	◐	-	-	○	○	-	○	◐	◐	-

		Back-haul				Tracking					Security						Remote			Maint.		
		Nearby or Indoor	Distant: LOS	Distant: BLOS	Geographically Remote	Indoor Machine Localization	Materials in Storage	Materials in Production	Tools	Personnel	Voice and Video Communication	Video Survellience	Drone-based Surveillance	Grounds Control	Spectrum Monitoring Data	Personnel Authorization	Well-head Monitoring	Pipeline Monitoring	Tank Level Monitoring	Machine Health Monitoring	Building Automation	Augmented Reality
Home/Office	IEEE 802.11	●	●	●	-	◐	ϟ	ϟ	ϟ	ϟ	●	●	●	●	●	●	◐	○	◐	◐	●	●
	IEEE 802.15.1	○	○	○	○	○	○	ϟ	●	◐	▼	▼	▼	○	○	◐	○	○	○	◐	○	▼
Industrial	IEEE 802.15.4 TDMA	▼	▼	▼	▼	◐	ϟ	ϟ	ϟ	◐	▼	▼	▼	◐	▼	○	●	●	●	●	●	▼
	IEEE 802.15.4 CSMA	▼	▼	▼	▼	◐	ϟ	ϟ	ϟ	◐	▼	▼	▼	◐	○	○	◐	◐	◐	●	●	▼
	IEEE 802.11 TDMA	-	-	-	-	⚹	-	-	-	-	-	-	-	⚹	-	-	⚹	⚹	⚹	⚹	⚹	-
	VLBR WAN	▼	▼	▼	▼	◐	◐	◐	◐	◐	▼	▼	▼	◷	○	○	○	○	○	◐	◐	○
Satellite	Geostationary	○	○	○	◐	○	○	○	○	○	◐	◐	○	◐	◐	◐	◐	◐	◐	○	○	◐
	Low-earth Orbit	○	○	◐	◐	○	○	○	○	○	◐	◐	◐	◐	◐	◐	◐	◐	◐	◐	○	◐
	VLBR WAN	▼	▼	▼	▼	○	○	○	○	◐	▼	▼	▼	◐	○	○	○	○	○	◐	○	▼
Tracking	RFID	-	-	-	-	○	●	●	●	●	-	-	-	-	-	-	-	-	-	-	-	-
Optical	Indoor Dispersive	⚹	○	○	○	⚹	ϟ	ϟ	ϟ	ϟ	⚹	⚹	○	○	⚹	○	○	○	○	⚹	○	○
	Free-space	●	●	●	○	◐	○	○	○	○	●	●	○	○	○	○	●	○	●	○	○	●
Cellular	Legacy	◐	◐	◐	◐	○	○	○	○	○	○	○	○	○	⚹	◐	◐	◐	◐	◐	▼	▼
	4G	◐	◐	◐	◐	○	○	○	○	○	●	●	◐	●	●	●	◐	◐	◐	○	○	○
	5G	●	●	●	○	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹	⚹
Land-mobile	All types	▼	▼	○	○	○	○	○	○	○	◐	○	○	●	○	◐	○	○	○	○	○	○
Specialty	Leaky Coax	◐	○	○	○	◐	●	●	○	○	○	○	○	●	○	●	○	○	○	◐	◐	○

Legend: ●: Technology fully supports problem domain, ◐: Supports problem domain with practicality, throughput, latency, reliability, or energy limitations, ϟ: Energy requirements of assumed battery-powered devices prevent applicability, ◷: Latency prevent applicability, ▼: Throughput prevents applicability, ⚹: Emerging technology or evolution may support problem domain, ○: Not recommended, -: Not considered by authors.

4

Wireless Workcell Architecture

Smart Manufacturing, also known as Industry 4.0, provides a vision of future manufacturing systems that incorporate highly dynamic physical systems, robust and responsive communications systems, and computing paradigms to maximize efficiency, enable mobility, and realize the promises of the digital factory. Wireless technology is a key enabler of that vision. A comprehensive graphical model is developed for a generic wireless factory work-cell which employs the Systems Modeling Language (SysML), a standardized and semantically rich modeling language, to link the physical and network domains in such a cyber-physical system (CPS). Our model identifies the structural primitives, interfaces, and behaviors of the highly-connected factory work-cell in which wireless technology is used for significant data flows involved in control algorithms. The model includes the parametric definitions to encapsulate information loss, delay, and mutation associated with the wireless network, and it identifies pertinent wireless information flows.

4.1/ Introduction

The fourth industrial revolution promises unparalleled productivity and capability advances in manufacturing. To support the manufacturing industry in this conversion, various programs have been established in several countries such as Smart Manufacturing in the U.S. [100] and Industry 4.0 in Europe [48, 79]. Propelled by economic pressure toward greater efficiency, factory agility, and product customization, future factories will have the technological ability to adapt to customer demands quickly, modify manufacturing processes automatically based on quality feedback, and fabricate products with a reduced environmental impact. Technological advances required for smart manufacturing to be successful include collaborative and mobile robotics [114], distributed machine autonomy based on artificial intelligence [23], improved process observability [137], and a high degree of interconnectivity among automation resources [134]. Work-cells are self-contained units of operation within a factory [13, 31, 119]. These work-cells are composed of various machines, conveyors, motors, edge devices, and robots. Robots will work together and with people to accomplish complex tasks or to tending to other machines within the work-cell. Robots will have the ability to roam between work-cells within a factory, learn their roles quickly, become aware of edge devices, and communicate with other actors within the work-cell to accomplish their goals. Efficient communications between robots and the other players in the work-cell are essential to the fulfillment of the robot-related tasks.

Current manufacturing architectures use wired connections through field-bus and industrial Ethernet protocols for sensing and real-time control [51, 65]. Indeed, through advances in time-sensitive networking, many of the promises of smart manufacturing are being realized; however, the true goals of smart manufacturing require a large deployment of sensing and actuation devices and mobile, perhaps autonomous, robotics actors [134]. The use of wires precludes mobility and makes deployment of edge devices more expensive as each requires power, cables, and conduit for communication. By adopting wireless for both sensing and control of machines within the work-cell, a lower-cost, untethered operation is achievable[1]. Once wireless is adopted as the primary mode of communication, questions arise as to the required latency, reliability, and scale of the wireless network especially when the network is used for the control of machines and the assurance of safety [134].

[1]The power for untethered operation can be achieved through the use of rechargeable batteries to power the untethered machine or robot for enough operating period.

The work presented here addresses the present need for a comprehensive architectural model of the factory work-cell in which wireless is a preferred mechanism for carrying information within the work-cell. We begin with an architectural analysis of the future collaborative work-cell that includes edge devices, robots, vision systems, and supervisory controllers. Our architectural analysis includes structural components, information flows, and parametric elements of the work-cell. We identify factors that limit reliability, latency, and scalability of the wireless network, and we conclude with a discussion of significant information flows. Significant information flows are defined as operationally critical or safety-related. Our contributions are:

- ⋆ First, we develop a comprehensive and extensible architectural model using the Systems Modeling Language (SysML) that provides primitives for describing the physical and networking components of a work-cell with parametric constraints[2];
- ⋆ Second, we provide a framework for analyzing cross-domain interactions of complex wireless work-cell deployments; and
- ⋆ Third, significant information flows are identified, annotated with rate constraints.

The remainder of this paper is organized as follows: In Section 4.2, previous related work is discussed and our motivation for constructing a model is presented. A brief introduction to systems modeling is presented in Section 4.3 and provides a primer on the SysML language. The conceptual architecture of the model providing a concept-of-usage is proposed in Section 4.4, followed by a detailed exposition of each package in Section 4.5. Then, in Section 4.6, significant information flows are discussed through introducing a case study. Section 4.7 concludes the paper and identifies opportunities for future research.

[2]We make the model publicly available for download. A valid license of MagicDraw 18.5 is required to use the model. A web-based report of the model is provided for read-only access.

4.2/ Related Work

Current modeling work on factory work-cells is mainly aimed at defining and characterizing the subsystems, such as human staff, robots, and machine tools, in individual applications. By following blueprints (schematics) of production tasks, the work flow can be divided into separate assignments which are distributed by a task dispatch system to individual machines [49]. Analytical models are thus obtained for performance analysis in work-cells. As an example, a mathematical model for real-time performance analysis of a gantry work-cell with robots is established with the timing and the randomness of tasks and disruptions are captured [135]. In [122], the same model is used to investigate the system natural properties such the system cycle and waiting times and to identify bottlenecks through studying the sensitivity of each machine. Similarly, the steady state analysis for production lines with uncertainties is performed through various decomposition methods [19, 44, 55]. In [44], a decomposition method is presented for the analysis of continuous flow lines. The presented model is used to analyze flow lines with single and multiple failure mode machines and machines subject to aging and having up and down times. In [55], a model to evaluate the performance of transfer lines with unreliable machines and finite transfer-delay buffers is presented. A decomposition method is introduced to model the transfer line, using the general-exponential distributions instead of the exponential distributions to approximate the repair time distributions of the fictitious machines. In [19], the authors present a model for evaluating the production rate and distribution of inventory of a closed-loop manufacturing system with unreliable machines and finite buffers. The model accounts for the different sets of machines that could cause blockage or starvation to other machines. In [25, 38], the performance analysis modeling for serial production lines with disruptions is explored by studying the impact of each individual downtime event in terms of permanent production loss and financial cost. These analytical models generally work well for simple systems with small number of components or few interactions between various equipment. Also, the analytical models can be used to abstract industrial systems to understand various performance trends without studying various details. As a result, we introduce a comprehensive model that include network and production impacts on the industrial work-cell.

Furthermore, the reconfigurable work-cell architecture is widely considered for automated manufacturing. The main advantage of reconfigurable work-cells lies in the flexibility of reconfiguration of work-cell components to adapt to varying production requirements where the assembly of the work cell is optimized for each specific task [13]. In the work-cell that hosts robots, robots are installed therein to allow for autonomous configuration within their workspace [31, 110, 120]. Approaches and performance criteria for reconfigurable robotic systems have recent developments in control architectures to achieve various levels of reconfigurability [73]. The National Institute of Standards and Technology (NIST) has defined a Network of Things (NoT) model which can depict the structure of work-cells by a group of NoT building blocks and model the behaviors of individual components in a work-cell [96]. The NIST NoT model is focused primarily on sensor networks and the collection of data. Actuation is cursorily noted, and, as such, cross-domain interactions between the physical system and the network are not addressed. Several other robotic work-cell architectures are discussed in the literature. In [28], a reference model for a control system functional architecture applied to open architecture robot controllers is presented. In [17], a methodology to develop self-adaptive factory automation solutions is illustrated, using a novel modular simulation based method. With the increase in complexity and reconfigurability of work-cells, studying various production criteria and networks impacts requires introducing new models to capture these interactions and to be abstract enough to model different configurations and scenarios of industrial work-cells.

In a work-cell model, data flows are used to capture the trajectory of system information exchange between work-cell components and identify their roles in specific operations [28]. For example, safety-related operations employ the vision system and various proximity sensors that generate proximity data and transmit them to the safety manager to define safety zones in an automotive assembly work-cell [81]. In another example, data flows are enabled in a work-cell to capture human operator gestures from embedded cameras in human-robot collaborations [24]. These gestures can be later regenerated in simulators based on the transmitted position data from the field to optimize work-cell safety operations [22]. Currently, most of the work-cell information in these scenarios are transmitted by wired networks. Wireless networks have gained increasing interests to enable data flows in the highly connected work-cells. Wireless standard bodies have proposed their network reference models in factory environments which include the work-cell cases in the data-centric architecture [29, 128]. In these models, individual work-cells are treated as a subnetwork of field instruments attached with data aggregations that manage network connections and transfer data traffic to edge and cloud servers in various applications. Wireless connections are featured with flexible network topology to agree with a variety of transmission needs, especially in reconfigurable work-cells. Meanwhile, data traffic flows are characterized by select performance metrics, such as transmission latency and link reliability, to categorize industrial use cases [128].

Current modeling efforts set the boundaries of their systems of study at the edge devices without further discussions on the impact of wireless performance on the operations of industrial systems. For example, the abstracted disruptions in [25, 38] that cause plant downtimes may include wireless network impacts which are not yet treated distinguishably with specific characteristics of wireless networks. As indicated by the earlier empirical studies [117], such physical systems may have different responses to network performance which will vary with the operational configuration such as the served "application" and the deployed control algorithms. In this paper, we incorporate the features of wireless communications networks into the modeling architecture of physical work-cells such that cross-domain interactions may be studied. Prior to introducing the model for wireless incorporation, we first provide the reader an introduction to SysML in the following section.

4.3/ Systems Modeling Using SysML

The goal of modeling a system is the capture of knowledge of a process in a simplified way [15]. A secondary goal of a system model is to provide a level of abstraction that may allow for the discovery of new knowledge such as how two systems will interact. There are multiple ways of designing and presenting system models. Well-behaved systems can be represented by a system of equations using mathematical tools [10]. Such models

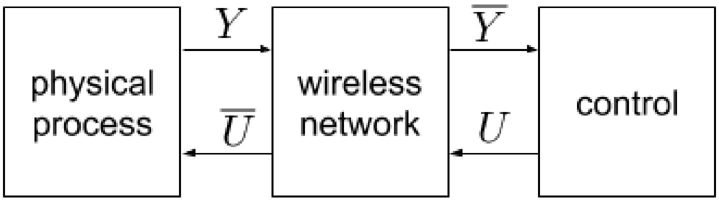


Figure 4.1: Functional block diagram of a cyber-physical system in which a physical process and an automation system interact through a wireless network.

provide excellent constraint definition, but lack the semantics to describe architecture and detailed information flow. Moreover, by deploying functional block diagrams, we are able to capture major functional components and flow of information or material. As shown in Fig. 4.1, a physical process interacts with a control system through a wireless network. Measured values, Y, from sensors flow to the controller through a wireless network and arrive at the controller delayed and modified, $\bar{Y}$. Similarly, commands, U, flows from the controller to the actuators through the wireless network. Such diagrams may be used to model feedback control systems in which the origination and routing of information are immaterial for study. However, the architecture and interfaces remain at a very high level of abstraction making analysis difficult. In such cases, delay and loss using such tools are often modeled stochastically. Using architectural diagrams helps identify components, interfaces, and information flow. For factory systems, architectural block diagrams are often manifested as schematics. However, such diagrams have their own limits in industrial practices. On one hand, they lack the semantics necessary to describe the constraints that formal equations and functional block diagrams offer. Meanwhile, they also lack the capability of capturing behaviors or complex interactions between the physical system and the information infrastructure such as a wireless network.

An alternative to schematic diagrams is SysML [121]. SysML is a general purpose modeling language that is often used for model-based systems engineering (MBSE) practice within industrial systems [74]. SysML provides structural, behavioral, and parametric semantics for the analysis of complex systems. For examples, systems analysis using SysML enables capturing and communicating system requirements and design which include hardware, software, firmware, information flows, and processes with graphical notations. Within the factory automation industry, engineers are adopting SysML in the form of MBSE to develop realizable operational models of the factory and data flow processes. MBSE models address verification of design through executable simulations depending on the modeling tool. The SysML specification is defined in [121]. In SysML, the basic semantic constructs of the language are Packages, Blocks, Ports, Interfaces, and Constraints, in addition to the constructs provided by the Unified Modeling Language (UML). Packages are logical grouping of model elements. Package relationships are captured using the package diagram (PKG). Relationships of these constructs are captured in the block definition diagram (BDD). The internal composition and connectivity of parts are captured in the internal block diagram (IBD). SysML includes other types of diagrams and semantic constructs that are not required for this analysis and are not explained here. The SysML model is comprehensive; however, the size and number of diagrams within the model are too extensive to include within this paper. Therefore, the reader is encouraged to explore the SysML model defined in [130]. A useful primer on SysML may be found in [72].

Examples of the use cases and methodologies of using different graphical models for the analysis of manufacturing systems are explored in [32, 42, 47, 80]. In [124], SysML is used to capture both composition and behavior of an additive manufacturing work-cell. A survey of applying graphical modeling languages in capturing information flows within a product service system which may be applied to manufacturing enterprises [30]. Our approach compliments these previous examples by combining the operational and wireless information transport systems together in a single model, thereby facilitating a single model that may be used for simulation and other systems engineering analyses.

While various architectures for the work-cell exist as exemplified in the literature, a common language and framework for communicating architecture and information flow has not been established for cross-domain interactions between the manufacturing system and its supporting communication networks. SysML contains the semantics for such engineering capture and provides an industry accepted language for communicating composition, interfaces, and information flow. Moreover, SysML provides the semantics for assigning properties to any model element such that those properties are made available for analysis using other tools such as Protégé [160] and the Web Ontology Language (OWL) [40]. It is important to understand that while SysML provides semantics for a formal capture of architecture, information flow, and parametric constraints, it may also be used for a higher-degree of abstraction provided by the functional block diagrams.

4.4/ Conceptual Representation

The remainder of this work describes a reusable model for representing a comprehensive wireless factory work-cell using the semantic constructs of SysML. We now follow with an exposition of our model beginning with the conceptual model followed by a detailed description of each component within the model. When discussing the model, the SysML term, *block*, is omitted for the sake of brevity where the meaning is clear.

4.4.1/ Packages

The factory work-cell is decomposed into one general and nine major structural packages as shown in Fig. 4.2. Packages include major logical groupings of structure within the model. These packages are enumerated in the following paragraphs.

4.4.1.1/ General

A set of reusable structural elements that is used for conceptual modeling or extended to produce more complex model elements. Each of the sub-packages within the General package extends basic features. The sub-packages within General include time and constraints for data, electro-magnetics, and motion.

4.4.1.2/ Network

Describes the components, blocks, interfaces, and limiting factors of the industrial wireless network (IWN). The IWN is modeled as the radio channel and the services provided by the network. Limiting factors are modeled as parametric equations associated with the radio channel and the services.

4.4.1.3/ Application

This package contains the model elements describing a component of behavioral functionality typically implemented within software or firmware but could be implemented in hardware. It describes the features and constraints of factory operation such as the logic of a supervisory controller or the feedback controller of a robot arm. The Application sets the performance requirements of the wireless network, i.e., the factory network performance requirements are derived from the requirements of the applications deployed to a work-cell.

4.4.1.4/ Devices

Describes the types of devices found within the factory work-cell to include any device that interacts with the environment such as wired and wireless input-output (IO) devices including sensors and actuators.

4.4.1.5/ Robotics

Describes the computational and communicative components of robot control including sensing, actuation, and command. Description of the robot itself is inconsequential to communication and therefore not included in the model.

4.4.1.6/ PLC

Describes the supervisory control components commonly handled by one or more programmable logic controller (PLC) components. This package includes the elements responsible for coordination of actors and handling of most input-output.

4.4.1.7/ Safety

Describes the allocation of safety qualities typically included in the supervisory controller. The Safety package includes devices, monitoring, and actuation of the safety behaviors within the factory work-cell.

4.4.1.8/ Vision

Describes the allocation of features to optical monitoring and tracking which are typical to the collaborative robotic work-cell.

4.4.1.9/ Spectrum Monitoring System (SMS)

Describes the qualities and interfaces of a factory spectrum monitoring system projected into the factory work-cell. The SMS includes monitoring nodes and agents localized to the work-cell and connected to the automation system for real-time adaptation to changing multi-path and interference.

4.4.1.10/ Human

Describes the features associated with human beings such as human motion, tasks, and carried equipment such as portable computing and communication devices.

Several examples of how to use the model are provided within the model [130].

Examples include: a robotic force-torque leader-follower, a robotic force-torque limiter, a collision avoidance, and a robotic pick and place work-cell. The parametric constraints are provided as examples and are intended to be used for communication to project stakeholders or replaced with executable computer code such as MATLAB or Python scripts, thereby making the model useful for simulation depending on the modeling tool selected.

4.4.2/ Conceptual Architecture

The conceptual architecture of the wireless work-cell model is depicted in Fig. 4.3. All the packages are included in this architecture, and the connections and relations between blocks are defined using the SysML semantics. This figure serves to orient the reader during the presentation of detailed model decomposition in Section 4.5. The work-cell model is composed of at least one Industrial Wireless Network (IWN) block and at least one Device block. More IWN blocks are used when multiple wireless networks coexist within the industrial work-cell. Applications are associated with Devices and performance constraints are applied to Applications. In this model, the Wireless Device is a subclass of Device, and the Controller is a further derivation of the wireless device. Moreover, the Controller is an abstract specialization of a wireless device that represents all types of devices intended to control other processes. The behaviour of a PLC or Robot is represented through two packages in the model. The production related behaviour is represented through the corresponding packages and the connectivity behaviour is represented through Devices such as the Robot Controller and the PLC which are special classes of Wireless Device containing all of the structure and behavior of the wireless device. Finally, an often overlooked component of any industrial wireless deployment is the spectrum monitoring system represented by the SMS Agent. Blocks in the model communicate through ports such as the *ant* port which represents the antenna or waveguide interface. Composition is further implied by the parts, constraints, and parameters associated with each block. These are listed within the compartments of each block.

4.5/ Detailed Model Decomposition

In this section, we describe in detail the decomposition of the model packages. The decomposition of each package includes the properties and the components of the package where the relation between the package and physical industrial work-cells is illustrated. Moreover, some of the packages may have various types with different properties and hence sub-packages are defined for these packages. This section also includes a general explanation of the packages rules in the work-cell and the behavioral interactions between the packages.

4.5.1/ General Package

The General package contains the reusable elements of the model. In particular, the General package contains elements that are not particular to any one work-cell component but can be reused or applied across several. The concepts of time, clocks, and synchronization are included within General. Moreover, several types of constraints are defined.

4.5.1.1/ Time

Time is an important construct within communication systems as well as industrial control systems. Time is realized as a set of one or more clocks. A work-cell will contain one to several clocks typically embedded within each device to allow those devices to synchronize to a common clock. The local clocks within the work-cell devices will synchronize to a master reference clock and usually one with a high degree of precision, accuracy, and stability. The degree to which the local clocks synchronize to the master will depend on the requirements of the applications that the local clocks serve. Clock synchronization can be costly in power, size, and monetary cost of the devices, but it may be necessary depending on the applications using a clock. Clock performance is a key driver of size and power consumption, and synchronization of clocks across a wireless network can be a challenge and is a highly studied field [111, 118]. Moreover, the Time package includes a constraint, Clock Performance, to represent the production of time and synchronization with a master clock.

4.5.1.2/ Constraints

Constraints provide limitations on the performance of an element within the model. Within General, several constraints are defined which may be applied to any block within the model. These constraints include motion constraints, radio channel constraints, and networking constraints as shown in Fig. 4.4a through 4.4c.

Motion Constraints When applied, these constraints provide the bounds of dynamical performance. For example, motion constraints determine the positions, velocities, and accelerations on a rigid body. The force vector equations (4.1) are the general governing dynamic laws of motion as forces on a vector of joints as exerted by the end-effector or set of end-effectors on the environment. The equations constrain the robot to operate according to the laws of physics, where the joint-space inertia matrix, H, is an $n \times n$ symmetric, positive-definite matrix, and q, $\dot{q}$, and $\ddot{q}$ are vectors of position, velocity, and acceleration, respectively. The variable f_{ext} is the six degrees of freedom (DOF) force acting on the end-effector, and c is the joint-space bias force required to produce a zero sum force on the end-effector [18].

$$\Gamma = H(q)\ddot{q} + c(q, \dot{q}, f_{ext}) \tag{4.1}$$

where Γ is the vector of forces exerted by the end-effectors.

This system of equations is controlled using a combination of digital feed-forward and feedback compensation in which the communication mechanism of the robot states directly impacts the controller's effectiveness. Joint control via a wireless network connection is typically avoided; however, monitoring of the linear and angular forces represented by f_{ext} as sensed by a 6-DOF force-torque (FT) wireless sensor can be advantageous for many industrial applications. As such, the performance of the wireless connection between a FT sensor and the controller can be a limiting factor in the performance of force-sensitive applications. Such a constraint may be applied to robot manipulators as defined in Section 4.5.5.

Radio Channel Constraint The radio channel constraint limits wireless information flow to the laws of propagation which includes path loss, reflection, diffraction, and interference. By applying this constraint to Wireless Devices described in Section 4.5.4.2, such devices experience the effects of a lossy communication medium. The radio channel when applied to a wireless communication link within the work-cell manifests itself in accordance of the illustration of Fig. 4.5. The parametric equations for the radio channel include path loss, multi-path, and interference. Path loss is generically modeled as the input signal divided by the bulk power loss in the channel. Path loss is often characterized as a two-piece linear function of distance [107]. Multi-path is modeled as convolution of the transmitted radio signal with a linear time-varying impulse response characterizing the electromagnetic propagation between transmitter and receiver antenna systems. Interference is then modeled as an additive component with power, bandwidth, and probability of excitation.

Data Constraints Delay, mutation, and loss of information within the industrial wireless network are encapsulated by the Network constraints block. The Network constraint is applied to wireless devices within the network and represents the impacts of the radio channel and network components and protocols. These constraints are illustrated in a parametric diagram of Fig. 4.6 in which the rules for delay, mutation, and loss are applied to a service of an industrial wireless network within a work-cell. As with any constraint, the rules for data loss may be modeled as equations, psuedocode, or executable computer code such as MATLAB script or C. These rules decide if information is lost due to delay or mutation. While it is easy to understand how mutation leads to loss through a mechanism such as a checksum, unacceptable delay can also lead to loss of data.

Delay is simply a function of time, the physical environment of the factory work-cell, and state of the network at time, t. Many features of the network and the physical environment will have an impact on the output of the delay equation and will include data transmission duration, radio wave propagation delay, signal-to-noise, protocol for reliability, routing, internal queuing, and processing. A generalized equation for information delay by the wireless network is given as the sum of processing delay, queuing delay, transmission delay, and propagation delay. Subsequently, information loss is modeled as a set of rules governed by the attributes of the network infrastructure, transport medium, and protocols shown in (4.2). These rules may include thresholds for unacceptable delay and the ability of the network to correct for data mutation or loss in the physical channel (i.e. the air interface).

$$\mathcal{Y}(t, \mathcal{X}, \mathcal{N}) = \begin{cases} \mathcal{X} & \text{if } \mathcal{X} \vdash \mathcal{L}(t, \mathcal{X}, \mathcal{N}) \\ \emptyset & \text{otherwise} \end{cases} \tag{4.2}$$

where $\mathcal{X}$ and $\mathcal{Y}$ are blocks of data traversing the network and $\mathcal{N}$ is the state of the network at time, t. We model the loss constraints as a general set of rules, $\mathcal{L}$, taking into account that each network system will have a different set of configuration attributes and protocols. The rules will therefore change for each operational system and the networks used. When the rules for loss are applied, the output of the network, $\mathcal{Y}$, becomes the input to the network, $\mathcal{X}$, when $\mathcal{X}$ satisfies $\mathcal{L}(t, \mathcal{X}, \mathcal{N})$.

4.5.2/ Application

Applications, commonly implemented as software and firm-ware, represent the intelligence of devices. The application defines the behavior and the information flow requirements of the work-cell [9, 11, 33]. As defined in the model, without Applications implemented in software, firmware, or hardware, the work-cell devices would not function. The definition of the Application block is shown in Fig. 4.7. The Application block is constrained by the Program constraint which defines the logic of the program, its expected data flow input rates, and its tolerances to delay and information loss. Devices host multiple applications each with a unique set of constraint properties. It is essential when constructing

Table 4.1: Constraints Pertaining to a Collision Detector

Constraint Property	**Typical Value**
Input Payload Size	1 KB
Subscription rate	125 Hz
Maximum Delay Tolerance	47 μs
Maximum Loss Duration	275 ms

a work-cell model that each application is identified and modeled appropriately. An example of an Application is a collision detection system within a robot controller. Table 4.1 illustrates sample parameters used in the collision detector Application.

Specification of Application constraints provides a clear picture of the requirements of the factory automation system which can be projected on the wireless network. Through this process, it is possible to determine such requirements as scalability, throughput, reliability, and latency of the supporting network services modeled as radio and data constraints in Section 4.5.1.2. Indeed, as the manufacturing system becomes more complex and wireless becomes essential to communication, the projection of manufacturing requirements onto the wireless communication system becomes less clear. Frequency planning, transmission scheduling, and error correction schemes become less obvious, and considerations of power, reliability, latency, and scale become optimization trade-offs. Such analyses are not within the scope of this paper but are important considerations for future research of manufacturing systems. As such, the architectural elements and information flows exposed by an abstract model are a necessary first step.

4.5.3/ Industrial Wireless Network

Central to the automation system is connectivity among devices and controllers [26]. More specifically, modern automation systems often employ networks to conduct inter-device communication [101]. The term *inter-device* is appropriate as the Device block serves as the basis for all other components that communicate through the network. Our model of the IWN is composed simply as a radio channel, a set of services, and a set of clocks as shown in Fig. 4.8a. This simplification of the model is necessary to allow the users of the model to provide as much or as little detail of the implementations of the radio channel and underlying services as required for their implementations.

Connectivity of a constructed IWN is shown in Fig. 4.8b. An IWN is internally modeled such that information flows as radio frequency (RF) energy through the *ant* port. A radio channel is applied, theoretically for each pairwise link, and the modified signal is passed to the services for processing. Network processing is modeled by the properties of network constraints as defined in Section 4.5.1.2. Once processed by network services, information is routed back through the radio channel through the *ant* port to other Devices connected to the IWN. Moreover, the Service block includes a parametric model as shown in Fig. 4.8. This IBD with exposed parametrics exemplifies the inclusion parameters such as information delay and loss caused by the IWN, but it also exemplifies the impact of protocols and infrastructure (throughput, memory, etc.) within the network. These effects are modeled as rules of loss shown in (4.2).

4.5.4/ Devices

4.5.4.1/ Device

A Device, defined in Fig. 4.9, is generic construct representing an element within the work-cell with processing, memory, and storage capability. Devices have the capability to run applications as defined in Section 4.5.2. Devices are sub-classed into Sensor and Actuator devices which generically refer to any type of sensor or actuator, and, in particular, the wired variety. The Device is further sub-classed to the Wireless Device which is the central theme of our analysis. Derived from the Wired Device are the Wireless Sensor and Wireless Actuator as well as the Controller. The Controller represents the base class for deriving work-cell devices such as the PLC and the Robot Controller, sections 4.5.6 and 4.5.5, respectively, and provides support for external input-output (IO).

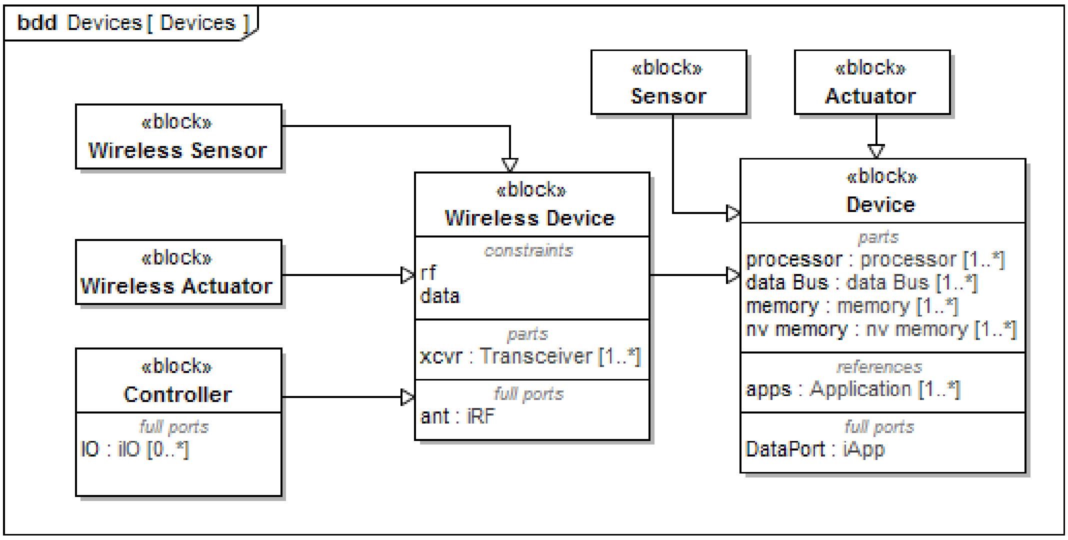


Figure 4.9: SysML block definition diagram of wireless devices within the factory work-cell.

4.5.4.2/ Wireless Devices

A Wireless Device is a subclass of Device that contains the various components necessary for untethered communication. These devices then communicate with each other through one or more industrial wireless networks (IWNs) which contains antenna systems, transceivers, protocols, and network services. The relationships and composition of the Wireless Device are illustrated in Fig. 4.10. As shown, the wireless device is composed of at least one transceiver and each transceiver is composed of at least one antenna system which is composed of at least one antenna element. The antenna system is constrained by its gain profile.

4.5.4.3/ Test Device

The Test Device is a subclass of Device that represents devices used for calibration or ground truth testing of properties of a work-cell. The block definition and internal configuration are illustrated in Fig. 4.11. A Test Device is constrained by its accuracy and precision as well as the algorithm for controlling measurement. An example of a test device is a calibrated force sensor that may be used as comparison to a 6-DOF wireless sensor mounted on the wrist of a robot arm as shown in the top left of Fig. 4.15. Test devices are useful and necessary elements of the wireless testbed to establish accurate and repeatable ground truth measurements. For example, a stationary precision force sensor may be used to establish a ground truth force value, and a high-accuracy vision tracking system is used for truth in position. Test devices are modeled such that measurements may traverse the operational wireless network or a stand-alone wired interface.

4.5.5/ Robotics

The robotics package contains elements specific to robot systems. Robot systems are composed of at least one robot controller associated with one or more robots, as shown in Fig. 4.12a. In manufacturing, robots interact with their surrounding to accomplish assigned tasks such as tending machinery, moving materials, welding, and inspecting. Robot controllers provide support for external IO devices. In addition, modern robot controllers will support a variety of open and proprietary network protocols allowing for interaction with other actors in the work-cell. The robot controller's main task is control of the rigid body dynamics of the robots which is usually conducted via real-time communication over a high-throughput serial field-bus. While joint control is conducted using wires, the robot controller is responsible for other tasks requiring reliable, low-latency communication in which wireless may serve a role. These tasks are captured in the model as applications (Fig. 4.12b) and explained as follows.

- **Robot States Publisher:** Transmission of robot states to external actors such as other robot controllers, supervisors, and safety systems.
- **Arm Controller:** Also known as manipulator control, serves to accept position commands as Cartesian or joint space trajectories and waypoints from other actors within the work-cell.
- **End Effector Control:** Command and control of the robot end-effector such as a gripper or sensor. The end-effector may be equipped with a high-throughput wireless sensor necessitating reliable communication.

- **Inverse Kinematics:** Converts Cartesian coordinates of the end-effector into joint positions.
- **Path Planner:** Determines the optimal geometrical trajectory to achieve a final pose given knowledge of self-collision and real-time knowledge of the surround environment. Path planning is a sophisticated part of a robot system and may be allocated to an external system depending on throughput and latency requirements.
- **Collision Detector:** This application monitors the states of other actors and obstructions within the work-cell. If possibility of collision is detected, the collision detector takes action.

These applications within the robotic work-cell define many information flows requiring careful analysis to achieve reliability and latency necessary for the safety and control of the manufacturing process. Information flows are identified in Section 4.6.

4.5.6/ PLC

The PLC is a specialized class of Controller. PLCs were originally developed to mirror relay circuits in software; however, the modern PLC is much more advanced and is usually equipped with multiple processors, a real-time operating system (OS), and capabilities to support various types of industrial IO devices. In addition, modern PLCs (also called automation servers) include both a general purpose OS with a real-time kernel and multiple network interfaces. Many network-routable protocols are also supported. With the addition of wireless protocols, PLCs now have the ability to support IO devices connected remotely without wires. Supervision of untethered robots is also possible using PLCs. The PLC is modeled as a Controller device with the work-cell model. Shown in Fig. 4.13, the PLC is modeled as a wireless device with transceiver, logic application, and safety applications. More sophisticated PLCs may be modeled by extending the PLC block. As applications, the logic and safety functions are constrained by application constraints. Finally, as Controller devices, PLCs are modeled with an IO port, thus IO can be connected to the PLC by wires or by wireless network connection.

4.5.7/ SAFETY

In a work-cell with interacting humans and robots, functional safety requirements are typically strict by specifying the rules related to four main safety criteria, namely, monitored stops, controlled speeds, separation distances, and power and force limits in order to prevent injury for humans and damage for equipment. The wireless safety package is composed of a safety controller and safety devices. Traditionally, the safety requirements of the work-cell is fixed and managed by the safety controller which receives safety-related measurements and takes the corresponding actions. Alternatively, the safety controller may be connected to the PLC where the current work-cell activities are supervised. The PLC will determine the required safety rating and the safety controller behaves accordingly. The dedicated safety controller is needed to achieve the required high reliability and low latency safety requirements and it can be a general PLC with safety modules.

The safety devices include non-safety-rated devices such as the various work-cell sensors and actuators and safety-rated input and output devices. Safety control input devices include Emergency-stop and enabling buttons while output devices include relays and switches for various work-cell equipment. The use of wireless in safety control loops allows installing a larger number of sensing devices including vision systems to monitor the human and robots activities, velocity and proximity sensors, and machine status sensors. Moreover, wireless allows to have mobile control panels where workers can activate a safety device at any time and location within the work-cell.

4.5.8/ VISION

The vision system considered in this subsection is the one used for work-cell monitoring and general object detection. It does not cover the machine-embedded vision systems which can be used for inspection and characterization of objects such as the shape, color, texture, or size of processed materials. The data collected by the work-cell vision system can be used for parts and mobile robots tracking, collision avoidance, object detection, security identification systems, and augmented reality devices and systems. The vision system communicates with the supervisory control, robotic controller, and the safety system to provide the work-cell state which contains the positions of various equipment, robots, and humans.

The vision system is composed of optical devices, vision processing unit, and interfaces to various work-cell systems. The optical devices are the cameras for capturing images at high enough speed to track and detect various objects. These cameras have wireless network interfaces to be connected to the vision processing unit to allow collaborative processing of the captured images and obtaining precise work-cell state. The vision processing unit performs data acquisition from the distributed optical devices and feature extraction to detect and track the positions of various entities in the work-cell.

The vision system communicates the corresponding data to the supervisory control, robotic control, and the safety system for decision making based on the captured work-cell state. The supervisory controller uses vision system data for robots and workers localization, parts detection and identification, and schedules tasks using this information. The robotics controller uses these data for motion control, path planning, and collision detection. Finally, the safety controller uses these data for safety requirements implementation such as enforcing safety stops, controlling the speeds of moving objects, and limiting power and forces of various work-cell components.

4.5.9/ Spectrum Monitoring System

A spectrum monitoring system (SMS) is an often overlooked yet valuable part of the wireless factory work-cell with requirements specified in [105]. The SMS is modeled as an atomic agent within the work-cell. The SMS Agent is one component in a larger enterprise-level spectrum monitoring deployment. The SMS agent shown in Fig. 4.14 includes a transceiver, an event detector, and a reporting agent. The transceiver can be implemented as an RF-to-baseband converter. The detector application is responsible for detection and estimation of anomalous spectral events and may employ machine learning to accurately detect anomalies and report localized spectral events.

The reporter application collects, filters, and reports event information to a central management console. SMS reports support identification of long-term patterns such as growth trends in particular wireless bands. Since the SMS Agent is part of a larger network of spectrum monitoring, it is presumed that reports are wirelessly transmitted back to the enterprise management console. These reporting events use bandwidth otherwise used for the factory operation, thus reports must be made concise and infrequent. This implies substantial filtering and intelligence in the local SMS agents This may provide opportunities for research.

Detection events may be routed to the local supervisor, robot controller, and safety system. By leveraging spectral awareness, work-cells can be made safer and more reliable. As SMS are not yet widespread in industrial applications; thus, standardized protocols are needed for reporting and integration with automation systems.

4.5.10/ Human

Humans can exist in a modern work-cell for short or long periods of time depending on the required task. Two categories of human-related aspects are captured in the work-cell model. First, the human existence in the work-cell leads to detection and identification of the corresponding worker for both safety and security. Also, human motion within the work-cell requires position tracking for environment monitoring and spectrum monitoring due to radio frequency channel variations with human movements. The second category includes the human interfaces with the work-cell process that include portable control devices, wearable sensors, and workers communication devices to get task commands. Moreover, depending on the process constraint, personal devices of workers may interfere with the work-cell communications if allowed.

4.6/ Results of a Work-cell Case Study

In this section we present a case study of a work-cell which includes a force-torque limiter robot application and a two-robot collaborative pick and place operation. The model for this system is depicted in Fig. 4.15. The number and type of wireless information flows will depend on the configuration of the work, the number of applications, and the places where wireless is applied. For this case study, the force limiter section is composed of a robot controller, a robot, and an FT sensor. A PLC is used for work-cell supervision, and a test device is deployed for ground truth measurement. An SMS agent monitors the electromagnetic spectrum. A Radio Emitter is included to model the transmission of interference. An IEEE 802.11n network is represented in the model by an IWN block. Properties of the radio channel and services of the communication system are therefore represented. Similarly, another example is implemented in [130] for a pick-and-place scenario where the model is composed of two robots, a PLC, an IWN, and an SMS Agent in addition to proximity sensors and an IEEE 802.11ax network.

Referring to these examples, typical information flows are easily identified as connections between Wireless Device blocks and the antenna port, *ant*, of the IWN. Recall that the IWN includes radio channel and services offered by the network itself. Therefore, all wireless information flows will traverse the IWN through the *ant* port. Applications are implied and produce and consume the information according to associated constraint properties. Information flows are generated by the interactions between actors and include the following:

- **Robot States:** The geometry states of the robot such as position, velocity, and acceleration of each joint or end-effector. Robot states may include Cartesian or joint space readings depending on the need of other applications or the capabilities of publisher. Robot states are usually transmitted at 30 Hz or faster [119].
- **Force Sensor Readings:** The readings from a sensor mounted on the wrist of each robot arm. These readings are typically in the format of wrenches (linear and angular forces) and are transmitted at rates from 15 Hz for monitoring applications

up to 500 Hz for force limiting and control applications [158]. Other sensors may produce data in the system such as proximity sensors which can generate data in the range of 1-50 Hz [157] and Tactile sensors which can have information flow rates faster than 1000 Hz [60].

- **Machine Health Monitoring:** Readings from sensors mounted within machinery such as mills, routers, and lathes used to sense and predict deviations of mechanical components from design tolerances. Readings for prognostics and health monitoring are often aggregated at the source with statistical metrics being communicated to a factory enterprise application; however, non-aggregated readings may also be transmitted to a remote signal analyzer. Health monitoring sensors measure temperature, vibration, acceleration, inclination, position, and rates of change of angles. Information flows from a single aggregation point may reach 200 kB/s on average for a 6-DOF sensor apparatus described in [136]. While the outputs of health monitoring sensors are usually wired into a local aggregation devices, it is desirable to transmit these readings to an on-line optimizer or PLC within the work-cell [98].

- **IO States and Supervisory Messages:** These contain both the boolean-valued readings and commands from sensors, and task orders in the form of short commands and lists of instructions which can originate from any supervisor within the network such as a PLC or other controller. Sensor readings (inputs) and actuation commands (outputs) are transmitted in periodically or pseudo-randomly at rates indicative of movements of machinery and materials through the manufacturing process. Typical analog and boolean IO states range from to 10 Hz to 100 Hz depending on the manufacturing process [153].

- **SMS Events:** The SMS agent will communicate state information and directives to controllers within the work-cell. These messages allow the automation system to react under anomalous spectrum conditions within the work-cell. These information flows may be necessary for safe operation of the work-cell. The data rate of reports from an SMS agent without processing or compression can be in the range of 1 to 10 megabits per second (Mbps) [71].

- **Vision Applications:** The vision system will communicate videos or images for processing and decision making. Typical Video flows can have the rates of 30 Hz for surveillance and 125 Hz for motion capturing [136, 155]. Information flow for Object tracking systems can have the rate of 10-200 Hz depending on the tracked objects and the required accuracy [133, 154].

4.7/ Discussion and Conclusions

A model was developed using SysML. The developed model is constructed of the elements necessary to construct useful representations of factory work-cells in which wireless networks are used to transport information necessary for automated control system operation. Reusable, derivable elements are developed and then extended to represent the constructs of the work-cell such as robot control, supervisory control, vision, safety, and spectrum monitoring. An industrial wireless network is then developed and constraints of the radio channel and network services are formalized. Using the architectural model, information flows are explored and incorporated within.

It is important to mention that this model includes an often overlooked component of any industrial wireless deployment which is the spectrum monitoring system and also considers the human-robot and robot-robot interactions in industrial environments. The current model includes various systems constraints including motion constraints, radio channel constraints, and networking constraints. The parametric constraints are provided as examples and can be replaced with executable computer code thereby making the model useful for simulation depending on the modeling tool selected. Furthermore, the applications within the robotic work-cell define many information flows requiring careful analysis to achieve reliability and latency necessary for the safety and control of the manufacturing process.

With increased dependency on wireless communications for more complex manufacturing systems, the projection of manufacturing requirements onto the wireless communication system becomes less obvious. Such analysis of this projection is essential for future research of manufacturing systems. As such, the architectural elements and information flows exposed by an abstract model are a necessary first step. Our model in its current state of development is comprehensive enough to support architectural and ontological analyses of the factory work-cell. As such, information about the relationships between components of a work-cell and attributes related to the wireless network may be discovered. Therefore, our model serves as a foundation for future systems engineering analyses. Moreover, our model may be used as a tool for academic and industry exploration of wireless testbed development. We make the model openly available through GitHub at [130].

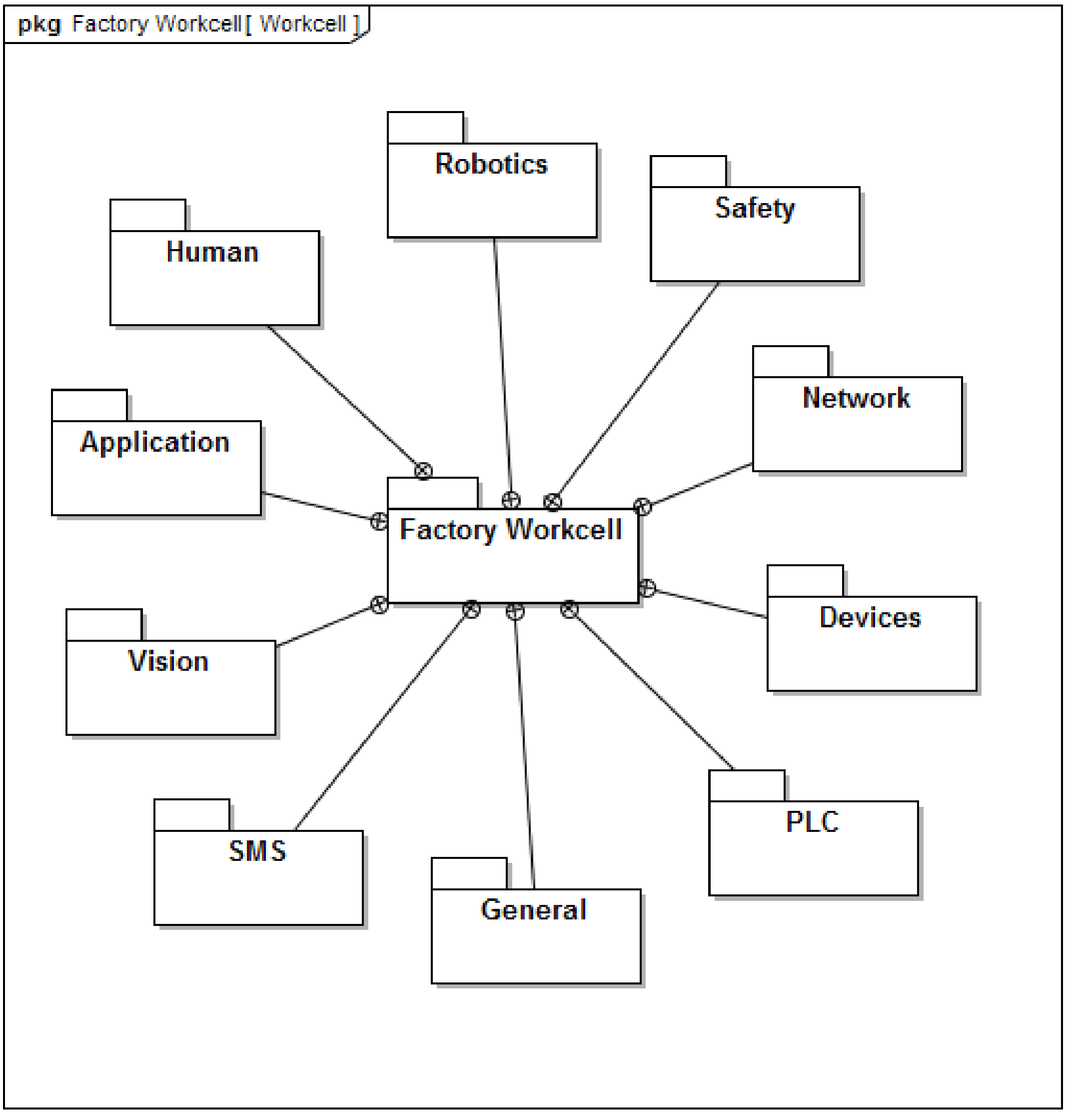


Figure 4.2: SysML package diagram showing the logical containment of the factory work-cell structural elements.

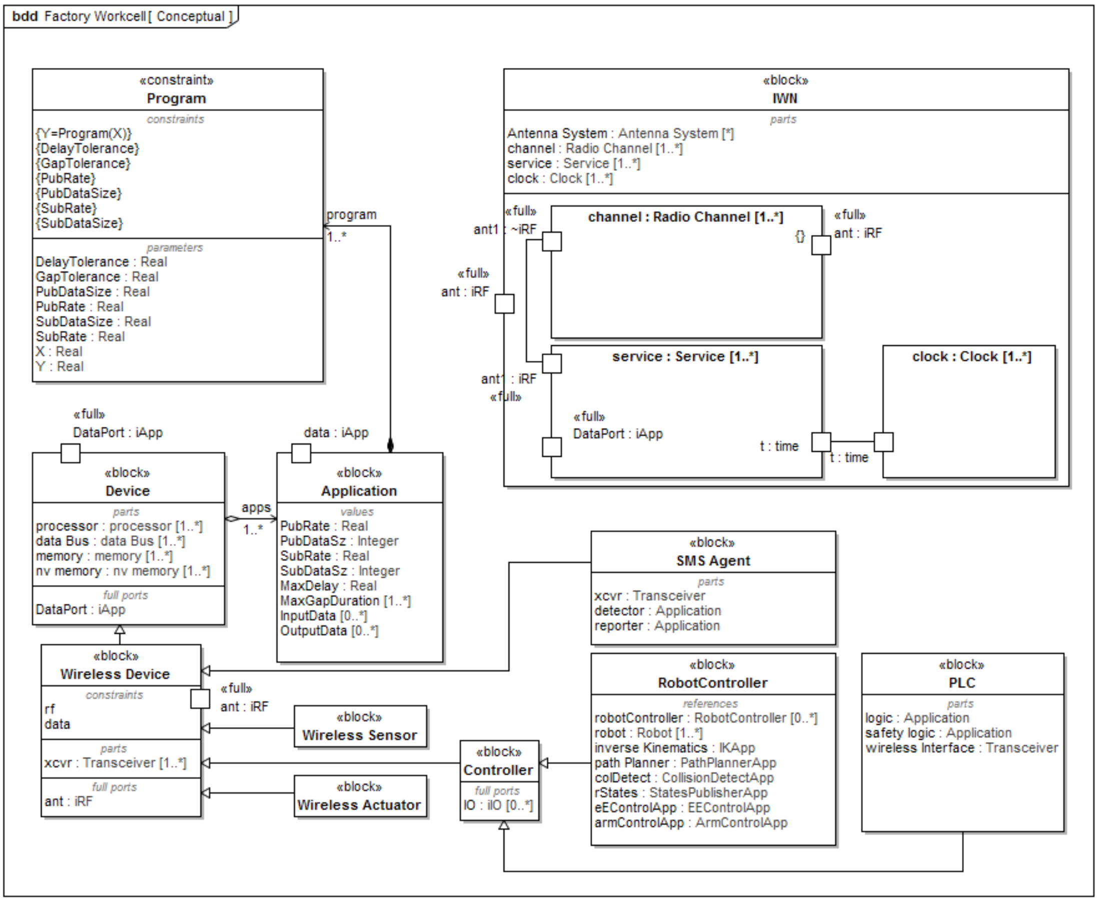
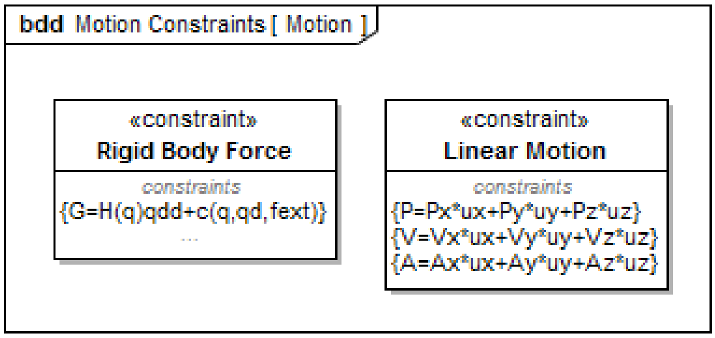
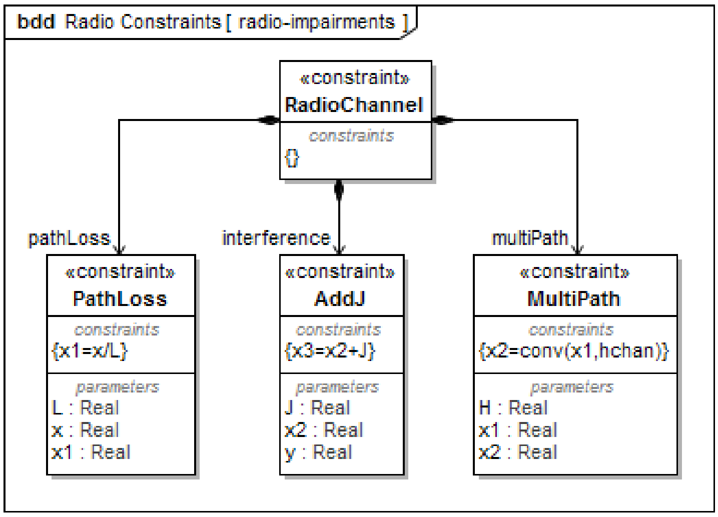


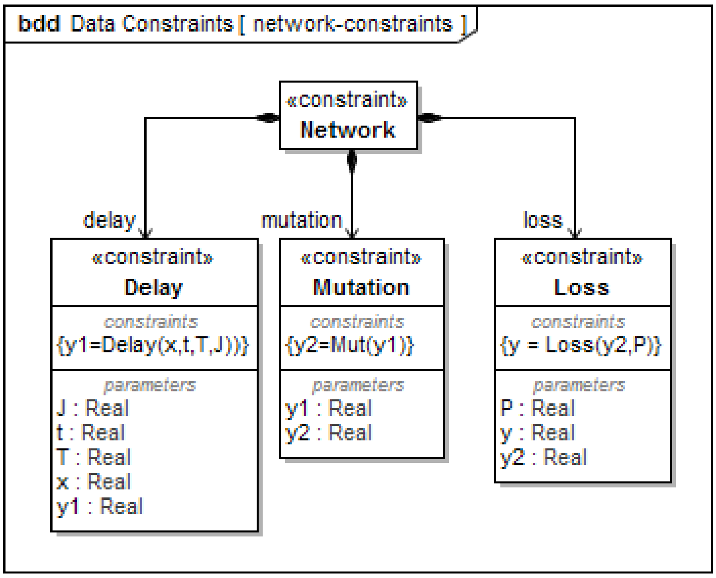
Figure 4.3: Architecture of the conceptual work-cell captured as a SysML block definition diagram. In this diagram, only the most generalized blocks necessary to construct a work-cell scenario are shown. More application-specific scenarios may be developed by deriving new blocks from the constructs shown here. The shapes and connectors used for expressing this model are defined in the SysML specification [121].



(a) Motion Constraints



(b) Radio Channel Constraints



(c) [Networking Service Constraints

Figure 4.4: Generalized network constraints consisting of rigid body motion (a), the radio channel (b) and the network services (c).

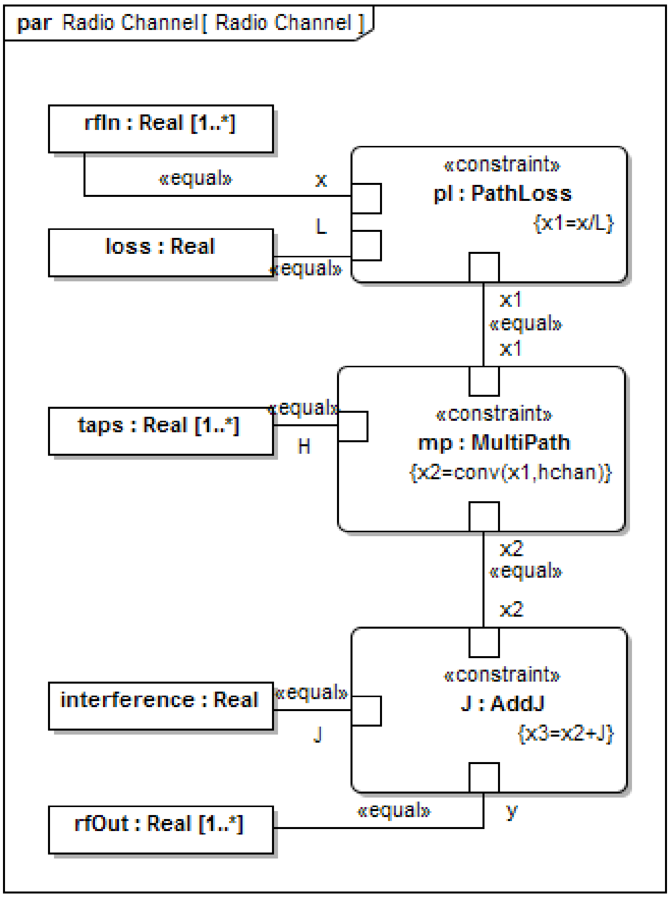


Figure 4.5: SysML parametric diagram of the radio channel constraints of the industrial wireless network.

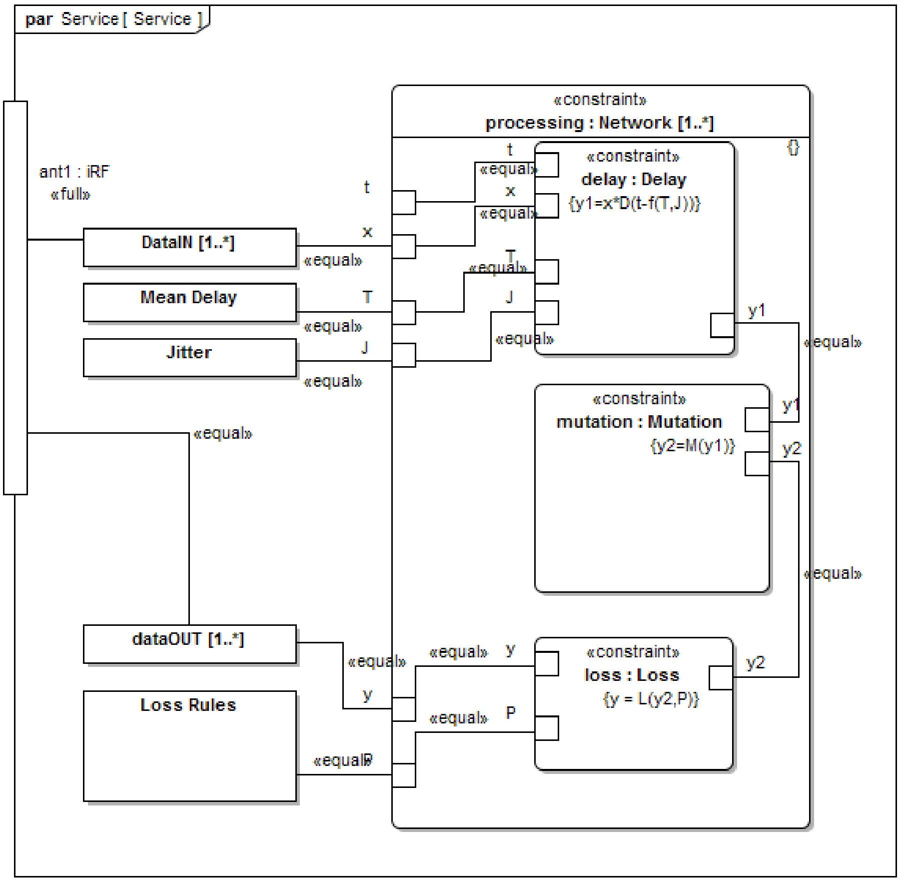


Figure 4.6: SysML parametric diagram of the data constraints applied to the industrial wireless network.

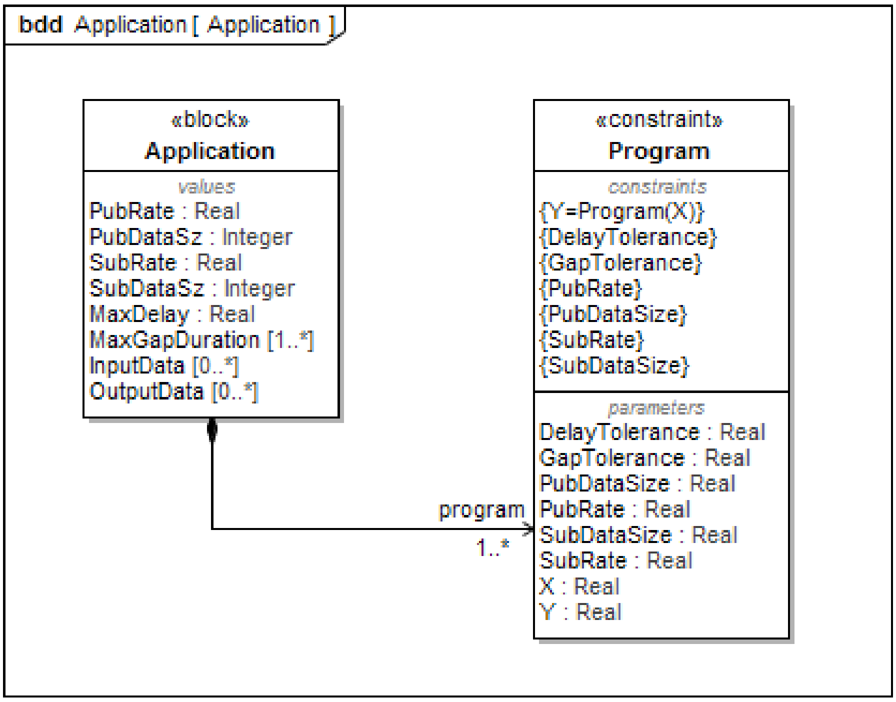
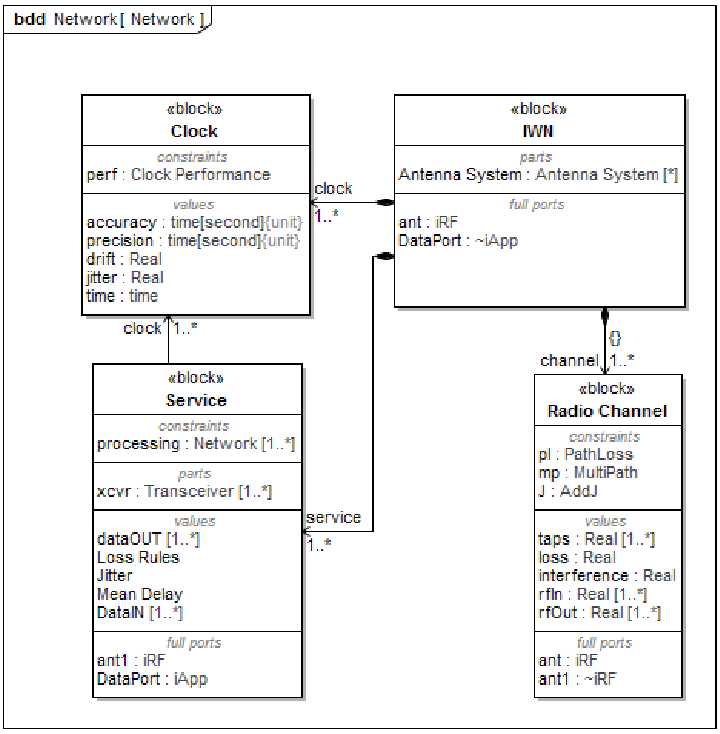
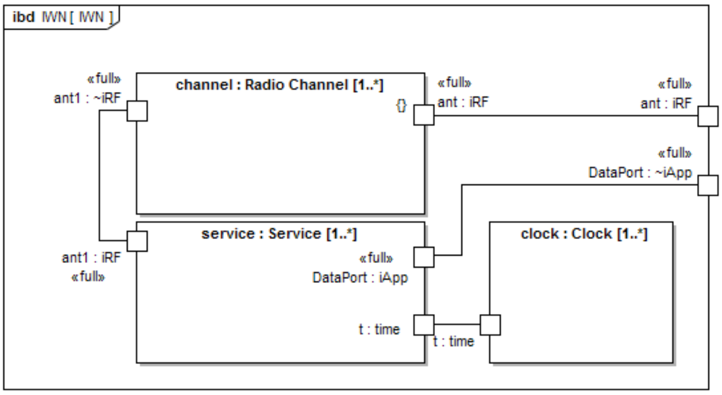


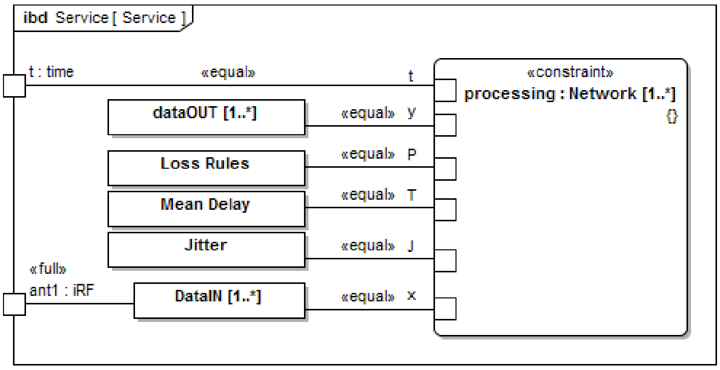
Figure 4.7: Block definition diagram of the Application.



(a) Put your sub-caption here

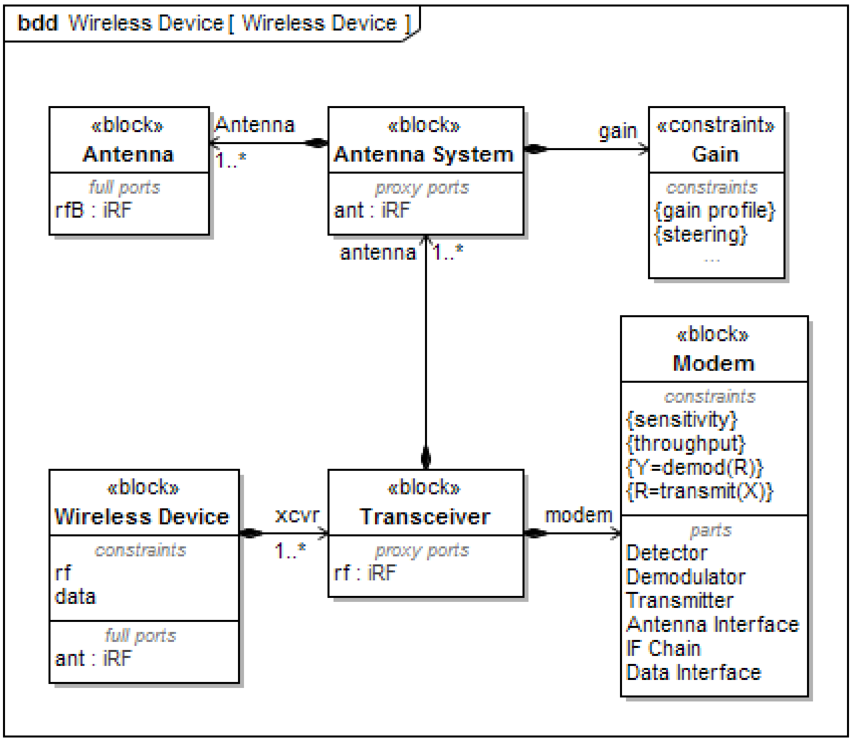


(b) Put your sub-caption here

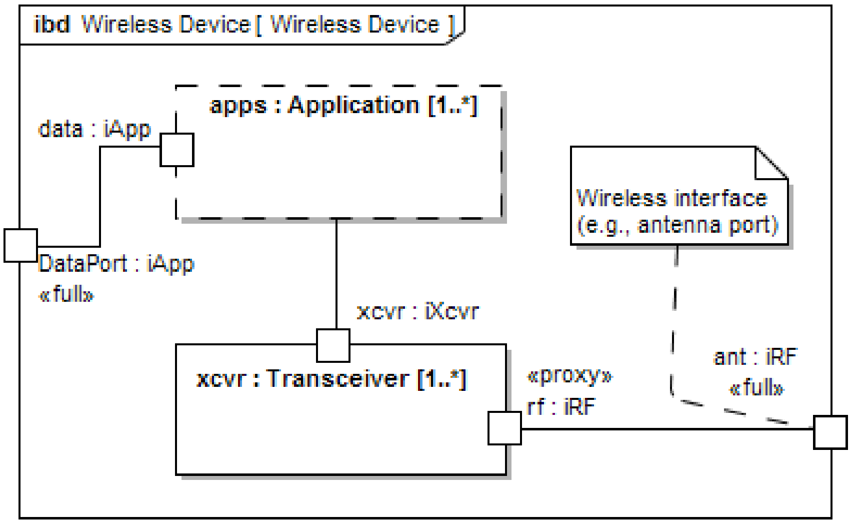


(c) Put your sub-caption here

Figure 4.8: The BDD (a) and IBD (b) of the industrial wireless network with parametric IBD (c) of the Services block.

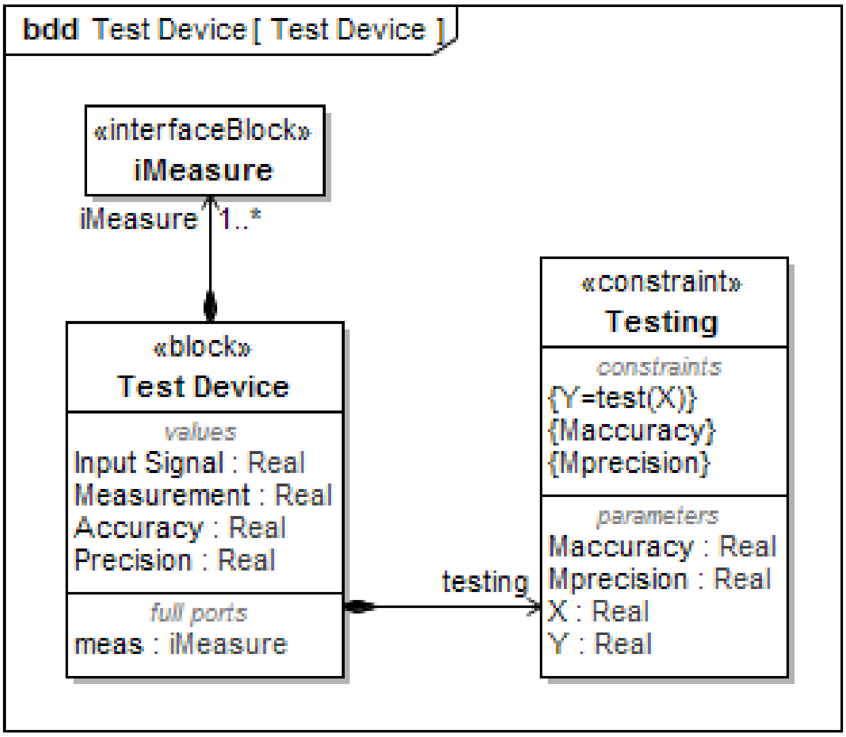


(a) Block definition diagram of the Wireless Device

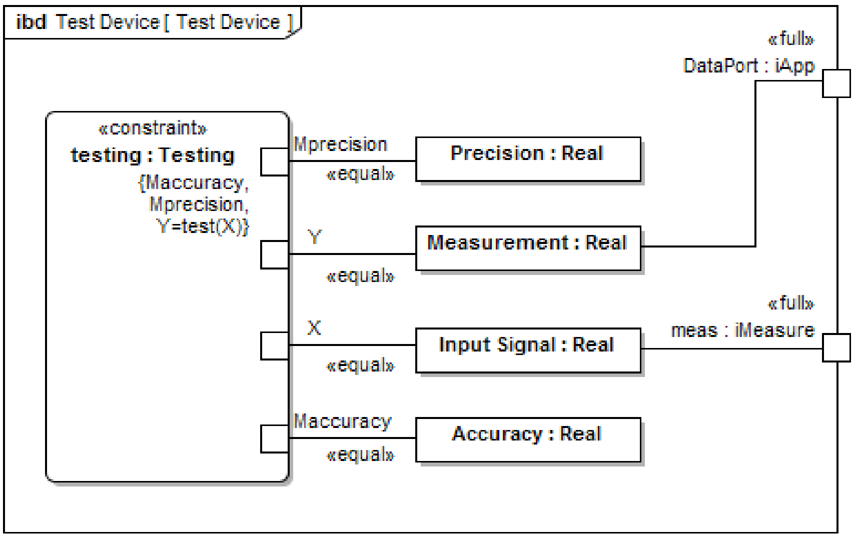


(b) Internal block diagram of the Wireless Device

Figure 4.10: Block definition diagram (a) and the internal block diagram (b) of Wireless Device.

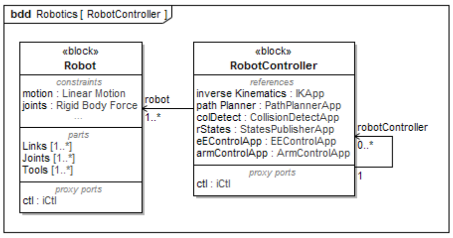


(a) Block definition diagram of the Test Device

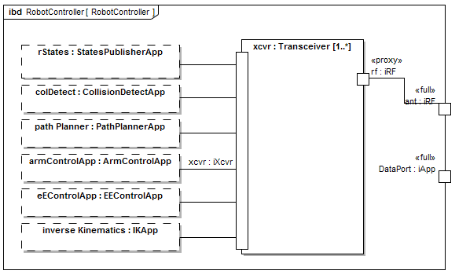


(b) Internal block diagram of the Test Device

Figure 4.11: PBlock definition diagram (a) and the internal block diagram (b) of Test Device.



(a) Block definition diagram of the Robot Controller



(b) Internal block diagram of the Robot Controller

Figure 4.12: The BDD (a), IBD (b) of the Robot Controller.

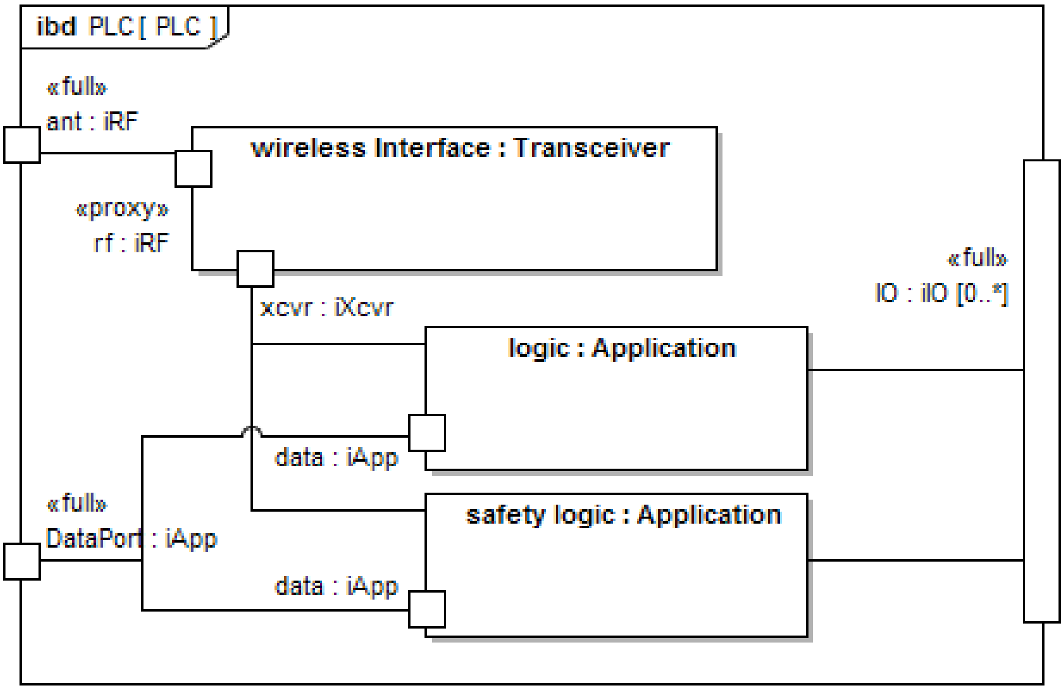


Figure 4.13: The IBD of the PLC showing composition and connectivity of the control logic and safety logic Application instantiations to the Transceiver interface.

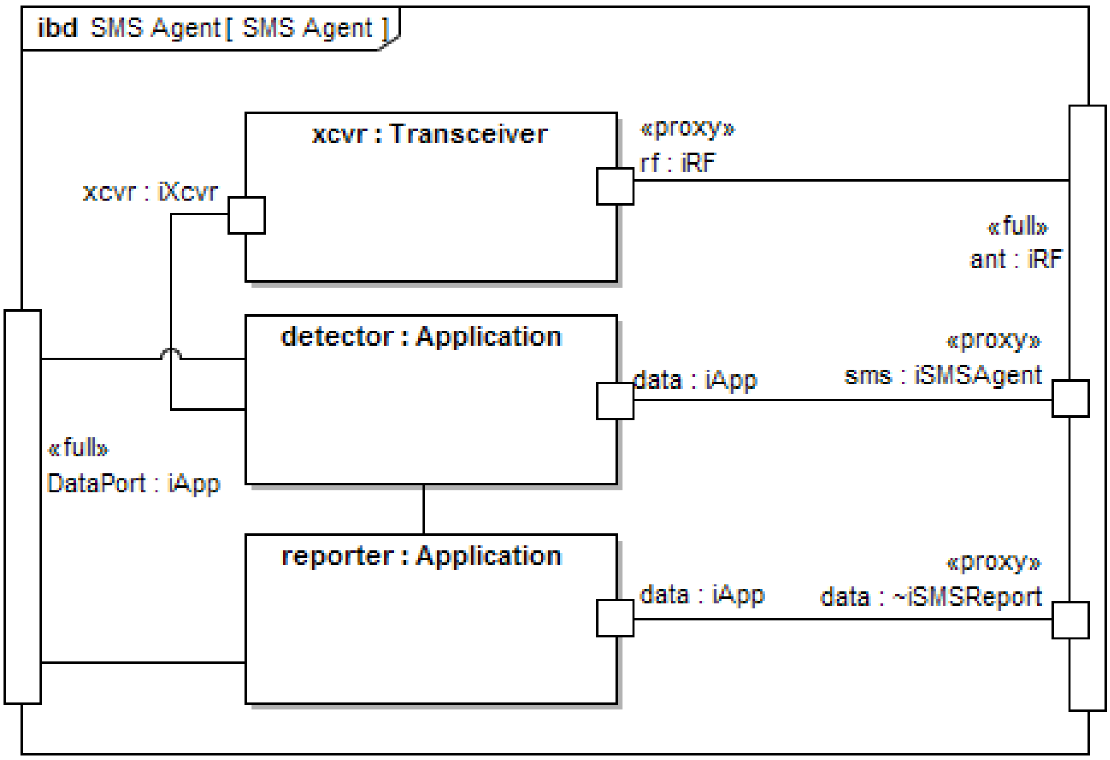


Figure 4.14: Spectrum monitoring agent composed of transceiver, detection application, and reporting application.

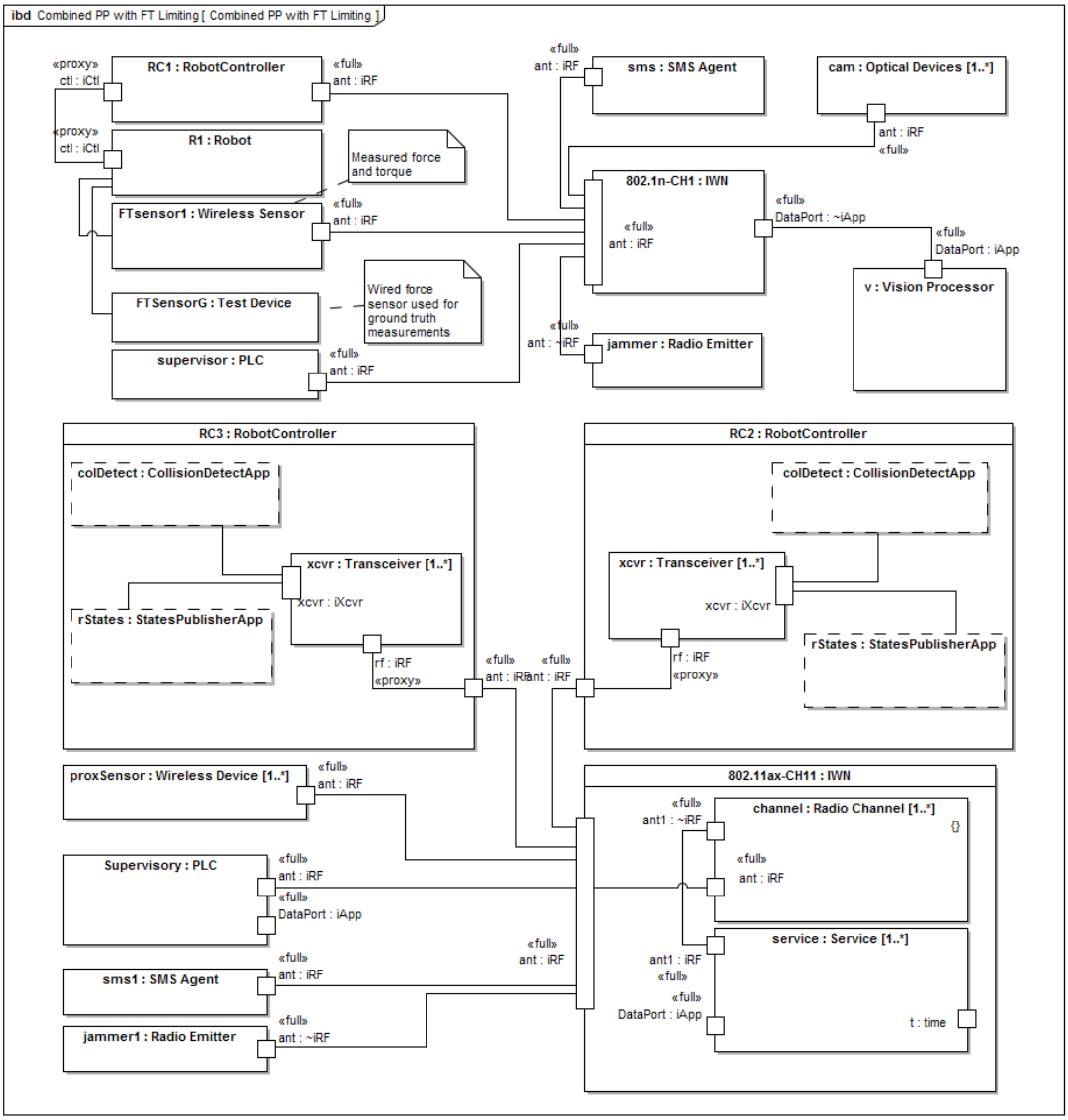


Figure 4.15: IBD of a work-cell employing multiple networks in collaborative robot operation coexisting with robot force limiting inspection station.

5

Application of Graph Databases

The workcell is considered a main building block of various industrial settings. Hence, it is examined as a primary testing environment for studying wireless communication techniques in factory automation processes. A new testbed was recently designed and developed to facilitate such studies in workcells by replicating various data flows in an emulated production environment. In this paper, an approach to storing and analyzing network performance data from a manufacturing factory workcell is introduced. A robotic testbed was constructed using two collaborative grade robot arms, machine emulators, and wireless communication devices. A graph database approach was implemented to capture network and operational event data among the components within the testbed. A schema is proposed, developed, and elaborated; a database is then populated with events from the testbed, and the resulting graph is presented. Query commands are then presented as a means to examine and analyze network performance and relationships within the components of the network. Additionally, we demonstrate how to extract correlations between receive signal power and network delay within the testbed using the graph database query language. Finally, using the inherently interconnected nature of the graph database, we discuss applying the graph database approach toward examining more complex relationships between the wireless communications network and the operational system.

5.1/ Introduction

Wireless communication is a key enabling technology for the modernization of factory workcells. Modern factory workcells are highly-interconnected networked control systems in which various devices interact and collaborate to accomplish complex and adaptive production orders. The workcell often contains mobile robots that collaborate with other robots or human beings. Requirements of the workcell include the incorporation of mobile collaborative robotics with real-time coordination of motion and tool actuation. As such, the communication of sensor and control information must be ultra-reliable and of low-latency to assure trustworthy operation [101]. Due to an increased demand for ease of installation, reduced costs of deployment and maintenance, and flexibility, wired networks are being gradually replaced with wireless networks. This presents a real challenge for networks and control systems. Compared with wired connections, wireless links have their unique advantages in connecting field sensors and actuators with reduced cabling costs and natural support of mobility [134]; however, most current communications systems lack the latency and reliability supports [132] mandated by factory owners [48,100]. New wireless protocols are being designed to address reliability and latency concerns of real-time systems such as those in manufacturing automation. These new protocols include advancements, such as the Institute of Electrical and Electronics Engineers (IEEE) 802.11ax standard and 5G cellular evolution as defined by the International Mobile Telecommunications-2020 (IMT-2020) Standard. Both of these two standards employ improved diversity techniques for multiple access of devices as well as 1 ms latency and greatly improved reliability [163].

Evaluation of such systems used in manufacturing environments requires not only rigorously analyzing network performance, but also studying the impacts of networks on manufacturing systems. Additionally, industry lacks effective and easy-to-use strategies for test and evaluation of such systems in a way that correlates network performance with operational performance. Furthermore, since factory operators desire the ability to control operations within the workcell using wireless technology, we present a novel method to simultaneously capture network and operational event information using a graph database (GDB). The use of a GDB allows for more intuitive inferences to be made through the stored relationships and graph theoretic models [21]. In this paper, we present a GDB approach to the capture and analysis of factory workcell performance utilizing the Neo4j database platform. We present a proposed schema of the database, the process for capturing both network and operational events, and examples of querying the database for cyber-physical performance evaluation of the workcell for our collaborative two-robot machine-tending workcell [150].

5.2/ Graph Databases

A GDB is the type of databases that uses nodes, edges, and properties to store and present data. A GDB is a part of a family of databases known as NoSQL databases that are used often to represent complex interrelated structures of data and their relationships. This can be very difficult with traditional relational databases. The GDB places a high priority on the relationships (edges) between units of information. In addition, the GDB does not enforce any particular schema or structure, and, therefore, provides greater flexibility in storing and representing information in which the parts of information may vary among units. The relationships within a GDB are efficiently queried because they are persistently stored within the database. In a GDB, queries can be made based on relationships. This, in particular, presents an advantage when storing information regarding systems with correlations that are apparent but difficult to visualize or quantify. The GDB approach was chosen for this specific purpose—to quantify and visualize relationships between non-ideal communications within a workcell and their impact on the physical system.

5.3/ Related Work

Multiple surveys about GDBs have been presented to describe the associated models, tools, and their features in [21, 77, 83]. Also, examples of applications and implementations of GDBs are presented in [64] to show their use on enterprise data, social networks, and determining security and access rights. It was found that GDBs provide the much needed structure for storing data and incorporating a dynamic schema. On the other hand, query languages are used to extract data including traversing the database, comparing nodes properties, and subgraph matching [41]. The performance of different GDB tools and methodologies is analyzed and compared in [50, 75]. Multiple comparisons in these articles have shown improved performance of Neo4j in the general features for data storing and querying, and data modeling features such as data structures, query languages and integrity constraints.

Furthermore, industrial data analytics play an essential role in achieving the smart factory vision and improving decision-making in various industrial applications. Five main industrial data methodologies are studied including highly distributed data ingestion, data repository, large-scale data management, data analytics, and data governance [140]. Industrial data processing offers valuable information about various sections of industrial applications including inefficiencies in industrial processes, costly failures and down-times, and effective maintenance decisions [78]. In [162], a platform for performing industrial big data analysis is presented where the performance requirements are introduced to achieve a cost-effective operation. Various other frameworks for industrial data analysis can be found in [156, 161], where the importance of using data analysis in decision making is emphasized.

Due to its advantages including scalability, efficiency, and flexibility, NoSQL databases are a popular alternative to relational databases in the case of large amounts of data in various applications [52]. The GDB is a kind of NoSQL database approaches that additionally handles complex relationships [127]. GDBs are widely adopted in various industry-related applications and use cases such as network operations, fraud detection, and asset and data management [84]. Relationships in social networks have been modeled using a GDB for structural information mining and marketing [37]. On the other hand, business solutions for scenarios with multiple large data sources require distributed processing in decision making for various problems such as fraud detection, trend prediction, and product recommendation [54].

5.4/ Case Study: Robotic Machine-tending

In this section, we present a two-robot machine tending workcell case study. We first present the design of the workcell followed by an elaboration of the database design called a schema. The information work-flow, i.e., the process for collecting, processing, and analyzing the network event data is presented. We then provide examples of the resulting graph and results of targeted queries that demonstrate the purpose of the database.

5.4.1/ Workcell Design

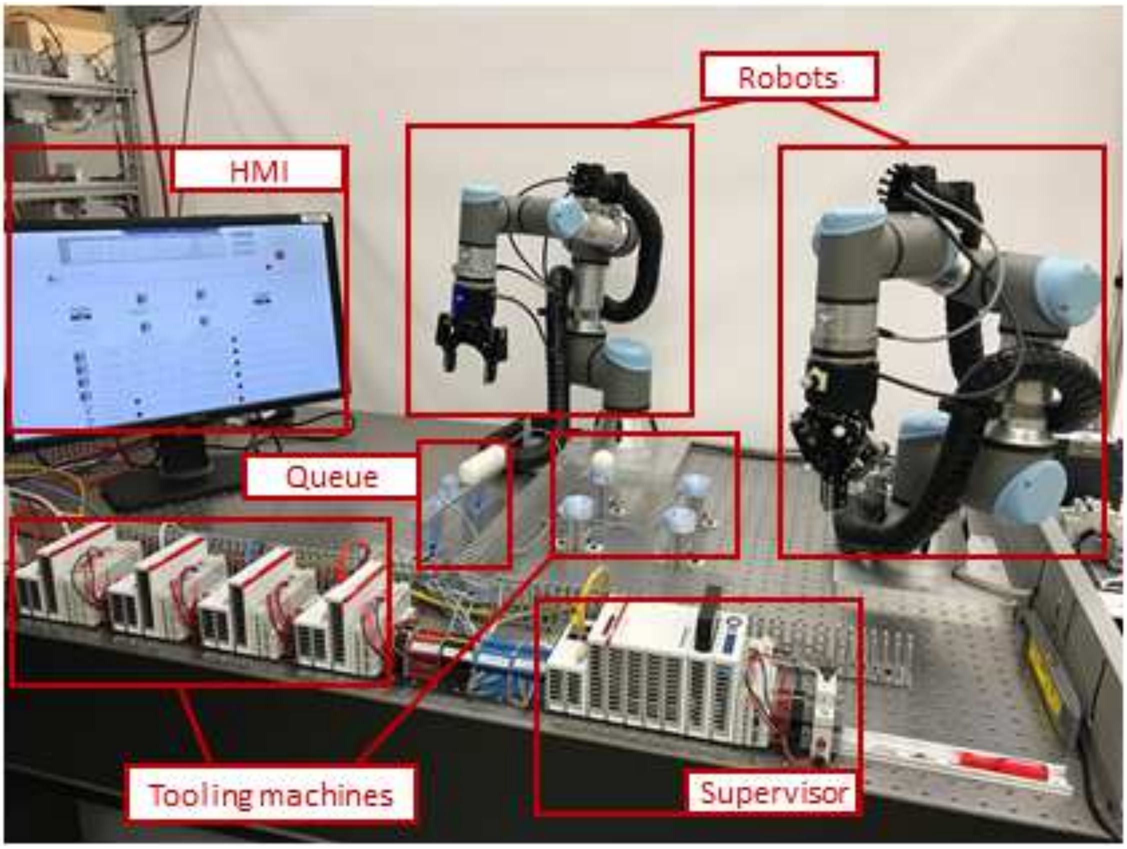


Figure 5.1: Collaborative work cell testbed

To facilitate wireless network research and showcase the power of wireless technologies in industrial practices, a testbed shown in Fig. 5.1 has been developed at the National Institute of Standards and Technology (NIST) as described in [150]. The testbed is composed of two collaboration-grade robots, a supervisory programmable logic controller (PLC) used for the control of the workcell, four smaller PLCs serving as computer numerical control (CNC) machine emulators, and a human-machine interface (HMI). Each robot is equipped with a six-degrees-of-freedom (DOF) force-torque (FT) sensor and a two-finger gripper. A Modbus/TCP server is included within the supervisor PLC and is used for communication between the supervisor and the robots. The PLCs themselves communicate to each other using the Beckhoff Automation Device Specification (ADS) protocol. All elements within the workcell are synchronized to a stable and accurate grand-master clock. Therefore, as described in [150], the operational, network, and measurement elements are all synchronized to the grand-master clock through a precision time protocol (PTP)-capable switch.

Work-orders for the workcell are submitted through the supervisor. Each work-order consists of a work-plan for a part, and the work-plan determines how each part moves through the workcell until it is completed. The inspection of each part is conducted at each machining station, and after the final inspection, the part is placed back into the input queue. Under normal operating conditions, the work continues until all work-orders have been processed. This continuous form of operation provides ample opportunity to collect statistically significant metrics of both the network and the operation of the workcell.

5.4.2/ Database Schema

GDBs are NoSQL databases such that the database does not contain any predefined structure or rules to enforce such structure. This is a major difference between relational databases and GDBs. Nevertheless, it was necessary to sketch a pseudo-schema to capture the intended nodes and relationships that would be stored within the database (the terms pseudo-schema and schema will be used interchangeably). Before describing the schema itself, it is necessary to first explain the requirements of the schema. Therefore, the requirements for our schema are as follows:

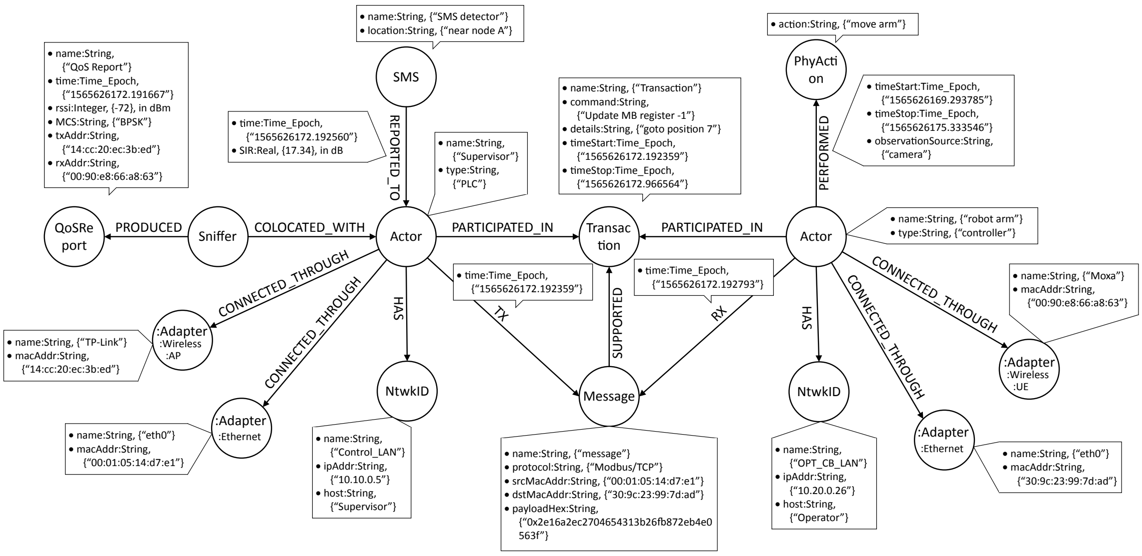


Figure 5.2: The intended schema (i.e., pseudo-schema) of the graph database used for each operational run of the NIST wireless factory testbed. The graph is organized into nodes and edges, where the edges signify relationships among network elements and physical operational elements.

- **Timestyle=sameline** Any manufacturing automation system is indeed a time-varying control system with network and operational events. The database schema must necessarily support time-based queries and, specifically, time-windowed queries.

- **Operational Eventsstyle=sameline** The schema must represent operational events such as the movement of a robot arm or the movement of a part.

- **Network Eventsstyle=sameline** The schema must represent network events such as the transmission of packets.

- **Message Groupingstyle=sameline** The schema must support grouping of logically related events such that those events can be correlated to a specific occurrence within the testbed.

- **Wireless Supportstyle=sameline** The schema must support the capture of both wired and wireless network traffic without special provisions within queries for either.

- **QoS Supportstyle=sameline** The schema must allow for the capture of quality of service (QoS) data when available.

- **Spectrum Monitoringstyle=sameline** The schema must support the capture and association of network events with observations from a spectrum monitoring system (SMS) if that information is available.

5.4.2.1/ Node Design

Given the fore-mentioned requirements, a sample pseudo-schema is shown in Fig. 5.2, which represents the intended structure of the information within the GDB. It is important to remember that since GDB schemas are not really schemas, such as those found in relational databases, but representations of intent, the schema represented here should be considered a notional example of the final product. Within the graphs, nodes represent logical elements, and edges represent the relationships between those elements. Both nodes and edges may contain properties providing more description and labels that define categories or classes of the said nodes or edges. Our schema is designed such that the data within the graph is intuitive to understand and allows for time-based queries to occur. The facilitation of time-based queries was an essential requirement of our database design. Our schema is represented using the following node labels:

- **Actorstyle=sameline** A physical component within the factory workcell such as a robot, PLC, or other networked item.
- **NtwkIDstyle=sameline** A network address item for an actor such as an Internet Protocol (IP) address.
- **Transactionstyle=sameline** A complete information exchange between two or more actors (multiple actors may participate in a transaction).
- **Messagestyle=sameline** A network transmission event that occurs between two actors (messages are essentially packet transmissions captured at the transport layer; multiple messages support a transaction).
- **Physical Actionstyle=sameline** A physical occurrence within a factory workcell associated with actors through multiple time based relationships.

- **SMSstyle=sameline** An SMS observes and records significant spectral events within the workcell and may report those events to actors within the workcell.

- **Snifferstyle=sameline** A measurement device that records all transmissions conducted over the wireless medium and includes wireless header information for each wireless transmission detected.

- **Adapterstyle=sameline** A device that serves to connect an actor to a network (adapters are divided into sub-categories depending on the type of interface to a network).

- **Adapter:Ethernetstyle=sameline** A subcategory of adapter representing an Ethernet interface.

- **Adapter:Wirelessstyle=sameline** A subcategory of adapter representing a wireless interface.

- **Adapter:Wireless:APstyle=sameline** A subcategory of adapter representing a wireless access point interface.

- **Adapter:Wireless:UEstyle=sameline** A subcategory of adapter representing a wireless user equipment interface.

- **QoS Reportstyle=sameline** A quality of service report of a message (not all messages will have a QoS report).

It is important to note that most network infrastructure components are not captured within the graph, but, instead, only basic interfaces between actors and the network are captured. Our intent when designing the graph was to make the graph network and protocol agnostic, such that the network is viewed as a black-box. Accordingly, the captured events of the physical system and the network are considered useful for the analysis of performance.

5.4.2.2/ Relationships (Graph Edges)

Relationships are edges within the graph that capture the informational interactions between nodes. Relationships, like nodes, can contain labels and properties. As shown in Fig. 5.2, nodes are connected through defined relationships. A subset of the relationships are defined as follows:

- **PARTICIPATED_IN:** Actors will participate in transactions. A transaction exists for each logical set of messages between actors such as the setting of a Modbus register or the sending of a command to a robot. Therefore, actors will participate in many transactions, and multiple actors may participate in a single transaction.
- **SUPPORTED:** Messages (i.e., packets between actors) are associated with transactions through the SUPPORTED relationship. Depending on the protocol and the quality of the channel, a single transaction could have one or many messages connected through this relationship.
- **TX/RX:** An actor may either transmit (TX) or receive (RX) a message. Both the TX and RX relationships contain a timestamp in the format of an epoch time which is a floating point number in seconds since January 1, 1970, with a resolution of microseconds.
- **PERFORMED:** When an actor performs a physical action, a relationship is created between the actor and the physical action node. This relationship contains start and stop time properties as well as the source of the observation such as a networked camera.
- **REPORTED_TO:** An SMS may be a passive or active listener within a workcell. When an SMS operates as an active listener, spectral reports from the SMS may be sent to an actor such that the actor can respond intelligently to the spectral event. Reports from an SMS to an actor are captured within this relationship.

Other relationships shown in the schema of Fig. 5.2 but not explained above are considered self-explanatory.

5.4.2.3/ Closer Examination

Examining the sample schema more closely, two actor nodes are represented. In this case, Actor A is the supervisory controller, and Actor B is a robot arm. Both nodes participate in a transaction, which, in this example, is a Modbus/TCP exchange. The transaction itself is associated with one or more messages (i.e., packets). Each message associated with a transaction manifests itself as a node in the graph. Multiple message nodes will exist for each transaction. Additionally, QoS reports may be associated with each actor node through a collocated sniffer node. By keeping QoS reports separate, we have the flexibility of supporting different wired and wireless protocols within the same graph. Recall, that a graph database has no enforceable structure and thus affords this type of flexibility. Each actor node may have network identities associated with it through the use of network identifier nodes. Each network identifier node may contain address information such as a hardware address or a network address; however, this is dependent on the protocols and addressing schemes being used, and a node could have many different identification nodes.

5.4.2.4/ Physical Actions

Finally, each actor in the graph may associate with physical actions. These actions exist in the database as automatons such that every time a new action occurs, a new edge would be added between the actor and the physical action. Timestamps within the graph represent “measurement time” denoting that all timestamps are accurately synchronized to the grand-master clock. The method of synchronization is outside the scope of this paper and is explained fully in [150]. This paper describes the database structure and the process for preparing and inserting the data into the database, which is described in the following subsection.

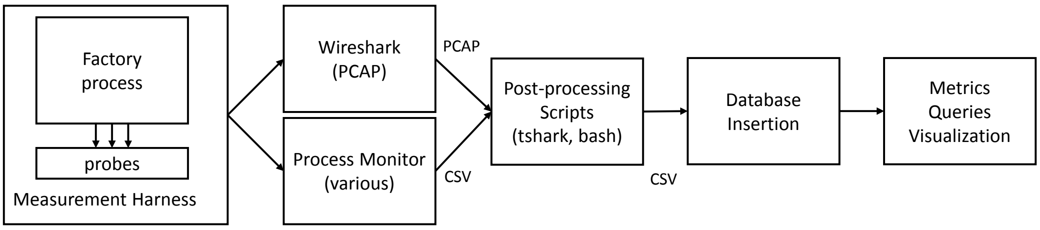


Figure 5.3: Data processing flow from factory workcell to database

5.4.3/ Information Workflow

The workflow for collecting, processing, and inserting measurement data into the graph database is multi-pronged, as shown in Fig. 5.3. The workcell, which in our case study is a two-robot workcell with four CNC machines, is instrumented with network probes that capture transmitted and received packets as well as probes to capture operational movements such as arm robot position and the state of the supervisor PLC. Network data is stored in packet capture (PCAP) files, while operational data is stored in comma separated value (CSV) files. We developed bash scripts to extract relevant information and prepare the data for insertion into the database. The scripts also contain rules for grouping packets together as transactions based on the application protocol and time. The scripts produce CSV files that are ready for insertion into the Neo4j database. Once the data resides within the database, we apply queries to extract information for the evaluation of workcell performance and visualization of network and operational events within the workcell. By tracking paths through the relationships within the graph, discerning how a network event such as interference is related to physical events such as position uncertainty or part throughput is possible. Various impairments may be introduced as a part of workcell operation. Examples of such impairments include competing wireless traffic, radio interference, and reflections and diffraction due to the multi-path environment [107]. We have shown that it is feasible to implement such impairments and measure the resulting physical performance manifestation [150]. This is accomplished through the use of a radio channel emulator as demonstrated in [144].

5.4.4/ Sample of a Resulting Graph

In the following, we show results from a trial run of the NIST industrial wireless testbed. In this trial run, a single physical wireless link is used between a wireless adapter connected directly to the supervisor and a wireless access point connected to all the other actors in the testbed. The wireless nodes represent IEEE 802.11b/g/n devices and are connected through a variable radio frequency (RF) attenuator that allows us to vary the channel quality. During the trial run, the production of 10 parts was emulated, which resulted in 10 minutes of network activity.

After populating the database with data captured from the trial run, the resulting realized schema is shown in Fig. 5.4. The schema visualization is produced by invoking the command

```
call db.schema.visualization()
```

in Neo4j. It is important to note that a realized schema shows only one representation of each node and relationship whereas the intended pseudo-schema shown in Fig. 5.2 was developed to exemplify the relationships between types of nodes, labels, and relationships. Where label inheritance is employed, such as the case for different adapter types, relationships are reproduced; however, this is a result of the visualization tool rather than the schema itself. Fig. 5.4 serves, therefore, to validate that the intended schema was indeed realized by the insertion of event data from the testbed. In the realized schema, inherited labels are shown as separate nodes.

As described in Section 5.4.2, the database includes every network transaction that occurs during the operation of the testbed. This includes any logical transaction nodes inserted into the database and any associated packets that happened to traverse the network. Therefore, for a short duration of time depending on packet transmission rates, the amount of data stored in the database can grow quickly. This presents a visualization challenge that graphs are designed to handle. A sample graph is shown in Fig. 5.5, which represents only 1 second of wired and wireless network data captured from the NIST two-robot pick-and-place wireless testbed described in [150].

Figure 5.4: Realized schema of the graph database fully populated after capturing network and operational data from the NIST industrial wireless testbed.

This visualization is produced by calling the following query in the Neo4j.

```
MATCH p=(a:Actor {name:'Supervisor'})--(t:Transaction)--(b:Actor)
    ↪ ,p2=(m:Message)-->(t) WHERE t.timeStart>T AND t.timeStop<T
    ↪ +1
RETURN p,p2
```

The colors of the resulting nodes follow the realized schema in Fig. 5.4 while only the actors, transactions, and messages are visualized in Fig. 5.5. The relationships be-

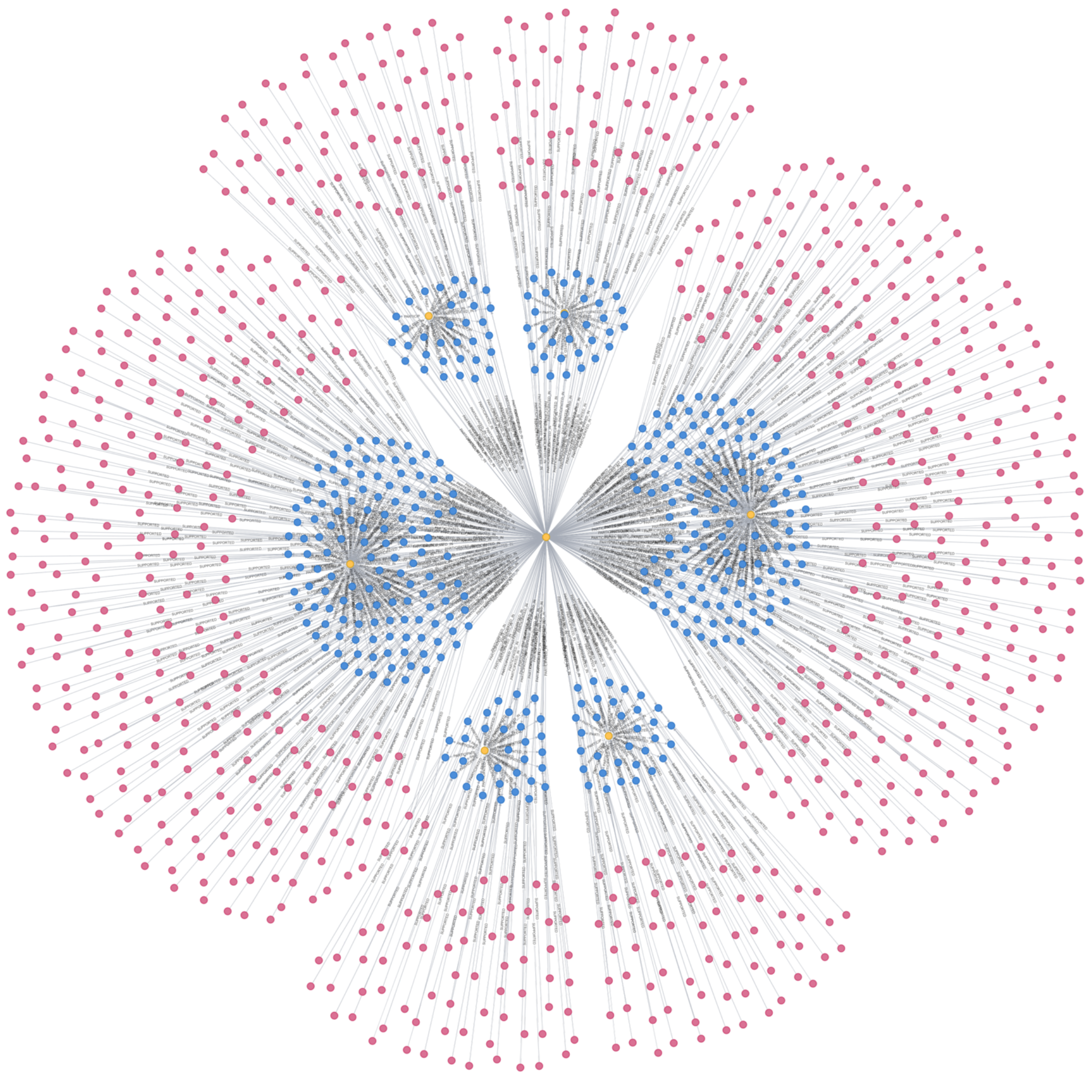


Figure 5.5: Visualization of a node graph resulting from a testbed experiment.

tween the messages and transactions are shown where a single transaction is connected to at least two messages to represent the communications between any two actors. The variable T in the query represents an arbitrary time variable in seconds within the trial run to capture the data within 1 second only.

We then show a more detailed visualization for all the nodes and relationships corresponding to a single transaction. This visualization is produced by calling the following query where Ts is an arbitrary time variable to specify the timeStart value for the single transaction.

```
MATCH p=(a:Actor {name:'Supervisor'})-->(t:Transaction {timeStart
```

```
↪ :Ts})<--(b:Actor {name:"CNC-1"})
WITH p, a, b, t
MATCH p1=(a)-->(m:Message)<--(b), p2=(m)-->(t), p3=(a)-[:HAS]-(),
    ↪ p4=(a)<-[:COLOCATED_WITH]-()-[:PRODUCED]->(q:QoSReport), p5
    ↪ =(a)-[:CONNECTED_THROUGH]-(),p6=(b)-[:HAS]-(), p7=(b)-[:
    ↪ CONNECTED_THROUGH]-()
WHERE q.time>t.timeStart AND q.time<t.timeStop
RETURN p,p1,p2,p3,p4,p5,p6,p7
```

In Fig. 5.6, the actor nodes are labeled by their names *CNC-1* and *Supervisor*, the transaction is labeled by its type *ADS*, the messages are labeled by their transmission role *Request* and *Response*, the NtwkIDs are labeled by their IP addresses, the Ethernet adapters are labeled by their names *eth0*, the wireless adapters are labeled by their names *Moxa* and *TP-Link*, the sniffer is labeled by its name *WLS1*, and the QoS reports are labeled by the received signal strength indicator (RSSI) value in dBm. This visualization includes only the QoS reports generated within the duration of the corresponding transaction.

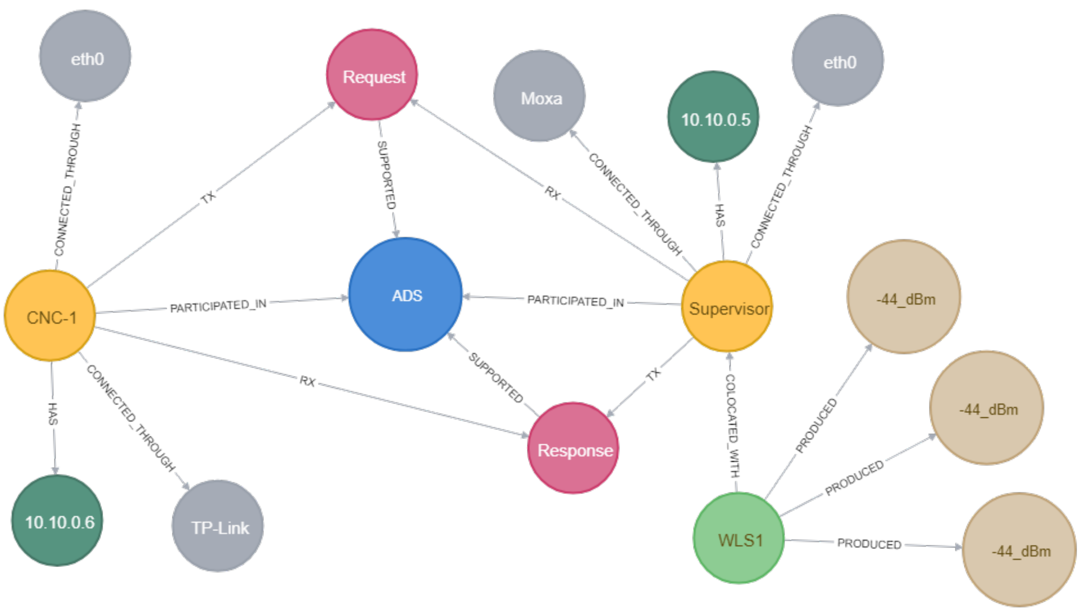


Figure 5.6: A detailed visualization resulting from a testbed experiment for all the nodes and relationships corresponding to a single transaction.

5.4.5/ CALCULATION OF METRICS

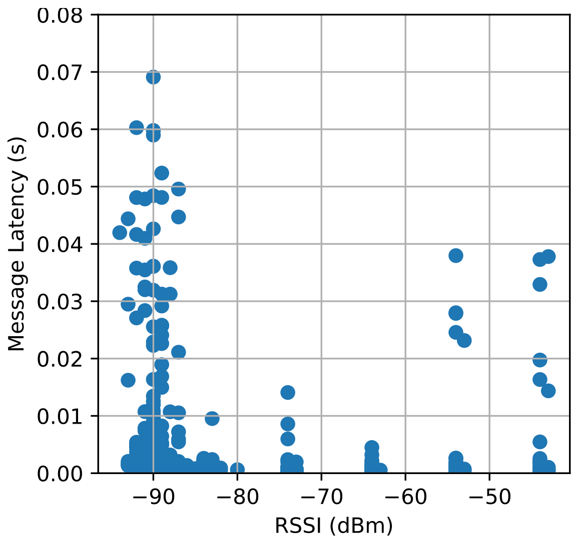


Figure 5.7: Correlation between the message latency and the RSSI values by the sniffer.

We now present an example of deploying the proposed GDB approach in industrial wireless analysis. During the trial run time, we varied an RF attenuator value in the single wireless link. The attenuation can take the values $\{0, 10, 20, 30, 40, 50, 60\}$ dB. We evaluate the message latency as the difference between the receive and transmit times of a message including transmission, processing, and retransmission times. Each message has been coupled to a QoS report that is the one reported at the closest time instant before the message transmit time. One of the parameters in the QoS report is the RSSI value captured by the Sniffer colocated with the supervisor's wireless adapter.

In Fig. 5.7, we present a scatter plot showing the correlation between the message latency in seconds to the measured RSSI values by the sniffer in dBm. The figure shows that the latency is higher at the lower RSSI values due to the increased number of retransmissions. Generally, an IEEE 802.11 transmission can occur using different IEEE 802.11 mode and modulation and coding scheme (MCS) based on the channel quality. At the RSSI of -90 dBm, the receiver should operate at the most robust communications mode and the lowest MCS index. However, retransmissions still occur due to having the received power near the sensitivity of the supervisor's wireless adapter. As shown in Fig. 5.7, retransmissions may occur at other RSSI values as well when the transmitter selects a higher mode of transmission and a higher MCS index. In this case, we assert that the receiver is operating close to the marginal sensitivity for a given mode (e.g., 802.11n) and MCS index. We observed that the transmitter switches to a lower MCS index for the retransmitted messages, which supports our supposition. Therefore, latency can in fact be high for better RSSI values. This effect is illustrated in Fig. 5.7 where certain messages can have latency values at -43 dBm, which are comparable to those in the case of -90 dBm.

5.5/ Future Direction

We have presented the general architecture of a performance evaluation database. Future work will include developing query algorithms for the calculation of performance metrics as well as correlation of network events to the physical performance of the manufacturing system. Algorithms will be developed to indicate locations in time of lost information making more direct performance correlations possible. Beyond performance evaluation of the manufacturing system, we believe that the graph database approach enables anomaly detection because relationships within the data are intrinsically stored and thus efficiently queried. The structure of the information is important within a graph database, and defining the relationships such that the paths through nodes may be discovered is essential to efficient queries and discovery of hidden correlations. Therefore, more research will be done in the modification of the presented schema. Machine learning will be applied for the detection of anomalies, performance degradation, signal quality, and network performance enhancement through more efficient resource allocation. Our plans also include online database insertions to enable the demonstration of online operation of the database. We also intend to examine the development of better control system strategies that mitigate network losses and delays. Since this approach is indifferent to the communications protocols used, we intend to extend our database approach to include various protocols, radio bands such as millimeter wave bands for 5G communications, and different use cases to include mobile robotic platforms and safety critical systems.

5.6/ Conclusions

We have presented in this paper a novel approach to capturing network and operational event information from a factory workcell with the purposes of 1) capturing and storing of network and operational events, 2) calculating performance metrics of the network, and 3) discovering performance dependencies between the network and the physical assembly of the workcell. Using a graph database, we have demonstrated that it is possible to construct such a database, compute network performance metrics and discover correlations. We have also developed the capability of examining the correlation between network events and the performance of physical actions. This will be a source of further research.

Future progress and measurement data will be deposited in the NIST public domain repository as a reference for industrial traffic modeling efforts and comparative studies on industrial wireless technologies [142].

6

Machine Learning Application: Force Seeking System

Cyber-physical systems are systems governed by the laws of physics that are tightly controlled by computer-based algorithms and network-based sensing and actuation. Wireless communication technology is envisioned to play a primary role in conducting the information flows within such systems. A practical industrial wireless use case involving a robot manipulator control system, an integrated wireless force-torque sensor, and a remote vision-based observer is constructed and the performance of the cyber-physical system is examined. By using readings from the remote observer, an estimation system is developed using machine learning regression techniques. We demonstrate the practicality of combining statistical analysis with machine learning to indirectly estimate signal-to-interference of the wireless communication link using measurements from the remote observer. Results from the statistical analysis and the performance of the machine learning system are presented.

Wireless communications plays an essential role in the vision of future cyber-physical systems (CPS) which includes having more sensors and actuators, and, hence, more information transferred wirelessly. Many system and environmental features of industrial CPS affect the success of wireless communications on the factory floor. In this article, we consider a representative industrial CPS use case of a robot arm control system equipped with a force-torque sensor. Movement of the arm is controlled by a robot controller applying a downward pressure on a spring assembly until a predetermined force is detected. This movement of the robot arm is tracked by a vision-based ground truth measurement system. This remote observer provides readings about the position of the robot arm where these readings are used to estimate the signal-to-interference ratio of the wireless link. A supervised machine learning (ML) approach is used for the wireless channel quality estimation. In this paper, we study the impact of selected system features on the estimation performance of various ML algorithms and compare their performance. Moreover, we investigate the impact of the training and the estimation period on the performance of the proposed approach. The results provide insights about the impact of wireless communications on cyber-physical systems and an example of employing machine learning to improve industrial wireless deployments.

6.1/ Introduction

Industrial wireless systems (IWSs) are being deployed in various industrial environments due to the advances of wireless protocols and devices for cyber-physical systems (CPSs). Application domains for IWSs include flexible manufacturing, safety, process control, alerting and monitoring [131]. The advantages of deploying wireless communications in industrial applications due to the absence of cabling include ease of scale, flexibility, and lower cost compared the wired counterpart. Nevertheless, there are challenges in wireless deployments [102, 123, 138]. The main cause of these challenges is the unpredictable and random nature of wireless channels. Challenges include latency uncertainty, error uncertainty, and increased information loss when operating in the presence of significant interference and limited spectral resources [103]. In addition, the quality of wireless data communications is impacted by various wireless channel impairments such as path loss, fading, multi-path, and interference. As a result, a careful design of wireless communications and control networks is required to deal with these impairments [94, 116].

One of the major challenges in designing IWSs and the underlying industrial systems is interference detection and mitigation. Interference can result from various narrow-band or wide-band sources including coexisting wireless systems, intentional jamming sources, and non-communications intended devices such as industrial equipment and microwave ovens [70]. Interference can degrade the communication quality of service (QoS) significantly and hence IWS designers consider various interference management techniques.

In [145], we have presented a method that deploys random forest regression to estimate the signal to interference ratio (SIR) of the communication channel within a robotic arm force-seeking scenario in which the force value signal is transmitted over a wireless local area network (WLAN) [46]. In that work, we have presented the testbed setup, the statistical relations between various measured features, and the performance of the proposed machine learning random forest algorithm as in [145].

In this work, we deploy the same testbed setup to explore, in more detail, the impact of machine learning on the performance of the detection algorithm. We also endeavour to understand the impact of various features in the training data set. Hence, we use position data from a vision-based tracking system, a distant observer, to train a channel quality estimator to infer the SIR experienced by both the wireless access point and the wireless station used within the experiment. Five different features are extracted from the position data captured by the vision system. We summarize the contributions of this paper as follows:

- We briefly explain the proposed algorithm for SIR estimation, the testbed setup, and the features extracted from the position data.
- We compare various machine learning regression schemes for SIR estimation, thereby demonstrating the superior performance of various ensemble-based approaches.
- We study the impact of individual features on the performance of the proposed algorithm to understand the correlation between the interference level to each of these features. Hence, we better understand the correlation between physical systems behavior and the underlying quality of the wireless communications channel.
- Finally, we study the impact of the measurement interval and the training size on the performance.

6.2/ Related Work

In the literature, two types of interference signals are considered, namely, intentional or unintentional interference. Methods to estimate, avoid, or mitigate interference are required for the deployment of reliable and deterministic IWSs. Machine learning has been widely used to detect and estimate interference information to enhance the performance of interference managment algorithms.

The interference analysis in cyber-physical systems (CPSs) has been considered in multiple works for various scenarios. In [141], in-network interference mitigation techniques are discussed for ultra reliable low-latency wireless communications systems. The paper focused on mutual interference mitigation in an industrial automation setting, where multiple transmissions from controllers to actuators interfere with each other. In [149], an interference mitigating receiver architecture is proposed. The application scenarios are smart homes and modern factories where dense wireless communications devices exist. Moreover, in [57], interference cancellation of transmissions from neighboring cells in a 5G cellular network is presented. In [113], a method using a dedicated node for link quality estimation (LQE) obtained through received data packets to identify interference and multi-path without introducing additional traffic is presented. In [36], a taxonomy of channel link quality techniques is presented providing a valuable survey on LQE algorithms and asserting the importance of link quality estimation in IWSs. In [126], failure analysis and wireless network troubleshooting are performed whenever the CPS is not functioning properly. Interference analysis is one major part of the troubleshooting procedure which is performed through traffic patterns and wireless spectrum analysis. Also, in [76], the use of spectrum analysis for interference detection and estimation is proposed for IWSs.

On the other hand, intended interference (i.e., jamming) can lead to service denial or poor performance in wireless networks. In [129], a literature review was presented which includes an overview of recent research efforts on networked control systems under denial-of-service attacks such as jamming attacks in wireless channels. One of the discussed challenges is how to achieve ultra-reliable low-latency ”signalling” within industrial applications. In [147], a discussion is also provided on the recent developments concerning the design of attack-resilient control and communication protocols. Generally, a jamming attacker can block transmission of packets by emitting strong interference signals to a wireless channel [16, 34]. Jamming attacks can target various wireless technologies and hence can become a major concern for control systems, since they are easy to launch [34]. It was shown in [61] that off-the-shelf hardware can be used for generating jamming attacks on wireless networks. In cases of physical-layer attacks, the jamming attacker targets a frequency band and is not required to follow the wireless protocol where it can cause a decrease in the SIR thus preventing the receiver from successfully detecting transmitted packets [61]. In the case of MAC-layer attacks, both the packet sender and the jamming attacker operate on the same channel; the jamming attacker's goal is to cause packet collisions. In [139], the authors evaluated the CPSs resilience to jamming attacks that disrupt wireless communications. They considered three jamming strategies which are the constant, random, and protocol-aware jamming. They showed through experimental results that various CPS control schemes are susceptible to constant and random jamming while the time-triggered control schemes are susceptible to protocol-aware jamming. Moreover, resilience of CPSs is also considered in [39, 63, 69, 109] where periodic jamming is considered in [39] while the jamming strategy in [63, 69, 109] is neither known nor pre-fixed.

Machine learning has been used for detection and estimation of jamming attacks. In [148], an unsupervised machine learning algorithm based on a multi-layer autoencoder is used to extract the interference source spectrum features. These features are then used to distinguish interference sources type and location without labeling measured data. In [112], an unsupervised approach using a recurrent neural network to detect anomalies in the CPS performance and identify attacked sensors. In [92], a behavior based machine learning intrusion detection approach is proposed to detect attacks at the physical process layer. The results are validated through experimental study of a real modern water treatment facility. In [43], the viability of machine learning methods in detecting the new threat scenarios of command and data injection is assessed. In that work, command and control communications in a critical infrastructure setting are monitored and vetted against examples of benign and malicious command traffic to identify potential attack events. In [58], the authors assessed discriminating types of power system disturbances through machine learning by detecting jamming attacks. They evaluated various machine learning methods as disturbance discriminators and discuss the practical implications for deploying machine learning systems as an enhancement to existing power system architectures.

Therefore, in the literature, it was shown that LQE is one important but insufficient aspect of assessing the impact of link quality on a CPS. We assert that by jointly observing the performance of the physical and wireless components of a CPS,the complete perspective of the quality of the wireless link and its impact on physical performance can be obtained. Since interference is such an important topic in the wireless CPS, we are motivated to propose a method that simultaneously (1) makes observations of the physical system using ground truth measurements, and (2) infers the quality of the wireless communication system in terms of SIR using an experimental model of a relevant use case found in industry.

6.3/ Robot Arm Force-Seeking Application

6.3.1/ General Construction and Operation

A robotic force-seeking apparatus is constructed using a Universal Robots UR-3 collaborative robot. As illustrated in Fig. 6.1, the robot is fitted with a six degrees-of-freedom (DOF) force-torque sensor (FTS) followed by a probe. The robot is programmed to apply a downward force, $F(t)$, in the z direction until a force exceeding a threshold, F_t, is reported to the controller. The robot encounters the force threshold through a fixed plunger-spring assembly. The force in the spring is governed by the equation $F(t) = kl$ where k is the spring constant and l is the spring deflection. The robot will push the spring downward repeatedly for the duration of 30 minutes. Plunger movement is limited by a hard stop which will reset the height of the robot arm. A photograph of the force-seeking apparatus is shown in Fig. 6.2. The illuminated spheres shown in the photo are infrared markers

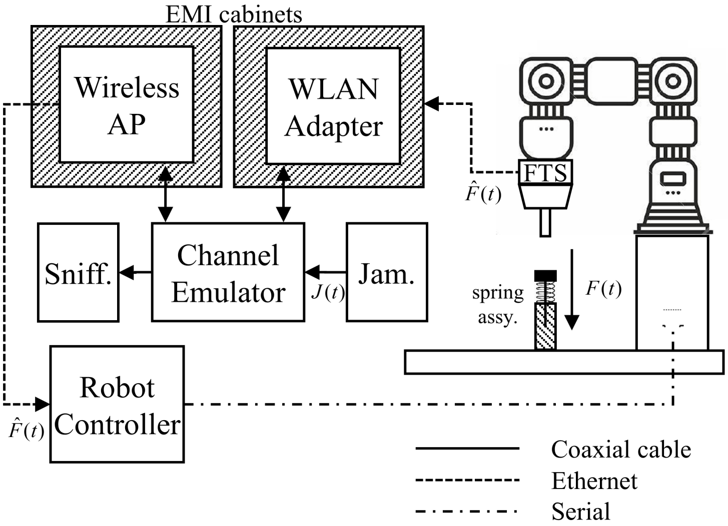


Figure 6.1: Robot force-seeking spring system with controlled wireless channel emulation and interference injection.

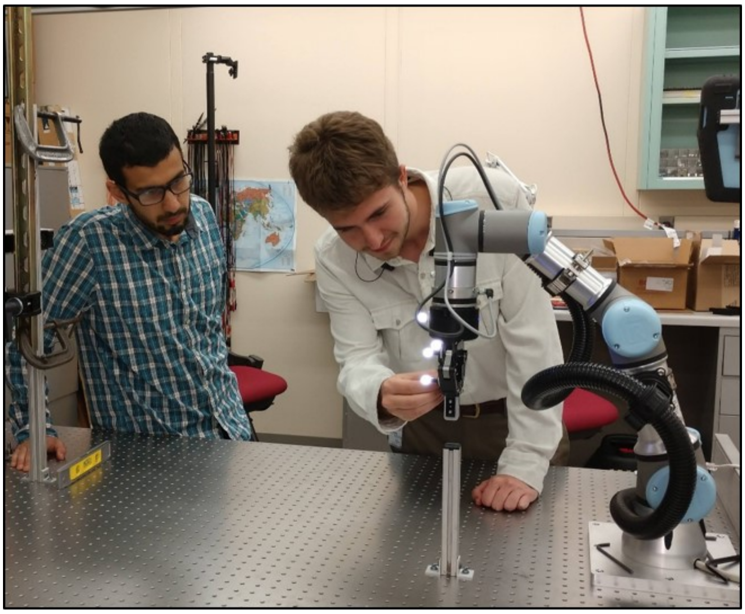


Figure 6.2: A photograph of the robot force-seeking experiment shows the robotic arm, the spring-based plunger, and the visual markers used for position tracking.

used by the remote observer to track the position of the probe.

6.3.2/ Components

Referring again to Fig. 6.1, the system is composed of the following components:

- **Robot:** The robotic arm applies a downward force along the z-axis to the plunger-spring assembly. The robot is a 6-DOF rigid body manipulator in which all joints have a full 360 degrees of motion. For the experiment, the robot is configured such that it would replicate the action of a robot applying a force to push a small part into place within an automotive assembly work-cell [89]. The robot is mounted on a motionless optics table in which mechanical vibration is dampened.

- **Robot Controller:** The robot controller (RC) provides the motion control function of all joints on the robot. The RC is responsible for controlling motion while searching for a force feedback signal.

- **Force Torque Sensor:** The force torque sensor (FTS) provides continuous force and torque readings at a rate of 125 Hz. Readings from the FTS include force measurements in Newtons along the three Cartesian axes, x, y, and z, and three torque readings in Newton-meters (N-m) about each axis. The FTS is designed to communicate with the RC through an Ethernet connection.

- **Robot End-effector:** The robot end-effector (REEF) is a rigid body probe attached to the end of the robot arm just after the FTS. The REEF is used to make contact with the plunger-spring assembly.

- **Wireless Components:** The wireless Ethernet adapter (WEA) replaces the Ethernet connection between the FTS and the RC with a Wi-Fi connection. The adapter supports the IEEE 802.11 b, g, n, and ac modes. The WEA connects to the RC through a wireless access point (WAP).

- **Jammer:** The jammer provides the source of interference, J, which is directly injected into the wireless channel. For simplicity, interference is injected as non-modulated additive white Gaussian noise (AWGN). The power of J at each receiver is determined by its distance to the jammer.

- **Channel Emulator:** The channel emulator (CE) provides the capability to control the electromagnetic channel between the WEA and the WAP. The CE supports frequencies between 1 GHz and 6 Ghz and has an instant bandwidth of 250 MHz. It also supports a channel impulse response of 13 taps with a minimum time resolution

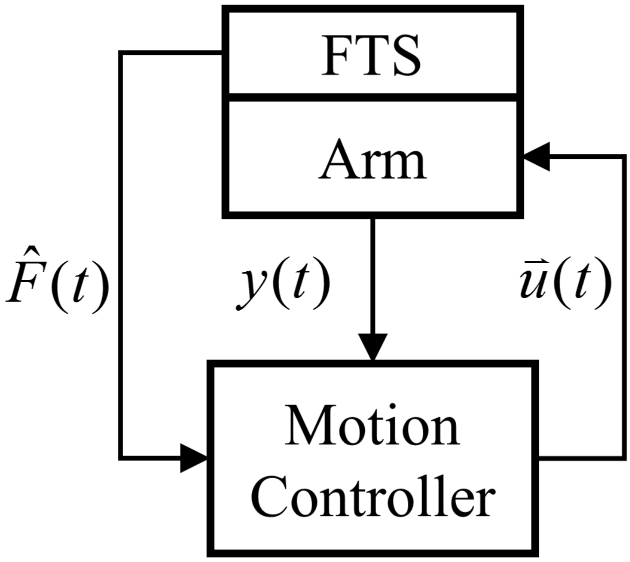


Figure 6.3: Feedback signal flow model of the force-seeking controller

of 4 ns making the replication of close-quarter multi-path reflections possible. As shown in Fig. 6.1, all wireless devices are connected to the CE.

- **Electromagnetic Interference Cabinets:** The electromagnetic interference (EMI) cabinets provide isolation between devices such that communication between devices does not occur through radiated leakage.

- **Wireless Sniffer:** A wireless sniffer (WS) is used to monitor wireless traffic during operation. The sniffer is connected to a laptop computer running Wireshark, and packet logs are used for offline analysis of network events.

- **Vision Tracking System:** An OptiTrack VS120 Trio is used as the vision-based tracking system (VTS) to produce accurate ground truth measurements of the probe position. Position estimates along the z-axis are captured at the maximum video frame rate of 120 frames per second. Each estimate includes time and position.

6.3.3/ Robot Arm Motion Control

A diagram of the control system for the robotic manipulator is shown in Fig. 6.3. The UR-3 is constructed of the manipulator assembly and the RC assembly. The internal

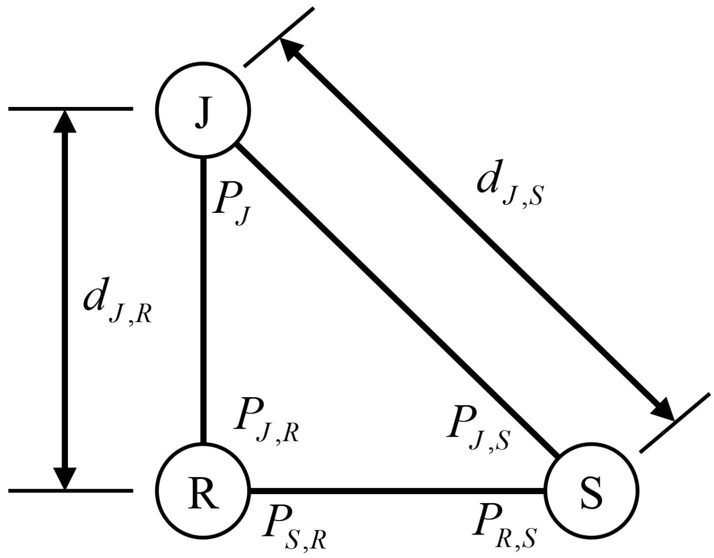


Figure 6.4: RF emulation scenario design of the robotic force-seeking scenario.

construction of the robot arm is irrelevant for this experiment, but it is assumed that the arm produces encoder positions $y(t)$ for each joint. It is also assumed that the robot arm accepts actuation signals $\vec{u}(t)$ from the motor drives located in the RC. Both $y(t)$ and $\vec{u}(t)$ are conveyed through wired connections. The force sensor signal $\hat{F}(t)$ is produced by the FTS and is conveyed via an IEEE 802.11 wireless connection. The RC is programmed to move a probe connected to the end of the manipulator downward along a linear path until a force of at least 5 N is detected. The RC will not move the arm during the force-seeking operation unless it receives an FTS signal; therefore, the duration and continuity of the movement of the arm will be impacted by unreliable communication between the FTS and the RC.

6.3.4/ RF Emulation Scenario

The CE is programmed using a graphical user interface in which the wireless scenario is modeled. Scenarios are composed of radios, platforms, and links. Platforms represent the physical machine on which a radio may be deployed. Platforms may be mobile or stationary, ground-based or aerial. Radios are assigned to platforms, and each radio is associated to a physical port on the emulator. Links are representations of the physical connections between radios. Each link has an associated path loss and multi-path representation. Path loss is implemented according to Friis equation [53] simplified as $P_r = P_t + C - 10\gamma \log_{10}(d)$, where P_r is the received power, P_t is the transmitted power, C is a characteristic constant representing characteristics of the channel and electronics, γ is the path loss exponent, and d is the distance between transmitter and receiver. For simplicity, we assume that path loss occurs in accordance with the square of the distance ($\gamma = 2$); however, in practice, the path loss exponent is usually greater, causing a more rapid loss of signal power over the same distance [107]. Since the focus of this work is to infer signal quality from ground truth measurements, the path loss exponent is inconsequential to our analysis.

Shown in Fig. 6.4 is the general scenario for the wireless communication system employed for the force feedback control system. In the figure, there are three nodes, a wireless router (R), a wireless station (S), and a jammer (J). The router and station transmit with nominal power that is dependent upon the 802.11 protocol. The jammer transmits with constant power, and its impact on the scenario depends on its position relative to the other nodes. The distance between J and R is denoted by $d_{J,R}$, and the distance between the J and S is denoted by $d_{J,S}$. The resulting signal-to-interference power ratio (SIR) for the router is defined in decibels as $SIR_{J,R} = P_{S,R} - P_{J,R}$ which is the power received by the router of the station signal divided by the power of interference experienced at the router. Similarly, the SIR experienced at the station is defined as $SIR_{J,S} = P_{R,S} - P_{J,S}$ which is the received signal power of the router at the station divided by the interference power experienced at the station.

For each experiment, the location of the J is adjusted to produce a desired SIR. Each time the location of J is changed, the robot is allowed to operate for a period of 30 minutes. This included periods of inaction by the robot when the SIR prohibits movement of the arm. The SIR setting was validated for each run using a real-time spectrum analyzer connected directly to the emulator.

6.4/ Initial Investigations

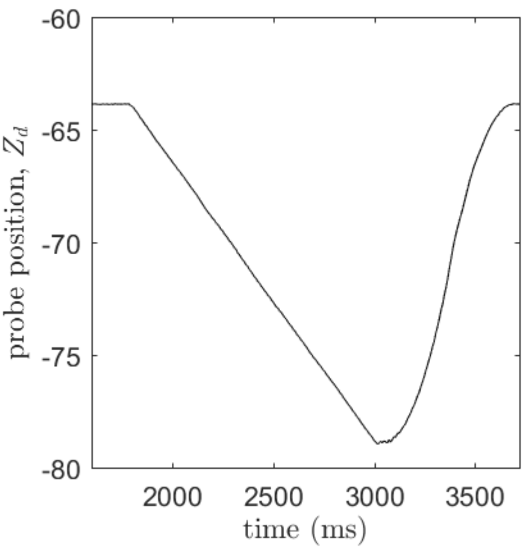
The contents of this section explain the approach, methodology, and results of the initial investigations using machine learning to infer the signal-to-interference of a single radio link using situational awareness information from a camera system as published in [146] with data made available [143].

6.4.1/ Data Analysis

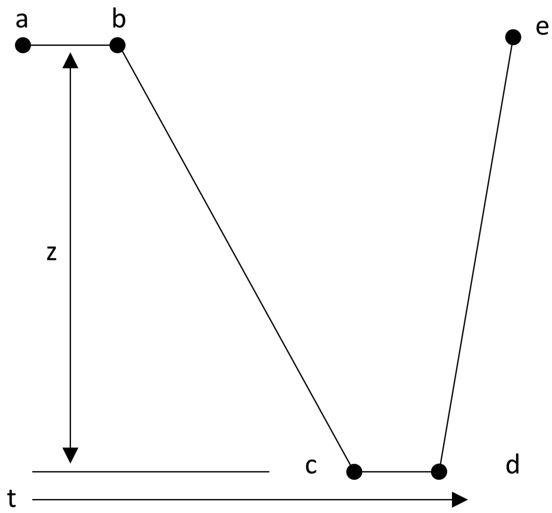
The data analysis process for the experiment is divided into four parts: raw data collection, data cleaning and feature extraction, training, and the operation of the SIR estimation. The raw data was produced as an output of the VTS as a time series of z-axis position. Feature extraction was conducted in MATLAB by following the time series and extracting or calculating features for each iteration. Once features were extracted, a statistical analysis of the features was conducted to determine the variability of the features as a function of SIR. Statistical analyses included visual inspection of histograms of each factor and an inspection of the correlation coefficients over the range of SIRs. A discussion of the statistical results is provided in 6.4.3.1 which demonstrates suitability of the use of position measurements for machine learning. Training of a machine learning algorithm followed. The machine learning algorithm was programmed in Python using the Sci-kit Learn library [5].

6.4.2/ Feature Extraction

Feature extraction begins with a time series of position of the probe through successive iterations of the plunger applying force to the spring and then returning to its home position. A sample time series of the z-axis position of the probe is as shown in Fig. 6.5a. Rather than using the time series directly, a more convenient and practical solution is to extract features that represent aspects that may be useful for analysis and machine learning algorithms. This reduces the number of learning dimensions and usually im-



(a) sample time series of probe position in mm



(b) feature extraction model

Figure 6.5: A time-series sample (a) of a single iteration of the measured z-axis probe position and (b) the corresponding model for feature extraction.

proves computation efficiency. The selected features are illustrated in Fig. 6.5b. Shown in the model, the probe begins at its home position, **a**. It will not begin its downward motion until it receives sufficient FTS readings. Marker **b** indicates the beginning of the probes descent. Marker **c** represents that point in which the probe descends below a predetermined threshold, and marker **d** represents the position in which the probe begins its return ascent to the home position. Finally the probe returns to the home position as indicated by marker **e**. Therefore, the extracted features of each successive iteration is defined as follows:

- **Feature Z_d:** The length of the probe's descent measured in millimeters,
- **Feature Δt_{ab}:** The duration in seconds the the robot waits before moving the probe along its descent,
- **Feature Δt_{bc}:** The duration in seconds of the time that the robot takes to move the probe beyond the threshold, Z_{th}, of -77 mm,
- **Feature Δt_{cd}:** The duration in which the probe dwells below Z_{th} and the speed of the probe remains under 0.15 mm/sec,
- **Feature Δt_{ae}:** The duration of the full iteration as measured from the home position, **a**, to the next home position, **e**.

6.4.2.1/ Statistical Analysis

Each factor was visually examined to assess its variability as a function of the SIR. In order to predict the SIR given a set of measurements of the dynamics of the physical system, sufficient variability is needed. This assessment was performed visually using histograms as a basis for comparison. The factors Z_d and Δt_{bc} were used for examination of the data using histograms.

In addition, it would be helpful to show that the factors are uncorrelated as a function of SIR demonstrating a further level of confidence that each factor will be useful to a machine learning algorithm. This assessment was accomplished by computing the correlation coefficient matrix of the extracted factors as defined by the Pearson product-moment method [164]. The correlation coefficient matrix is a covariance matrix that is normalized by the product of the standard deviations of two factors being compared according to $\rho_{X,Y} = cov(X,Y)/(\sigma_X \sigma_Y)$. Since each factor correlates exactly with itself, a correlation matrix should have values of 1 along the diagonal. Other elements of the matrix will take on values between -1 and 1. A visual inspection of the coefficient matrices will show how strongly selected factors vary together. Correlation can be viewed as a function of SIR to verify that factors are independently applicable to a learning algorithm. The objective of factor selection is, therefore, to choose factors that are highly uncorrelated and yet still vary appreciably [8].

6.4.2.2/ Machine Learning

In order to learn the SIR level from observing the various features, we leverage the random forest model [12]. Random forest is an ensemble of decision trees with random feature selection which can be used for classification or regression based on the predicted output space. Deploying random forest in machine learning has been successful in various applications such as [35, 66, 85]. Its main advantages are that it is stable, fast to compute, and insusceptible to over-fitting.

In this work, we deploy the random forest model for SIR regression using the five features defined in 6.4.2. These features are evaluated for each iteration of the probe movement. We define a data segment which is composed of a number of successive iterations and we denote the segment size by M. As a result, we use the random forest regression model to get an input vector of size $5M$ and regression output of the corresponding SIR value. The random forest is selected because it is computationally efficient with high-dimensional data and it is robust for outliers and data non-linearity.

We start by training the random forest regression model by taking a fixed number of segments for each SIR labelled data. We denote the size of the training set for each SIR level by T. The rest of the measurements are used for testing. In general, the proposed machine learning approach will deploy a sliding window approach of size M to collect the features of the force-seeking use case to estimate the current level of SIR at various nodes of the wireless network.

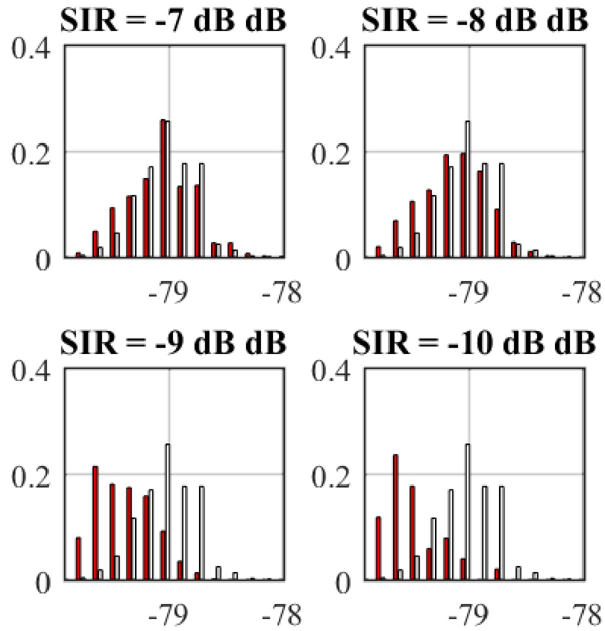
6.4.3/ Results

The results in this section are presented from an experimental run in which the jammer **J** interferes with the router, **R**, while communication is conducted using a mixed mode of IEEE 802.11 b and g [46]. Analyses using histograms and covariance are presented in Section 6.4.3.1 followed by results of the machine learning application in Section 6.4.3.2.

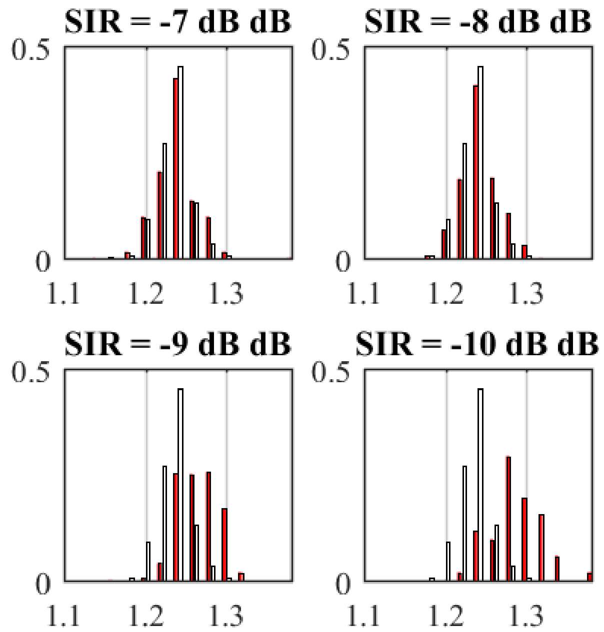
6.4.3.1/ Statistical Analysis

Analysis of Factors Using Histograms The results of the histogram analyses for the z-axis position of the probe and the probe descent delay are shown in Fig. 6.6a and Fig. 6.6b, respectively. The expectation of the histogram analysis was that Z_d and the ΔT_{bc} would exhibit appreciable variation that may be observed through a visual inspection. This was indeed the case. Referring to Fig. 6.6a, a visual inspection reveals that the minimum z-axis position for each iteration skews to lower positions for lower SIR values and higher positions for higher SIR values. This implies that the controller algorithm responds faster to force sensor readings at higher SIR values than lower values. Similarly, by observing the plunge delay, Δt_{bc}, the controller takes more time to respond at lower SIR values than at higher values. This behavior is exemplified by the probability skew shown in the histograms.

Factor Correlation Coefficient Analysis Correlation coefficients were calculated for each of the five factors defined in Section 6.4.2 and correlation coefficients matrices were produced for each of the SIR values used. The correlation coefficient matrices for SIR values of -9, -8, and -7 are shown in Tables 6.1-6.3, respectively. Inspection of the correlation coefficient tables indicate that the factors are mostly uncorrelated across SIR values except for the clear correlation between plunge delay and plunge depth. Low correlation values demonstrate a necessary but not sufficient condition for the independent applicability factors to machine learning. If desired, either Δt_{bc} or Z_d could be omitted as they are strongly correlated and therefore provide redundant information.



(a) z-axis positione



(b) Plunge delay

Figure 6.6: Variations in probability distributions of the z-axis position (a) and the plunge delay (b) indicate that machine learning may be effective in inferring information about the underlying communication channel. In the figure, the baseline case of infinite SIR is depicted as a histogram with white bars, and the experimental case is depicted as a histogram with red bars.

Table 6.1: Correlation Coefficients for $-9\ dB$ SIR

	Δt_{ab}	Δt_{bc}	Z_d	Δt_{cd}	Δt_{ae}
Δt_{ab}	1	0.04	0.04	0	0.56
Δt_{bc}	0.04	1	-0.96	-0.08	0.18
Z_d	0.04	-0.96	1	0.03	-0.01
Δt_{cd}	0	-0.08	0.03	1	0
Δt_{ae}	0.56	0.18	-0.01	0	1

Table 6.2: Correlation Coefficients for $-8\ dB$ SIR

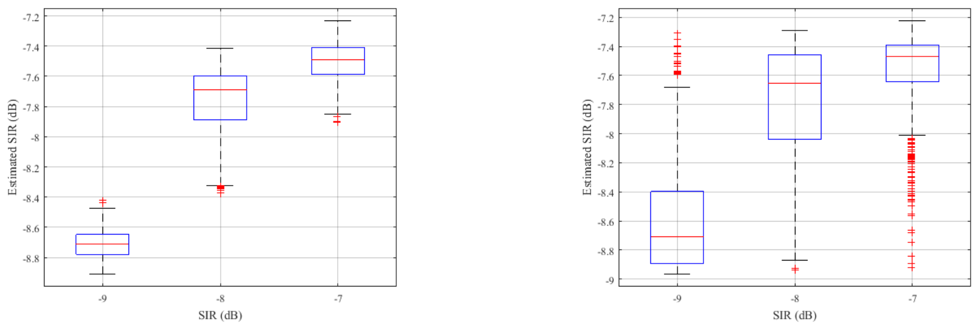
	Δt_{ab}	Δt_{bc}	Z_d	Δt_{cd}	Δt_{ae}
Δt_{ab}	1	0.01	-0.05	-0.06	0.58
Δt_{bc}	0.01	1	-0.99	-0.13	0.1
Z_d	-0.05	-0.99	1	0.07	-0.1
Δt_{cd}	-0.06	-0.13	0.07	1	-0.03
Δt_{ae}	0.58	0.1	-0.1	-0.03	1

Table 6.3: Correlation Coefficients for $-7\ dB$ SIR

	Δt_{ab}	Δt_{bc}	Z_d	Δt_{cd}	Δt_{ae}
Δt_{ab}	1	-0.05	-0.04	0.09	0.01
Δt_{bc}	-0.05	1	-0.93	-0.17	0.05
Z_d	-0.04	-0.93	1	0.08	-0.05
Δt_{cd}	0.09	-0.17	0.08	1	-0.02
Δt_{ae}	0.01	0.05	-0.05	-0.02	1

6.4.3.2/ Machine Learning Results

We deploy the proposed machine learning approach to three values of the SIR, -9, -8, and -7 dB. We start by showing the output of the random forest regression model for two values of the segment size M. We set the training set size $T = 200$ for each SIR value. We use the random forest model with a number of estimators of 500 and a tree depth of 5. In Fig. 6.7, we present the box plots of the predicted SIRs against the correct value of the corresponding SIR for $M = 100$ and $M = 1$. Generally, increasing the value of M increases the acquisition time for the input data for the random forest model while enhancing the performance of the algorithm. By setting $M = 1$, we notice that the predicted values of SIR are widely spread around the median and a large number of outliers exists. However, by increasing M, we have much less variations in the predicted SIRs and a smaller number of outliers.



(a) [$M = 100$ (b) [$M = 1$

Figure 6.7: Predicted SIR versus actual SIR for the cases of (a) $M = 100$ and (b) $M = 1$. The box plots show the median value while the bottom and top edges of the box indicate the 25th and 75th percentiles. Statistical outliers are shown as red + signs.

In Fig. 6.8, we present the two criteria for measuring the performance of the proposed SIR estimation algorithm. We show the performance against the segment size M. The first criterion is the mean squared error where the mean of the squared error between the estimated SIR and the actual SIR values is calculated. The second criterion is the variance score which is a statistical measure of how close the data are to the fitted regression line. We use the r-squared variance score that is defined as the ratio between the total variance explained by model and total variance of the data [108]. In this figure the improvement in the performance against the segment size is demonstrated.

6.4.4/ Conclusion

In this paper we have presented a practical use case of a wireless force-torque feedback control system that could be deployed in a manufacturing assembly system such as a pick-and-place or assembly operation. A 6-DOF force sensor was connected to a robot controller tasked with moving a probe along a linear path until an opposing force exceeding 5 N was detected. We demonstrated that the reliability of the wireless communication system directly impacts the repeatability performance of the physical system. We also demonstrated that the quality of the underlying wireless channel may be inferred by observing the position of the probe along a single spatial dimension and applying machine learning to predict the signal-to-interference ratio. Our findings provide motivation for applying machine learning to larger more complex systems with high degrees of free-

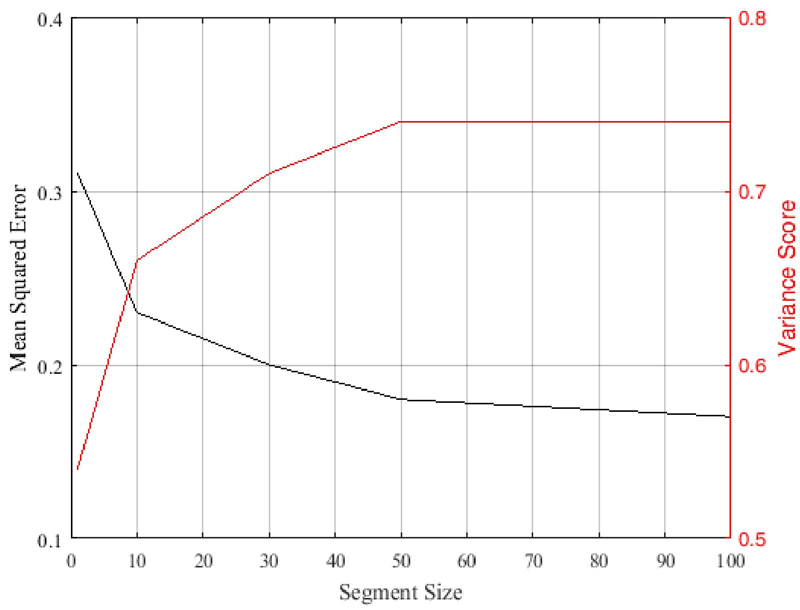


Figure 6.8: The performance of the random forest regression model against M.

dom. Future work will extend to the inclusion of more descriptive factors, the addition of network information such as the wireless protocol mode, and the addition of a larger number of variables tracked by many remote observers. Experimentation with neural networks and deep learning to improve prediction accuracy and better generalization will be of great values to wireless operations in factories. Finally, the applications of online machine learning techniques to this and other use cases could provide significant benefits to the manufacturing community.

6.5/ Subsequent Investigations

The contents of this section explain the subsequent analysis explanding on the approach, methodology, and results of the initial investigations using machine learning to infer the signal-to-interference of a single radio link using situational awareness information from a camera system as published in [146]. In this further investigation, the performance of the machine learning algorithms themselves were investigated to determine optimal selection given the particular use case. Publication is forthcoming [152].

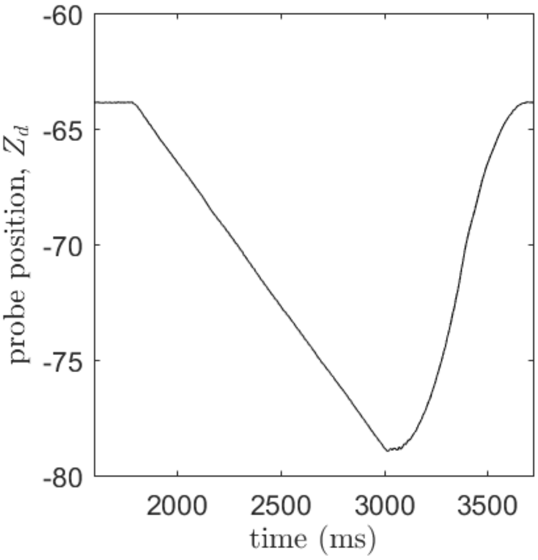
6.5.1/ Data Analysis

The data analysis process for the experiment is divided into four parts: raw data collection, data cleaning and feature extraction, training, and the operation of the SIR estimation. The raw data was produced as an output of the VTS as a time series of z-axis position. Feature extraction was conducted in MATLAB by following the time series and extracting or calculating features for each iteration. Once features were extracted, a statistical analysis of the features was conducted to determine the variability of the features as a function of SIR [145]. Training of a machine learning algorithm followed. The machine learning algorithm was programmed in Python using the Sci-kit Learn library [5].

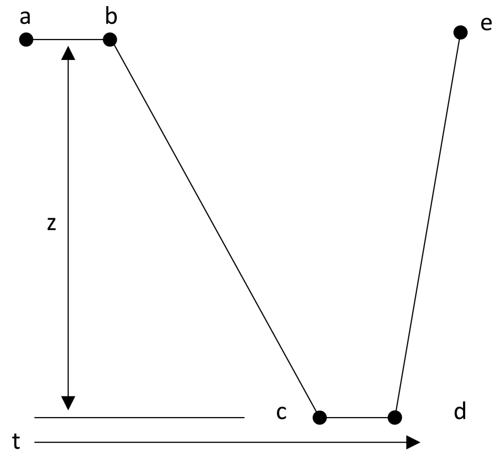
6.5.1.1/ Feature Extraction

A sample time series of the z-axis position of the probe is as shown in Fig. 6.9a. Rather than using the time series directly, a more convenient and practical solution is to extract features that represent aspects that may be useful for analysis and machine learning algorithms. The selected features are illustrated in Fig. 6.9b. Shown in the model, the probe begins at its home position, **a**. It will not begin its downward motion until it receives sufficient FTS readings. Marker **b** indicates the beginning of the probes descent. Marker **c** represents that point in which the probe descends below a predetermined threshold, and marker **d** represents the position in which the probe begins its return ascent to the home position. Finally the probe returns to the home position as indicated by marker **e**. Therefore, the extracted features of each successive iteration is defined as follows:

- **Feature Z_d:** The length of the probe's descent measured in millimeters,
- **Feature Δt_{ab}:** The duration in seconds the the robot waits before moving the probe along its descent,
- **Feature Δt_{bc}:** The duration in seconds of the time that the robot takes to move the probe beyond the threshold, Z_{th}, of -77 mm,



(a) sample time series of probe position in mm



(b) feature extraction model

Figure 6.9: A time-series sample (a) of a single iteration of the measured z-axis probe position and (b) the corresponding model for feature extraction.

- **Feature Δt_{cd}:** The duration in which the probe dwells below Z_{th} and the speed of the probe remains under 0.15 mm/sec,

- **Feature Δt_{ae}:** The duration of the full iteration as measured from the home position, **a**, to the next home position, **e**.

6.5.1.2/ ML-based SIR Estimation

In order to learn the SIR level from observing the various features, we can leverage supervised machine learning regression schemes. In this work, we compare the deployment of various machine learning algorithms for SIR regression using the five features defined in 6.5.1.1. These features are evaluated for each iteration of the probe movement. We define a data segment which is composed of a number of successive iterations and we denote the segment size by M. As a result, we use each regression model to get an input vector of size $5M$ and the regression output of the corresponding SIR value.

We start by training each regression model by taking a fixed number of segments for each SIR labelled data. We denote the size of the training set for each SIR level by T. The rest of the measurements are used for testing. In general, the proposed machine learning approach will deploy a sliding window approach of size M to collect the features of the force-seeking use case to estimate the current level of SIR at various nodes of the wireless network.

6.5.2/ Results

In this section, we consider the experimental results for 4 different settings. The dataset of all the collected data is available online [143]. The four settings are defined as follows: i) setting b/g-Router: the jamming signal impacts the router and IEEE 802.11 b/g is deployed [46], ii) setting b/g-Station: the jamming signal impacts the station and IEEE 802.11 b/g is deployed, iii) setting b/g/n-Router: the jamming signal impacts the router and IEEE 802.11 b/g/n is deployed, and iv) setting b/g/n-Station: the jamming signal impacts the station and IEEE 802.11 b/g/n is deployed.

When the jamming signal has an impact on the router, we consider 3 values of the SIR which are -9, -8, -7 dB while having 1, 2, 3 dB for the settings in which jamming has an impact on the station. Except otherwise mentioned, we set$M = 50$ and $T = 200$.

6.5.2.1/ Machine Learning Algorithm Comparison

In this subsection, we compare various regression approaches using two performance criteria, namely, the mean squared error (MSE) and the R-squared variance score [108]. R-squared variance score indicates the percentage of the variance in the dependent variable that the independent variables explain collectively. The used version of R-squared in the Sci-kit Learn library measures the strength of the relationship between your model and the dependent variable on a convenient -1 to 1 scale. The best possible outcome is 1 when predicted values capture the variance of the independent variable. It takes a value of 0 when the predicted value is constant and negative values when the regression model cannot follow the trend of the data. We present the performance for different values of M. The compared algorithms are the random forest, gradient boosting, extreme gradient boosting (XGBM), decision tree, support vector machine (SVM), k-nearest neighbor, kernel ridge, and linear ridge [5, 87].

Table 6.4: MSE values of various ML algorithms for jamming setting b/g-Router

	M = 1	M = 10	M = 30	M = 50	M = 100
Random Forest	0.61	0.54	0.49	0.48	0.46
Gradient Boosting	0.56	0.55	0.47	0.45	0.44
XGBM	0.62	0.53	0.45	0.43	0.41
Decission Tree	1.07	0.99	0.87	0.91	0.97
SVM	0.92	0.99	0.98	0.97	0.96
KNN	0.73	0.74	0.73	0.74	0.77
Kernal Ridge	0.97	0.73	0.71	0.71	0.71
Linear Ridge	0.7	0.7	0.7	0.71	0.71

In Table 6.4, we present the MSE performance of various algorithms at setting b/g-Router. The ensemble-based algorithms, which are the random forest, gradient boosting, and XGBM, perform better than non-ensemble algorithms. This happens because the ensemble-based algorithms learn from the training data without having an initial model to fit thus allowing for capturing the randomness impacts on the collected data. Moreover, the XGBM gives slightly better performance than the random forest and gradient boosting algorithms except at $M = 1$. The XGBM performs gradient boosting over random set of trees and hence the superior performance. We also find it has superior variance score as well in Table 6.5. Generally, in Table 6.5, similar trends as Table 6.4 can be found for various machine learning algorithms where ensemble-based algorithms have the best performance among others and their performance is enhanced by increasing the segment size M of the measured data.

Table 6.5: Variance score values of various ML algorithms for jamming setting b/g-Router

	M = 1	M = 10	M = 30	M = 50	M = 100
Random Forest	0.15	0.2	0.3	0.35	0.35
Gradient Boosting	0.02	0.2	0.34	0.37	0.42
XGBM	0.12	0.25	0.36	0.4	0.43
Decission Tree	-0.57	-0.44	-0.36	-0.3	-0.22
SVM	-0.34	-0.38	-0.37	-0.37	-0.32
KNN	-0.05	-0.02	-0.02	-0.08	-0.04
Kernal Ridge	-0.48	-0.05	0	0	0
Linear Ridge	0.01	0.01	0	-0.01	0

Similarly, in Table 6.6, the ensemble-based algorithms perform better than other algorithms and the XGBM is the best among them. In this setting b/g/n-Station, the interference impacts the router and hence the MSE values generally higher than the corresponding cases in setting b/g-Router. In this case, the interference has a larger impact and hence larger MSE. That leads to larger distinction between the performance of the machine learning algorithms.

Table 6.6: MSE values of various ML algorithms for jamming setting b/g-Station

	M = 1	M = 10	M = 30	M = 50	M = 100
Random Forest	0.88	0.79	0.76	0.69	0.7
Gradient Boosting	0.95	0.71	0.61	0.56	0.56
XGBM	0.85	0.73	0.59	0.52	0.48
Decission Tree	1.48	1.46	1.33	1.33	1.32
SVM	1.34	1.36	1.36	1.39	1.49
KNN	1.01	1.04	1.03	1.05	1.13
Kernal Ridge	4.42	1.25	0.98	0.97	0.99
Linear Ridge	0.93	0.94	0.94	0.95	0.99

6.5.2.2/ Tuning the Random Forest and Gradient Boosting Regressors

In this subsection, we study the impacts of the number of estimators and the depth for gradient boosting and random forest algorithms. The XGBM parameters are optimized automatically when the function is called to be executed. We show the MSE performance results for setting b/g-Router while same trend holds for other system settings as well.

For random forest algorithm, we show in Table 6.7 that the tree depth has more impact on the performance than the number of the estimators (# est.). However, increasing the depth improves the performance till the value of 5 where increasing the depth cause slight improvements.

For gradient boosting, we show in Table 6.8 that a similar trend as a random forest exists where depth has a larger impact on the performance. However, increasing the depth more than 7 causes the MSE performance to degrade significantly.

Table 6.7: MSE of Random Forrest regression parameters for jamming setting b/g-Router

Depth \ # est.	100	200	300	400	500	600
1	0.64	0.64	0.64	0.63	0.63	0.63
3	0.53	0.53	0.53	0.53	0.53	0.52
5	0.5	0.5	0.5	0.48	0.48	0.48
7	0.49	0.49	0.48	0.48	0.48	0.48
9	0.48	0.48	0.47	0.47	0.47	0.47

Table 6.8: MSE of Gradient Boosting regression parameters for jamming setting b/g-Router

Depth \ # est.	100	200	300	400	500	600
1	0.48	0.47	0.46	0.46	0.45	0.46
3	0.47	0.47	0.47	0.47	0.46	0.47
5	0.48	0.47	0.47	0.47	0.47	0.47
7	0.48	0.48	0.48	0.48	0.46	0.49
9	0.58	0.51	0.5	0.5	0.57	0.58

6.5.2.3/ Impact of Data Segment Size M

In this subsection, we study the performance of the ensemble-based algorithms against the segment size M. It was shown in [145] that increasing the value of M increases the acquisition time of measurement data used for decision making and lowers the spread of predicted values around the correct value for various SIR values. In this paper, we study the impact of the three optimized algorithms employing the MSE and the variance score as performance metrics.

In Fig. 6.10, we present the performance of the random forest, gradient boosting, XGBM, and the linear ridge regressors. The linear ridge is used as a simple model-based regressor which practically cannot not be used for prediction while it is used for comparison. In this figure, increasing the value of M enhances the performance of the ensemble-based algorithms significantly. Generally, the prediction accuracy increases when multiple measurement cycles are deployed in decision making with diminishing improvement as M increases. The linear ridge algorithm shows no improvement with increasing M implying that SIR does not vary linearly with the feature set presented.

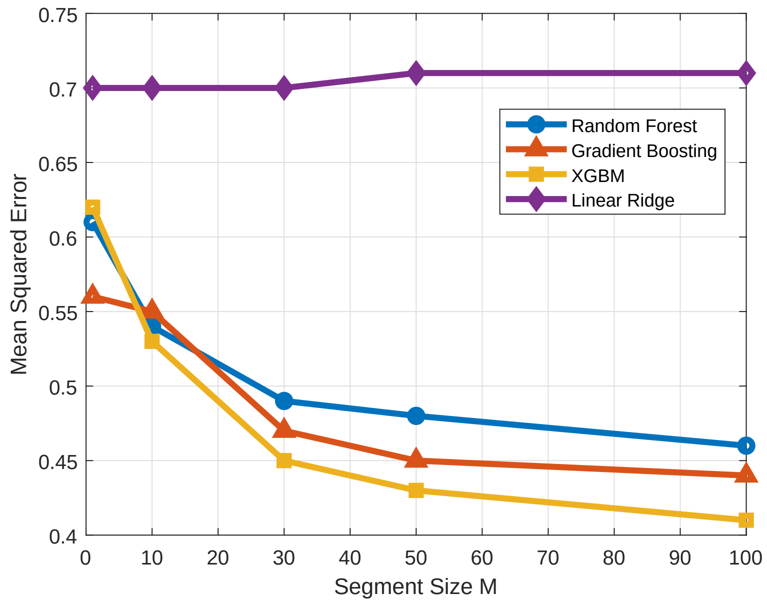


Figure 6.10: The mean squared error performance for jamming setting b/g-Router of various algorithms against M.

In Fig. 6.11, we present the variance score for the same setting b/g-Router where a similar trend is found. The ensemble-based algorithms can achieves a variance score above 0.35 when M is larger than 50.

In Fig. 6.12, the MSE of the ensemble-based algorithms is shown for Setting b/g-Station where the router is impacted by the jamming signal. The MSE values in this setting are lower than those of setting b/g-Router where the predicted SIR values are smaller because the router has better capabilities to detect signals at lower SIRs.

Finally, in Fig. 6.13, a similar scenario to Fig. 6.12 is presented where the router is impacted by the jamming signal. The difference is that at setting b/g/n-Station, a mixed IEEE802.11 b/g/n mode is allowed instead the IEEE802.11 b/g mode in setting b/g-Station. By allowing the IEEE 802.11n mode, the signal is more susceptible to interference and hence it is harder to predict the same SIR values.

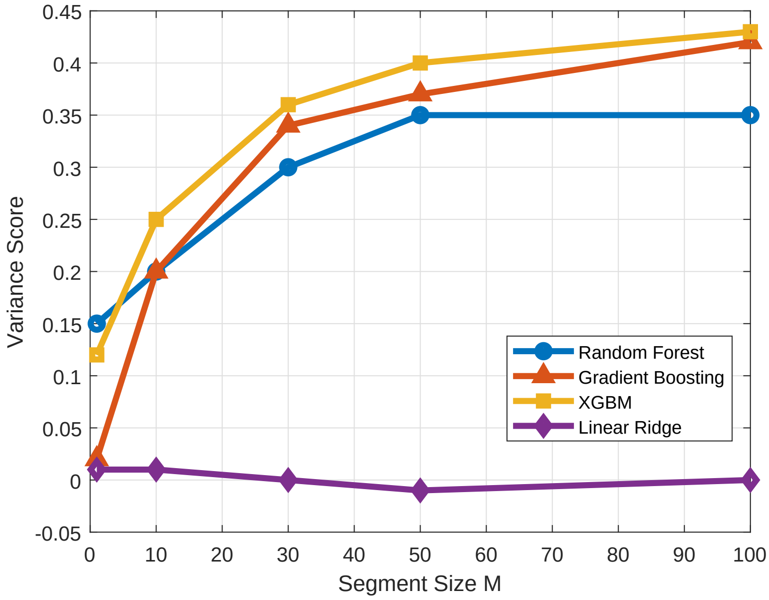


Figure 6.11: The variance score performance for jamming setting b/g-Router of various algorithms against M.

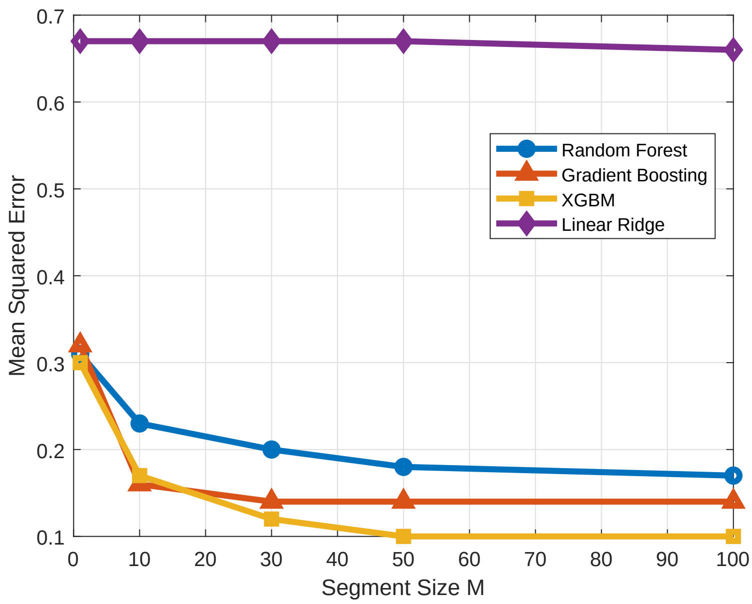


Figure 6.12: The mean squared error performance for jamming setting b/g-Station of various algorithms against M.

6.5.2.4/ Impact of Training Sequence Length T

In this subsection, we briefly discuss the impact of the training length on the performance of various algorithm. The parameter T is the length of the training sequence where each

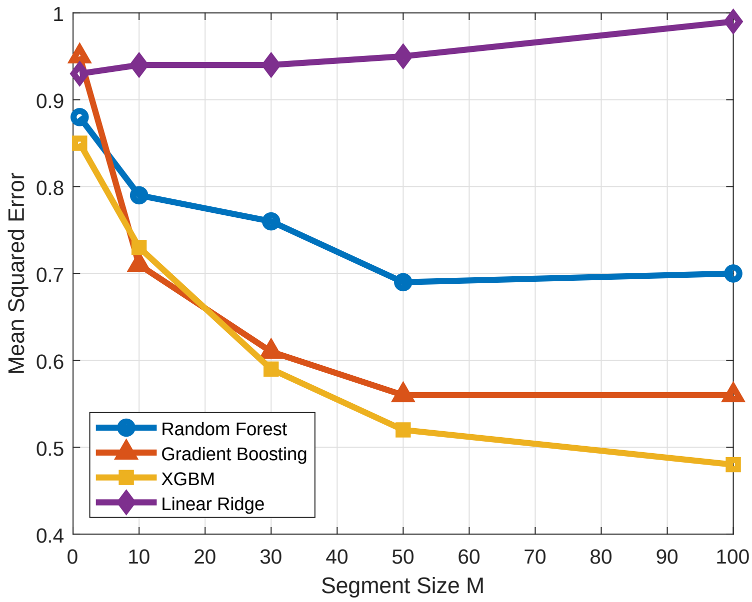


Figure 6.13: The mean squared error performance for jamming setting b/g/n-Station of various algorithms against M.

element contains M of the force seeking cycles. In the following figures, we show the MSE performance curves against T for M = 30 and 100.

In Fig. 6.14, increasing the training size T can improve the prediction performance significantly. Gradient boosting and XGBM have higher improvement rate with T than the random forest algorithm.

6.5.2.5/ Impact of Individual Features

In this subsection, we study the impact of the individual features on the performance of the ensemble-based machine learning algorithms. Understanding the importance of each feature on the prediction algorithms is essential in selection of features and hence reducing the required processing power for an algorithm. We show the results for XGBM algorithm for brevity and because the similarity of the behavior of various ensemble-based algorithms performance.

In Fig. 6.15, 6.16, and 6.17, we present the MSE performance for setting b/g-Router, the variance score for setting b/g-Router and the MSE for setting b/g/n-Station,

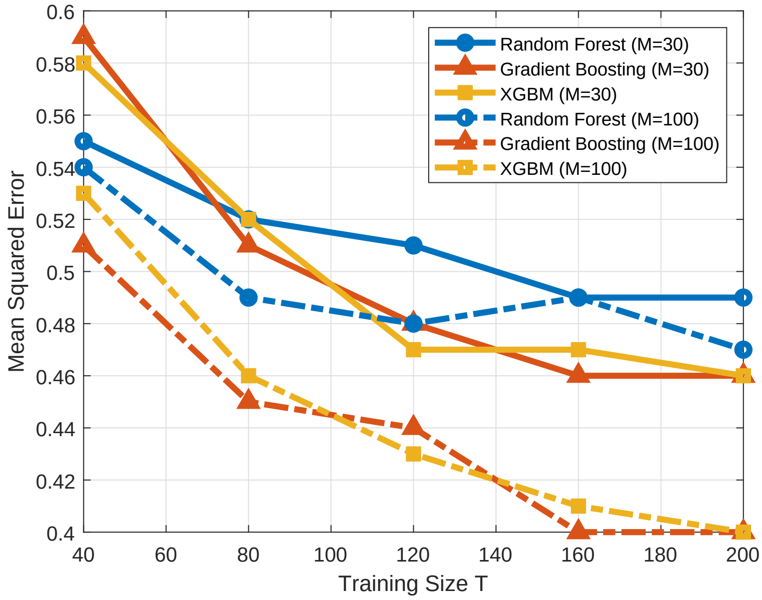


Figure 6.14: The mean squared error performance for jamming setting b/g-Router of various algorithms against T.

respectively, against the segment size M. In all the three figures, we refer to Δt_{ab}, Δt_{bc}, Z_d, Δt_{cd}, and Δt_{ae} by "t_high", "t_plunge", "Descent Distance", "t_bottom", and "Total Cycle", respectively.

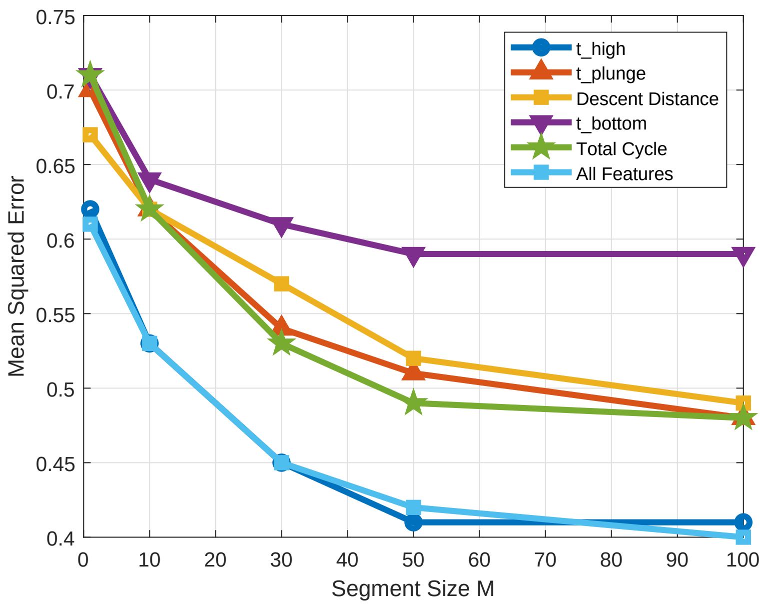


Figure 6.15: The mean squared error performance for jamming setting b/g-Router of XGBM algorithm against M including individual features impact.

The feature Δt_{ab} is the most one impacted by the SIR value where the prediction

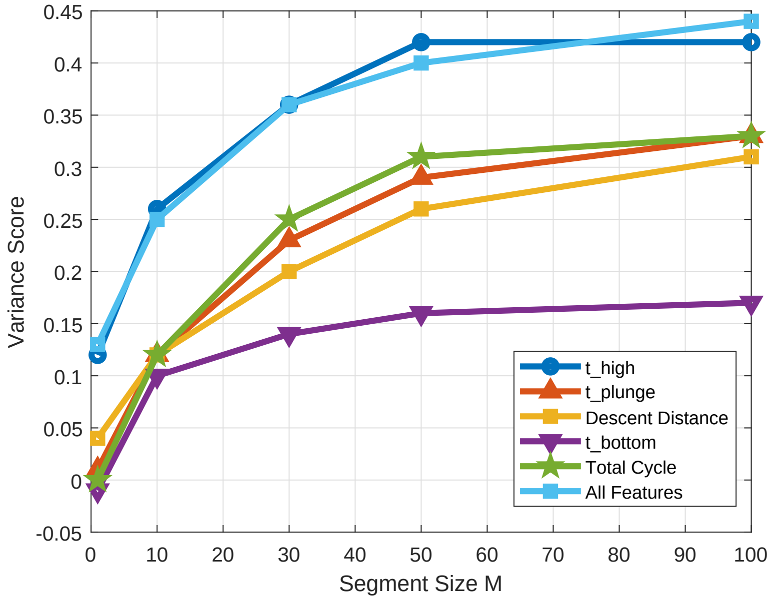


Figure 6.16: The variance score performance for jamming setting b/g-Router of XGBM algorithm against M including individual features impact.

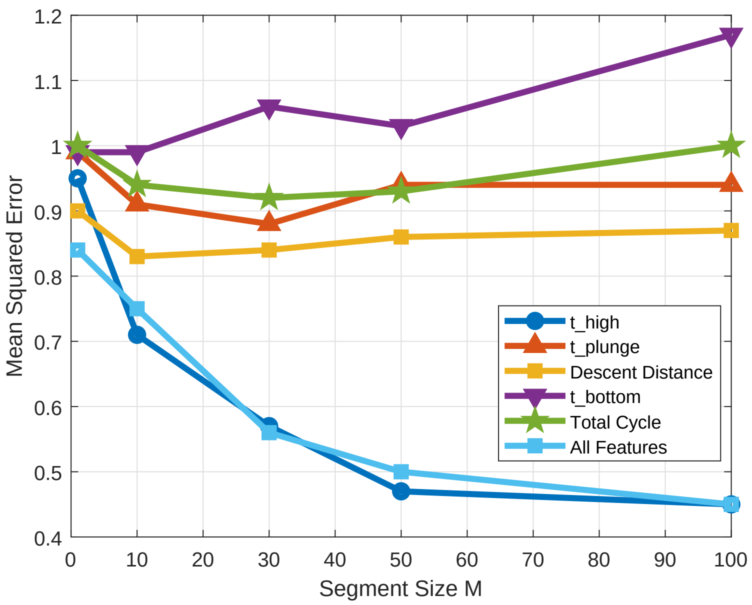


Figure 6.17: The mean squared error performance for jamming setting b/g/n-Station of XGBM algorithm against M including individual features impact.

performance by using this individual feature is almost identical to the performance of using all the features. This result can be explained by knowing that in the robot arm force seeking program, the FTS has to be zeroed before resuming the loop and hence there is a direct impact of the wireless transmissions and the value Δt_{ab}. On the other hand, the feature Δt_{bc} is the least one impacted by the SIR value. This feature is defined as the reflection time of the robot arm to reverse its direction and hence it is minimally impacted by the SIR value. The rest of the features are impacted by the SIR to a certain level. Generally, adding an unnecessary feature can degrade the performance. As a result, in this work, we concluded that using Δt_{ab} can substitute all the five features to get the same MSE and variance score performance with much less processing.

6.5.3/ Conclusion

In this paper we have presented a practical use case of a wireless force-torque feedback control system that could be deployed in a manufacturing assembly system such as a pick-and-place or assembly operation. A 6-DOF force-torque sensor was connected to a robot controller tasked with moving a probe along a linear path until an opposing force exceeding 5 N was detected. We demonstrated that the reliability of the wireless communication system directly impacts the repeatability performance of the physical system. We also demonstrated that the quality of the underlying wireless channel may be inferred by observing the position of the probe along a single spatial dimension and applying machine learning to predict the signal-to-interference ratio. As a result of our exploration of various machine learning algorithms on the prediction of signal quality, we found that ensemble-based algorithms have superior performance compared to other regression algorithms for data presented. Additionally, our analysis shows that careful study of the MSE and variance score is useful in selection of features used for training the algorithms. We conclude for this particular force-torque control system scenario that the dwell time of the robot before descending was the most useful feature for training the algorithm. Our findings provide motivation for applying machine learning to larger more complex systems with higher degrees of freedom. We conclude by stating that future experimentation with neural networks and deep learning to improve prediction accuracy could be of value to improving the reliability of wireless operations in factories. The applications of online machine learning techniques to this and other use cases could provide significant benefits to the manufacturing community through integration of link quality detection with programmable controllers.

7

Conclusions

7.1/ Future Works

7.2/ Conclusions

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LIST OF DEFINITIONS

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PREMIER CHAPITRE DES ANNEXES

B

SECOND CHAPITRE DES ANNEXES

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