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Improving Industrial Corrective Maintenance by Efficient Realization of Self-Diagnosis in Automated Production Systems Reusing Their Engineering Data

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Abstract

Maintenance refers to the set of activities required to keep the functional state of any system. Maintenance is of different types and can take place with or without prior knowledge of occurrence of faults in a system. The corrective maintenance refers to the maintenance function that takes place with prior knowledge of occurrence of faults in a system. Within the domain of industrial manufacturing, the state-of-the-art corrective maintenance is human intensive. Hence, any human error or incapability affects the industrial corrective maintenance negatively. Many researchers have highlighted the importance of improving corrective maintenance for improving the industrial production in the future. Consequently, this thesis examines means and methodologies for improving the efficiency of humans in corrective maintenance, and hence improving the industrial corrective maintenance in the future.

This thesis identifies enablement of visual assistive and self-diagnosis features in industrial automation systems, as a means to improve human efficiency in industrial corrective maintenance. However, many researchers identify high effort and cost for realization as the deterrents, for enabling self-diagnosis in industrial automation systems. Consequently, this thesis further focuses on approaches for cost and resource efficient realization of self-diagnosis in future industrial automation systems. Foreseeing the future automation systems to be component based, this thesis proposes effectively reusing the engineering data for realizing the self-diagnosis in automation components and systems of the future. A visual model of the corrective maintenance activity flawlessly integrates the self-diagnosis within it and assists the human for performing industrial corrective maintenance.

It is crucial to note that, the proposed solution is evaluated with two application examples. The first application example confirms the substantial improvement in industrial corrective maintenance, by efficient realization of self-diagnosis in automation systems. The results from the second application example prove the scalability of the solution to an industrial environment. By improving the industrial corrective maintenance, this thesis establishes the foundation for improving the industrial production in the future. Hence, by enhancing the solution a significant progress in the domain of industrial manufacturing is foreseen.

Kurzfassung

Instandhaltung umfasst jene Aktivitäten, die erforderlich sind, um den funktionstüchtigen Zustand eines Systems aufrecht zu erhalten. Es gibt verschiedene Arten von Instandhaltung, abhängig davon, ob vor der Durchführung Kenntnis von Fehlern in einem System vorliegt. Der Begriff der korrektiven Instandhaltung bezieht sich auf Tätigkeiten, die unter Kenntnis bereits aufgetretener Fehler durchgeführt werden. Nach dem aktuellen Stand der Technik werden im Bereich der industriellen Fertigung Maßnahmen der korrektiven Instandhaltung von Menschen ausgeführt. Fehlerhafte Ausführung infolge menschlichen Versagens und Verzögerungen aufgrund fehlender Informationen können erhebliche zusätzliche Kosten verursachen. Die Verbesserung der korrektiven Instandhaltung, insbesondere in der industriellen Produktion, wurde bereits von vielen Forschern als relevantes Feld für Verbesserungen identifiziert. In dieser Dissertation werden daher Mittel und Methoden herausgearbeitet um die korrektive Instandhaltung im Bereich der industriellen Fertigung zu verbessern.

Als geeignete Mittel, um den Ausführenden bei der korrektiven Instandhaltung von Maschinen und Anlagen in der industriellen Fertigung zu unterstützen und seine Effizienz zu steigern, wurden in dieser Arbeit Selbstdiagnose sowie visuelle Werkzeuge identifiziert. Selbstdiagnose in industriellen Automatisierungsanlagen ist zum aktuellen Stand der Technik allerdings nur aufwändig und kostspielig realisierbar. Um ihren Einsatz dennoch zu ermöglichen, werden in dieser Dissertation Methoden zur kosten- und ressourceneffizienten Realisierung der Selbstdiagnose entwickelt. Es wird angenommen, dass es sich bei zukünftigen Automatisierungssystemen um komponentenbasierte Systeme handeln wird. Diese Dissertation schlägt daher die Wiederverwendung der Konstruktionsdaten von Komponenten und Systemen zur Realisierung der Selbstdiagnose vor. Die zur Selbstdiagnose befähigten Komponenten und Systeme werden außerdem in ein visuelles Modell integriert, das den Anwender bei der Durchführung der korrektiven Instandhaltung unterstützt.

Die vorgeschlagene Lösung wird anhand von zwei Anwendungsbeispielen evaluiert. Das erste Anwendungsbeispiel weist eine signifikante Verbesserung der industriellen korrektiven Instandhaltung durch die effiziente Realisierung von Selbstdiagnose in Automatisierungssystemen nach. Die Ergebnisse des zweiten Anwendungsbeispiels bestätigen, dass die Lösung für eine industrielle Umgebung skaliert. Durch die Verbesserung der industriellen korrektiven Instandhaltung schafft diese Dissertation die Grundlage für die künftige Verbesserung der industriellen Produktion.

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Chapter 1

Introduction

1.1 Background

Industrial manufacturing is said to be one of the key pillars of the modern globalized economy. The rise and development of economically leading nations in the world, such as the USA, Germany, etc., have been triggered by industrialization [1, 2]. Industrial manufacturing has gone through dramatic changes in the past 100 years, in response to economic and social challenges [3]. Correspondingly strategic and paradigm changes have been applied on engineering, operation and maintenance; which are the sequential phases in the life cycle of a manufacturing plant as shown in Figure 1.1. The structural elements of a manufacturing plant, namely (production) resources, processes and products [4] have also gone through drastic changes accordingly.

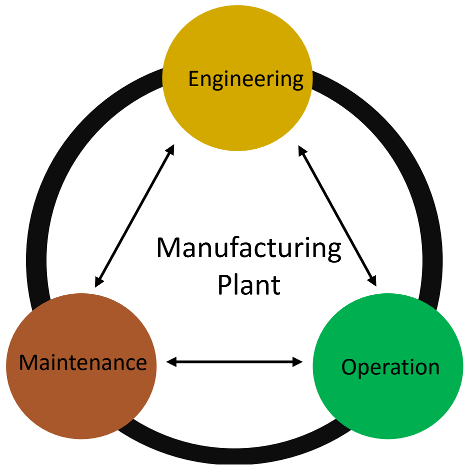


Figure 1.1: Life cycle of an industrial manufacturing plant.

Recently because of globalization unpredictable market changes, varying product demands and fluctuating customer requirements have started influencing the manufacturing industries [3]. Thus, the effects of globalization triggered a competitive landscape to the manufacturing industries. Different studies [5, 3, 6] show that industrial manufacturing requires a reformation to form so-called ***Factories of the Future (FoF)*** to strive whilst global competition and market changes. Several studies, for instance [5, 7, 8, 6, 9] have been conducted, concerning the characteristics, life cycle and structural elements of FoF. Consequently, the foundations of FoF have already been established.

A strategic project named Industry 4.0 (I4.0) [5] initiated in Germany affirms flexibility, human assistive nature and cognition as the fundamental characteristics of the FoF. With these characteristics, manufacturing companies can timely respond to the customer requirements without compromising on products' quality and enact a market driven production. On achieving a flexible, human assistive and cognitive manufacturing plant a fourth industrial revolution (I4.0) is anticipated in the near future [5, 10, 11].

According to Monostori et.al [9] the FoF are envisaged as a result of applying the latest and foreseeable further developments of Computer Science, Information and Communication Technologies (ICT), Manufacturing Science and Technology on the structural elements of current manufacturing plants. They assert that the resources in the FoF take the form of automation components or systems known as ***Cyber Physical Production Systems (CPPS)***. The CPPS based production resources provide flexibility, modularity and information exchange capabilities [12]. The products in the FoF take the form of smart products, having capabilities of data storage, communication and self-awareness. CPPS along with smart products shape the future manufacturing plants as smart factories [5]. The smart factories possess distributed and high performance control features for their manufacturing process [12]. Smart factories also apply further manufacturing technologies and ICT to integrate the stakeholders of the production in horizontal and vertical directions. The smart factories implement a human centred design [13] and hold flexible, human assistive and cognitive features [5].

Vyatkin et.al [8] and Vogel Hauser et.al [6] identify that the FoF will require novel engineering and operation functions to handle the complexities of FoF. Recent studies on industrial maintenance [14, 15] show that maintenance function will also need novel characteristics in the FoF. The overall aspects of FoF are depicted in Figure 1.2.

The changes required in the engineering function of FoF have been analysed in many studies [16, 17, 18, 19]. Accordingly, there are efforts [20, 21, 16] in the research community to enact modular and flexible characteristics to the engineering functions of FoF. Several studies [8, 6, 20, 21, 16] identify component based, service oriented and vendor neutral characteristics to the engineering function of FoF. It is found that the employees will require higher qualification and skills for the operation functions of the FoF [22].

The state-of-the-art industrial maintenance can be classified into two types; namely, preventive maintenance and corrective maintenance [23, 24]. The aim of the maintenance is to keep the functional state of the production resources [4] or to restore them in case of any failure [23]. Preventive maintenance refers to scheduled maintenance activities carried out to prevent any

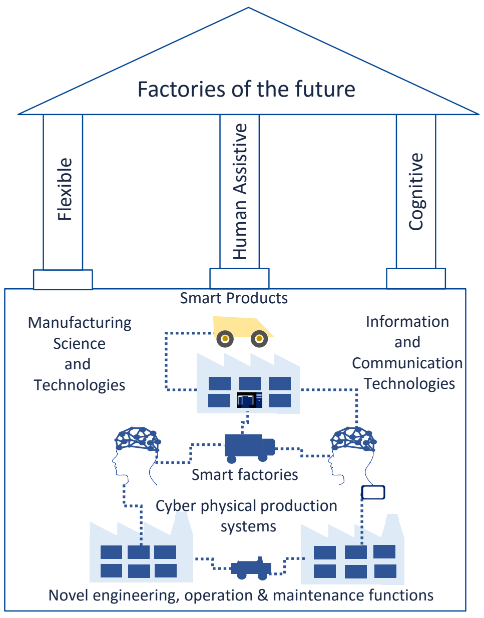

Factories of the future
Flexible
Human Assistive
Cognitive
Smart Products
Manufacturing Science and Technologies
Information and Communication Technologies
Smart factories
Cyber physical production systems
Novel engineering, operation & maintenance functions

Figure 1.2: Different aspects of factories of the future.

kind of failure of the production resources and thus to avoid any disruption in the manufacturing process. Corrective maintenance refers to the maintenance activities applied to restore production resources under downtime back to their functional state. Hence, it aims to correct the faults of a production resource with prior knowledge of their occurrence.

The recent studies on maintenance of FoF [14, 25] show that in the context of FoF, the preventive maintenance will be replaced by prognostic and predictive approaches. By applying prognostic and predictive approaches, any failure or performance degradation of a system can be predicted. Therefore, this thesis foresees that corrective maintenance will be applicable in three cases in the future as shown in Table 1.1. The first case occurs when a production system breaks down, and the second case occurs when the predictive maintenance system predicts a future failure. Third case is triggered when the predictive maintenance system finds performance degradation of a system [18]. In case of a breakdown, the downtime is accidental and may lead to an emergency. The corrective maintenance is carried out as an unscheduled activity and has a critical nature in some cases of breakdown. In the other two cases, the down time is planned or even no down time occurs and the corrective maintenance is carried out as a scheduled activity.

1.2 Problem Description

Summarizing the previous section, this thesis makes the assumption that the concept of FoF will be materialized in the near future. Accordingly, this thesis presumes the following fundamental aspects of FoF to be true:

Table 1.1: Corrective maintenance: Application context and types in factories of the future.

Initiating Events	**Type of Downtime**	**Type of Corrective Maintenance**
Breakdown	Unplanned down time	Unscheduled corrective maintenance
Future failure prediction	Planned down time	Scheduled corrective maintenance
Performance degradation prediction	Planned down time/ No down time	Scheduled corrective maintenance

1. The future factories will have flexible, human assistive and cognitive characteristics.
2. The future production resources take the form of CPPS.
3. The engineering, operation and maintenance functions will have novel characteristics in the context of FoF.

Efforts have been made to reform the maintenance function of the FoF, with prognostic and predictive approaches [14, 26, 27]. However, studies show that though every effort is made to keep a production resource as reliable as it can be with means of preventive or novel predictive techniques, they do fail frequently [28, 29]. Failure of a production resource leads to a downtime in the manufacturing process and hence makes production losses. Each time a production resource fails, or the predictive maintenance system predicts an upcoming failure, or finds a performance degradation, it triggers a downtime and subsequently a corrective maintenance function. Thus, corrective maintenance can be inferred as an imminent activity even within the context of FoF.

The state-of-the-art corrective maintenance is human intensive and has a sequence of steps [24], which is depicted in Figure 1.3. The first step in this sequence is the “fault detection”, which identifies the occurrence of a fault in a production resource or the process. As a second step in the sequence the maintenance personnel perform “localization”, which identifies the location of the fault. The next step in the sequence is “diagnosis” of the fault, where the causalities of the fault are identified. After the diagnosis, the “corrective action” is taken and finally the “checkout” step is carried out.

A fault is defined as a deviation of operational behaviour of a production resource or process from its expected or ideal behaviour [30]. The expected or ideal behaviour of a production resource or process is defined, during its engineering process [16]. The “fault detection” thus depends, partly on the engineering and partly on the operational aspects of a plant. On detecting a fault, based on the type of the fault and its criticality, the scheduled/unscheduled corrective maintenance is assigned to a maintenance personnel. The “localization” and “diagnosis”, steps have strong dependencies on the engineering aspects of the failed resource or process. The fault

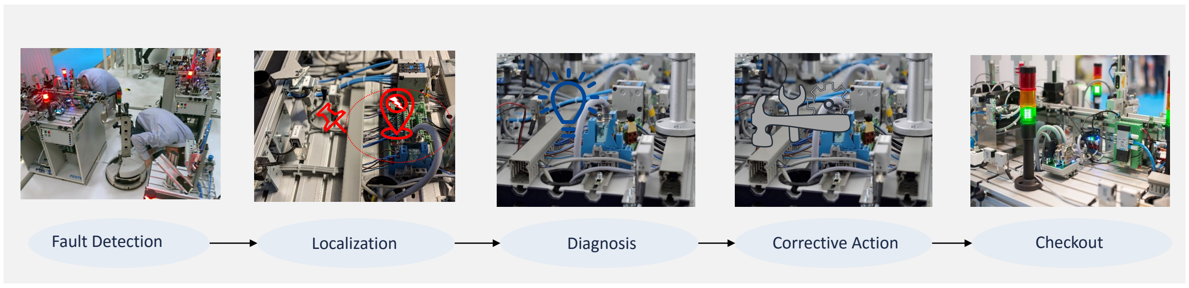


Figure 1.3: Sequence of activity in a corrective maintenance function according to Dhillon [24].

localization identifies its origin within the resource or process, based on their engineering data. The diagnosis step requires to derive the causalities of the fault, based on the engineering and operational aspects of the resource or process. Further steps in the maintenance function, namely the corrective action and the checkout step also depend on the engineering and operational aspects of the plant.

The aforementioned paragraph clarifies the strong relation of corrective maintenance function with the engineering and operational aspects of a plant [31, 32, 29]. Different studies clarify the basic concepts for engineering and operating the FoF. These studies show that the engineering and operation of the FoF will undergo a paradigm shift within the context of FoF [3, 6, 8, 16]. However, the corrective maintenance aspects are not yet upgraded accordingly.

Many researchers [24, 28] highlight human error as one of the key issues that makes industrial corrective maintenance unreliable. Apart from that, many studies [6, 8, 28] identify complexity as a big challenge to any human related activities within the FoF, including maintenance. They establish that the complexity will affect the efficiency of human workers within the FoF. Vyatkin [8] and Vogel-Heuser [6] predict that the FoF will be software intensive in nature. They point out the complex nature of software intensive systems and hence the software intensive nature as a challenge within the FoF. Colombo et al. [33] illustrate that the CPPS combine complex software and physical aspects together and they have a frequently reconfigured architecture. Thus, the source of complexity in the FoF may also arise from the CPPS nature of the production systems. Gao et al. [34] state that the interconnected nature, multiple control loops, varying loads, etc., of CPPS also induce complexity in future industrial systems.

An example of a CPPS based complex production resource, in a frequently reconfigured future factory according to the definition of sources of complexity from [8, 34, 33] is depicted in Figure 1.4. The problem of complexity is not yet addressed within the context of corrective maintenance [27, 35]. Referring back to Table 1.1, corrective maintenance can be of scheduled or unscheduled type. The type of failure can be different in each case, and the maintenance personnel has to react individually to each of these cases. Therefore, corrective maintenance function can be foreseen as more challenging and error prone in the future [27, 35].

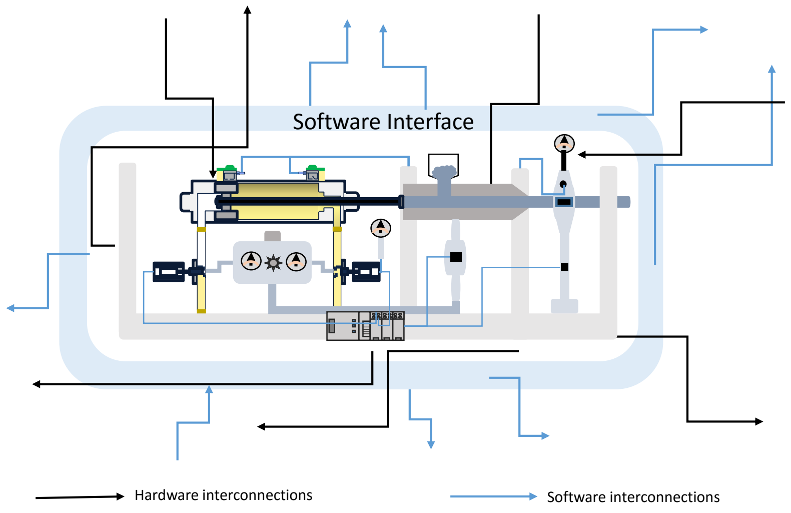


Figure 1.4: Example of a complex system in factories of the future.

1.3 Motivation

Recent studies [14, 35] show the importance of improving corrective maintenance function in the context of FoF, even in presence of predictive and prognostic approaches. Lee et al. [14] show that within the FoF, the corrective maintenance function is also market driven. This comes from the fact that, any downtime of the production resources prolong time to market and hence production losses. Any kind of human error in corrective maintenance thus cannot be afforded as it lengthens the production downtime. The longer the human takes to complete the corrective maintenance, the longer is the time to market and higher is the production loss. Hence, not only the human error, but also the efficiency of a human to carry out a corrective maintenance influence the production loss and time to market.

The statistical analyses of cost of corrective maintenance in the state-of-the-art factories as in [24, 36, 37] show that cost of corrective maintenance may count up to 40% of the operational cost of a plant. As per [24], a large part of the rise in cost of corrective maintenance is attributed to the human error. In a global competitive market the rise in the cost of corrective maintenance cannot be afforded. Thus, acknowledging the current issues and foreseeing the characteristics of FoF, it is necessary to reduce the human error and improve the efficiency of humans in corrective maintenance function. In addition, the challenge of complexity and proposed reformations in the engineering and operation functions of FoF, points to the requirement of reforming the corrective maintenance function accordingly.

1.4 Research Objectives and Contributions

Considering the problem described in Section 1.2, this thesis aims to develop means and methodologies for a cost effective and human assistive corrective maintenance function in the context of FoF. As a result, the length of production downtime can be reduced and the manufacturing companies can respond to customer requirements timely without compromising on quality. Accordingly, this study provides a framework for addressing the following objectives within the context of the FoF in a cost efficient manner:

1. Minimize possibilities of erroneous activities and increase efficiency of the human involved in corrective maintenance function.
2. Handle complexity whilst corrective maintenance function within the FoF.
3. Reform the corrective maintenance function for the FoF.

It is crucial to note that the proposed solution is evaluated with two application examples. The first application example illustrates how the objectives are achieved with minimum resources and cost. The second example evaluates the scalability of the proposed solution to an industrial environment.

1.5 Thesis Structure

Chapter 2 presents the literature review, concerned with the problem described previously in this chapter. The review of the literature identifies, enablement of self-diagnosis in production resources as a potential solution for improving corrective maintenance within the FoF. Further, it analyses the existing gap in enabling self-diagnosis within industrial systems and derives the research questions. Chapter 3 lists the requirements for enabling self-diagnosis within the corrective maintenance of future automated production resources. Further, it derives the methodology for addressing the research questions.

From Chapter 4 onward, the research contributions of this thesis are elaborated. Chapter 4 details the methodology for modelling self-diagnosis in the automation components. It derives the prerequisites and methodologies for creating reusable models for self-diagnosis within automation components. Chapter 5 describes the methodology for realizing self-diagnosis in automation systems composing automation components. This chapter also addresses the challenge of bringing flexibility and reconfiguration to the developed systems.

The aspects for improving the development and application of the self-diagnosis based corrective maintenance in FoF are addressed in Chapter 6. Chapter 7 describes the overall implementation of the system. An evaluation of the approach with two application examples is elaborated in Chapter 8. Chapter 9 concludes the thesis with concepts for future work.

Chapter 2

State-Of-The-Art Review of the Literature

The previous chapter clarifies that the characteristics and building elements of FoF will change considerably with that of the state-of-the-art factories [6, 8, 38]. Many studies [6, 8, 38, 39, 18, 16] assert that the maintenance of FoF requires changes accordingly. The inter-relation between maintenance and other phases in the life cycle of a manufacturing plant, such as engineering and operation were also clarified in the previous chapter. Based on this foundation, the state-of-the-art review of literature of this thesis is divided into five sections.

Section 2.1 extensively reviews the building elements and fundamental characteristics of the FoF. The important aspects concerning the engineering and operation of a manufacturing plant, which influence its maintenance are reviewed in Section 2.2. Section 2.3 reviews the state-of-the-art industrial maintenance and describes corrective maintenance in detail. Section 2.4 describes the self-diagnosis and methodologies for applying self-diagnosis within industrial corrective maintenance. The research focus of this thesis and formulated research questions are detailed in Section 2.5.

2.1 Fundamentals of Factories of the Future

The manufacturing industries have gone through dramatic changes in the past 200 years. Different manufacturing paradigms have been applied to address the social and economic scenarios and corresponding requirements during this period [7]. The Industrial revolutions occurred as a result of the changes in manufacturing paradigms applied during the past 200 years. The first Industrial revolution occurred in the 1800's as a result of steam-powered mechanization of manufacturing industries, providing high production volume compared to manual labour [1, 40]. The second industrial revolution occurred in the last quarter of the 18$^{\text{th}}$ century because of applying electricity and oil driven manufacturing. The second industrial revolution happened in response to the requirement of cost effectiveness in mass production. The third industrial revolution took place in the last quarter of the 19th century. The third industrial revolution was a result of introduction of automation technologies, leading to further cost optimization and starting of mass customization [1, 40].

From 1990's onward, the effect of globalization has been influencing the social and economic circumstances once again. With globalization the market turned volatile and on the provision of freedom to choose their products from multiple providers, the customer demands started to vary [7]. Nowadays the companies are forced to satisfy the varying requirements of customers to survive whilst global competition. In order to facilitate the industries to face the social and economical challenges of the modern world, the concept of FoF was put forward [3, 5, 8, 14]. One of the key projects on FoF, which attained global attention is the strategic initiative by the German government named I4.0 [5]. The basic concepts of FoF presented in the initial study on I4.0 [5] have been improved since then. The required characteristics of the FoF to address the social and economic challenges of the future market have been instituted in many other studies. An extensive study of the proposed characteristics and building elements of the FoF are described in the following sections.

2.1.1 Basic Characteristics of Factories of the Future

One of the key problems faced in the state-of-the-art factories is that the production facilities are not flexible and most of the manufacturing companies follow mass production paradigms [40, 41]. The mass production paradigm (American system of manufacturing) was introduced by Henry Ford to produce large quantities of one kind of a product, employing automated manufacturing facilities. The main characteristic of mass production is to reduce the cost by increasing the volume of production. An example is the mass production of Ford motor model T, trusting on its popularity and expecting mass requirements from the market at a lower price [42]. The state-of-the-art manufacturing paradigm followed by most of the automotive companies are of type mass customization [43]; means providing variety in mass, from which nearly everyone can find what they can afford. However, once the production is started, no changes are expected or allowed [42].

As shown in Figure 2.1, the fundamental characteristic of FoF is that manufacturing will be market driven [3]. This means that the future manufacturing companies will have to offer high individualization to their customers with high variability of products [42, 44]. Koren [3] states that high individualization can be achieved, if the manufacturing plants possess flexibility and reconfigurability.

Recent studies [6, 44, 38] show that the flexibility and reconfigurability of a plant can be improved, if they hold the following characteristics:

- Modular and distributed architecture.

- Seamless interoperability.
- Intelligence and cognition.

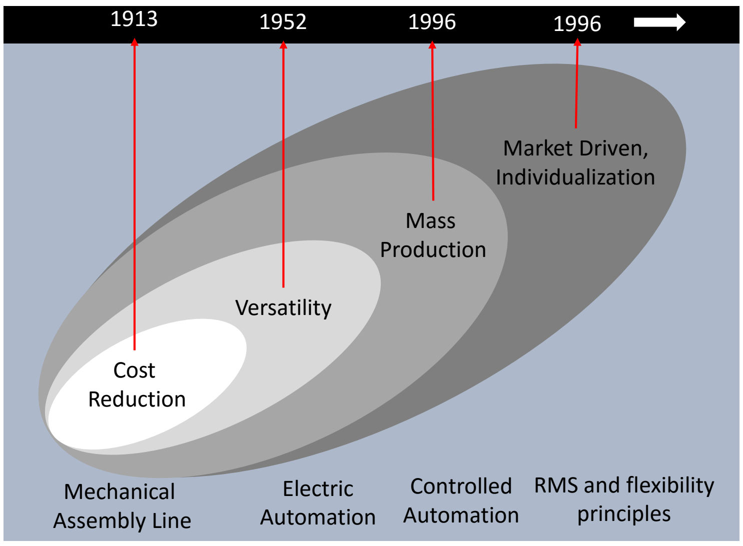


Figure 2.1: Manufacturing trends in the past century as shown in [7].

Modular and distributed architecture: The state-of-the-art manufacturing systems are built for a specific application or a limited amount of variability in products, hence they form a single system, controlled centrally [43]. Vogel-Heuser et al. [6] and Vyatkin [8] state that flexibility and reconfigurability of a manufacturing plant in the FoF can be achieved with modular automation systems controlled in a distributed manner.

According to Mabhkhot et al. [45] modularity in manufacturing can be defined as, the capability of a production system to be separated into loosely coupled independent units which can be added, rearranged or relocated in the production line based on customer requirements on time. A distributed control architecture is one in which embedded computers enable autonomous behaviour to the modularized physical artefacts [46]. Such distributed control units interact with their environment via sensors and actuators and will make decisions on their own, un-subordinated to the central control unit. Hence, the modular and distributed production units can adapt their manufacturing processes based on individual order [39]. Vogel-Heuser et al. [6] asserts that within the context of FoF, the modularity and distribution can be achieved by employing CPPS based production resources. An example of a modular production system controlled in a distributed manner is depicted in Figure 2.2. In the figure, each island represents a CPPS based production resource. They are controlled in a distributed manner and interact seamlessly with the neighbouring units based on requirements.

Seamless interoperability: IEEE standard computer dictionary [47] defines interoperability as "the ability of two or more systems or components to exchange information and to use the information that has been exchanged". In the manufacturing domain, interoperability can

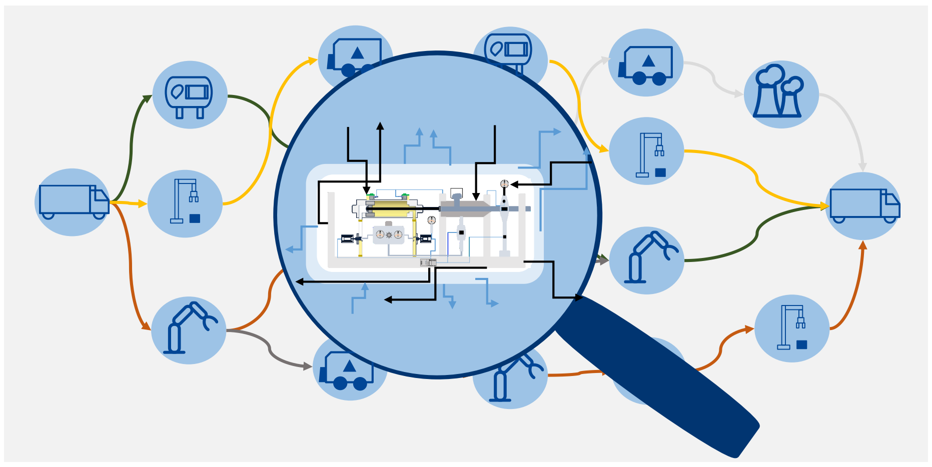


Figure 2.2: Example of modular and distributed systems that can interact and organize seamlessly: Zoomed in view of a single system with its own controller is shown in the middle.

be defined as the ability of heterogeneous production systems to exchange information with one another by interaction with each other [48, 49]. Industrial automation systems generally employ interoperability in different areas of the system. They are depicted with the help of an automation pyramid in Figure 2.3.

In a production system composed of CPPS, they interoperate and organize themselves to form production systems [39]. This type of interoperability, which occurs within a single layer of the automation pyramid is called horizontal interoperability. Interoperability between different layers of the automation pyramid is called vertical interoperability. The vertical interoperability can occur between different systems within an automation pyramid such as Supervisory Control and Data Acquisition System (SCADA), Manufacturing Execution Systems (MES), Enterprise Resource Planning systems (ERP), etc [44]. In addition, FoF envisions machines and humans as co-workers. Hence, components of the automation pyramid need to interoperate with the humans within the factories [50, 51].

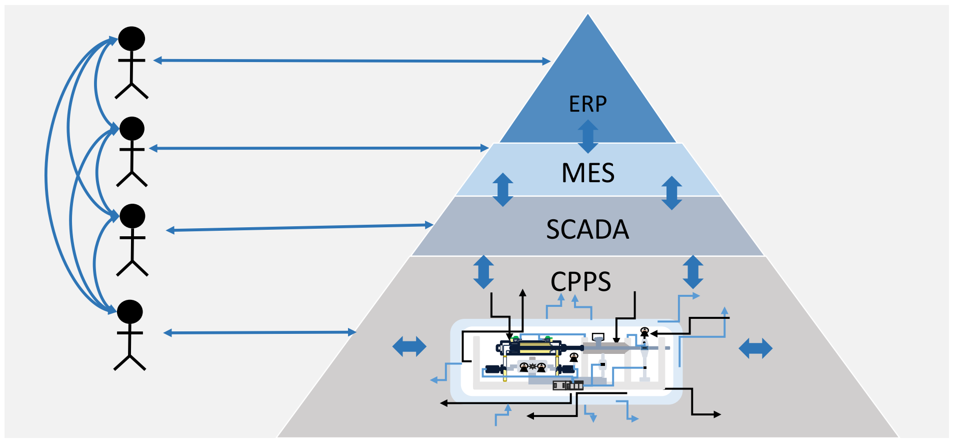


Figure 2.3: Automation pyramid and interoperability plot in an I4.0 plant.

Intelligence and cognition: The automation of processes and hence improvement in the cost efficiency and volume of production, was the key to the third industrial revolution [7]. In most mass-producing factories, fully automated production technologies improve the lead time and quality of production compared with that of human workers [42]. Similar technologies are applied also in mass customization with modular solutions for the predefined varieties of products. However, human workers with their cognitive ability and problem solving skills are the single solution found so far, to handle the flexibility and adaptability required for small lot size production [52]. The human brain with their computational mechanism helps the human to act competently under uncertainty, handle unpredictable events in a reliable manner, and adapt to changing tasks and environments. The future production systems in the era of FoF are supposed to bear cognitive capabilities that are comparable to humans, hence they can meet the requirement of individualized production requirements [52].

The concept of FoF envisions smart factories, which configure and control themselves [45]. Smart factories will comprise CPPS and smart products. The capabilities of CPPS based production resources are elaborated in the aforementioned paragraphs. Smart products possess self-awareness and are integrated within their production steps within the smart factory. Smart products have capabilities to know their characteristics, the ongoing status of their production and can be integrated to the customer requirements [53, 45]. A smart factory pulls and analyses massive data from the production systems, to improve the system performance and optimize the resource utilization [46].

2.1.2 Humans as the Strategic Decision Makers

Humans are one of the most important elements of the state-of-the-art factories [35]. There were previous efforts to run the industries completely automated in the form of ghost factories. However, these approaches are found to be inefficient due to lack of flexibility in production facilities [50]. FoF envision cognitive and human assistive production environments. Technologies assist humans to realize their full potential and adopt the role of strategic decision makers and flexible problem solvers [54]. Mabkhot et al. [45] argue that when automation systems compose autonomous self-organizing components, more complex manufacturing challenges can be achieved. When humans are integrated into these self-organizing automation systems, the flexible problem solving skills of humans can be leveraged. Gorecky et al. [50] assert that the factories combining human cognition with self-organizing automation systems can achieve more compared to a ghost factory.

Martin et al. [51] assert that, in the FoF the employees will require skills that are different from the current factories. With self-organizing automation systems, the primary task of humans is envisaged to be dictating the production strategy. Many researchers [55, 56] agree that humans will need to interoperate with machines in the future, since production systems have a human assistive nature. Foreseeing a human-machine collaborative environment, they recommend application of visual human-machine interfacing technologies such as augmented reality or virtual reality.

2.1.3 Complexity as a Key Problem to be Addressed

Complexity is found to be the intrinsic nature of FoF [6, 8, 9]. Monostroi et al. [9] found that the complexity issue will have larger significance in the future. According to them, complexity has to be handled mitigating the negative aspects while leveraging its positive ones. Elmaraghy et al. [57] find that complexity of FoF begin right from the design phase, and stems from the complexity of the emerging technologies applied. The US National Science Foundation highlights the complexity of engineering the CPPS and identifies that it will lead to adverse consequences [58]. They assert that the advanced methodologies of software systems engineering are required to handle the complexity of engineering CPPS based manufacturing systems.

Vyatkin [8] mentions in his study that the software ratio in the machine building process has increased from 20% to 40% in the last decade. He asserts that the software ratio in the manufacturing process is going to increase further and the complex nature of software used in automation systems will affect the engineering, operation and maintenance of manufacturing systems in the future. According to him, FoF will require reusable component based architecture. The designing, developing, and maintaining components for reuse is a very complex process. Though complex software engineering uses formal methods, the knowledge of formal methods is not common among automation and control engineers. Therefore, the education threshold required for training of engineers in the future will be complex and difficult to execute.

Brandenbourger et al. [16] and Vathoopan et al. [18] show that the complexity of future factories can also arise from the distributed control architecture employing CPPS. Each CPPS integrates physical systems, actuators and sensors together and their control software. In an overall application, several CPPS are organized into a distributed modular architecture as shown in Figure 2.2 and thus forms a system of systems architecture. Vathoopan et al. [59] further indicate that in a future factory, the CPPS interact seamlessly and group themselves to yield a manufacturing process and corresponding product. The distributed CPPS are added, removed or relocated themselves to satisfy the flexible nature of production required in FoF, which makes engineering, operation and maintenance of these systems also complex.

2.2 State-Of-The-Art Review of Plant Engineering and Operation

This section reviews the state-of-the-art literature of plant engineering and operation, which have association to the plant maintenance. As shown in the previous section, the FoF hold complex and reconfigurable nature and compose distributed, modular CPPS based production systems. Different studies [38, 8, 6, 18] show that these changes also affect the life cycle of the manufacturing plant. Therefore, the different phases in the life cycle of manufacturing plants namely engineering, operation and maintenance has to be revamped to satisfy the proposed aspects of FoF [38, 6].

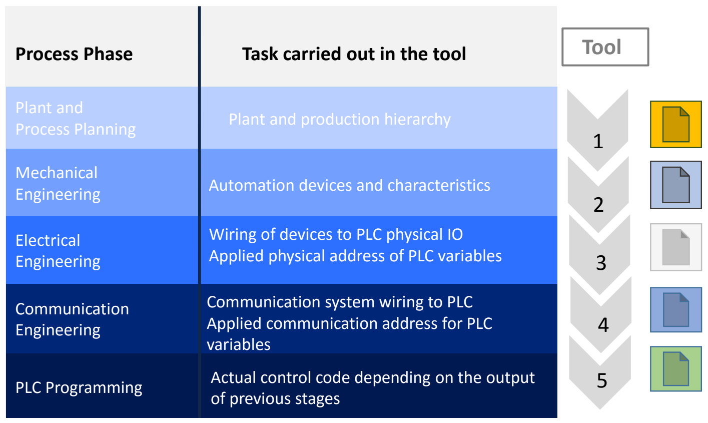
The first and foremost step in the life cycle of a manufacturing plant is its engineering. Plant engineering is used as a collective term for all technical oriented services, and working methods applied to conceptualize, implement and commission an industrial plant based on customer specific requirements. This is applicable to different sectors of business such as chemical processing, power generation, assembly, etc [60]. The operation of a plant comes as a next phase within the life cycle of a manufacturing plant. Operation is a collective term for all the activities applied whilst a manufacturing plant produces some product [22].

The Section 1.2 clarifies the strong relation of corrective maintenance function with the engineering and operational aspect of a plant. The corrective maintenance is dependent on the characteristics and methodologies of engineering of a plant. Further, it requires information exchange with an operating plant. Hence, the following sections reviews the characteristics and methodologies of state-of-the-art plant engineering. In addition, a review of the important aspects of information exchange and communication within the operation of a plant is also presented.

2.2.1 Increasing Digitization and Data Generation in Engineering

Every plant engineering process intends to develop a manufacturing plant capable of producing a required product. The technical services and working methods involved in plant engineering generate enormous data from various means. Within the context of FoF, the amount of generated data is expected to increase further [14]. Some of the means of data generation and effort towards more digitization within the context of FoF are elaborated below.
Integration of components, systems and stakeholders: Every plant engineering process is unique and specific to the requirements of the customer (manufacturing company) and their specific product [60]. Plant engineering is typically performed by a system integrating company using components and systems from suppliers and contractors to deliver a plant that can manufacture the required product by the customer (manufacturing company). Plant engineering thus involves multiple stakeholders such as the system integrating company, the customer (manufacturing company), suppliers of manufacturing system components, contracting companies providing construction services, etc [39]. Each of these stakeholders, components and systems hold their specific data within the plant engineering process. A typical plant engineering process integrates different components, systems and different stakeholders to yield a manufacturing plant and thus integrate the data from the stakeholders inherently.

Application of domain specific tools: The engineering process as a whole involves multiple stakeholders and domains. In modern plant engineering, different stakeholders and domains employ software tools specific to the stakeholders or the domain [61]. Advanced digitization techniques are applied in different stages of the engineering process of manufacturing plants in the form of software tools [8]. Each of these tools produces tool specific or domain specific engineering data. The example of an engineering process and digitized tasks performed in its each step are shown in Figure 2.4. In the process shown in the figure the tools are employed in a sequential manner. Creating the plant and production hierarchy is performed in the first (plant and process planning) phase with a software tool. This tool produces a domain specific engineering data. In the next stage (mechanical engineering), the automation devices and their characteristics are defined with a different software tool and so on [62].



Process Phase	Task carried out in the tool	Tool
Plant and Process Planning	Plant and production hierarchy	1
Mechanical Engineering	Automation devices and characteristics	2
Electrical Engineering	Wiring of devices to PLC physical IO Applied physical address of PLC variables	3
Communication Engineering	Communication system wiring to PLC Applied communication address for PLC variables	4
PLC Programming	Actual control code depending on the output of previous stages	5

Figure 2.4: A sequential plant engineering process employing different tools; modified from [43].

Electronic data exchange as a means for integrating tools and stakeholders: Considering the sequential nature of plant engineering, Lüder et al. [62] and Drath et al. [63] find interoperability among tools as one of the key challenge to be addressed to reduce the complexity of engineering FoF. For example in Figure 2.4, tools applied from first phase to last phase have sequential dependencies; each tool or task receives some data as input from the preceding tool. In such cases, it is necessary that the tools should interoperate. Lüder et al. [62] and Drath et al. [63] propose a standard electronic data exchange known as Automation Mark-up Language (AML) for enabling interoperability among tools in the plant engineering process. Vathoopan et al. [39] identify that a universally acceptable electronic data exchange format will facilitate integration of different stakeholders involved in the engineering process such as component manufacturers, system integrator, and the customers, etc.

2.2.2 State-Of-The-Art Methodologies of Plant Engineering

Different studies [8, 6, 38] show that in order to achieve the key characteristics of future factories such as flexibility, human assistive and cognitive nature, the state-of-the-art engineering process has to be revamped. Many researchers [8, 11, 64] find complexity as the key challenge to be addressed considering the engineering of FoF. Vyatkin [8] points out the continuing increase of software ratio in manufacturing system. Hence, he suggests the use of software engineering techniques such as component based development [8, 6], service orientation [65, 66] and model driven engineering with code generation [67] in the design and engineering of FoF.

Mitigating Complexity with Automation Systems Engineering: In the modern context plant engineering and automation engineering are used alternatively, as most of the plant engineering is attributed to the automation engineering process [63, 16]. Inspired from [6, 8], Brandenbourger et al. [16] proposed a methodology for engineering FoF by using CPPS based automation components. They apply CPPS as the basic building units of future manufacturing plants and assume a software component for each hardware counterpart. They propose that standard software components can be created reflecting the hardware components and thus reuse of both hardware and software components can be implied in a reconfigurable manufacturing scenario.

Ovtcharova et al. [68], suggest the importance of developing a functional model. Since product function remains the same for all, they propose a functional model to improve the collaboration process and close the significant gap existing in cross-domain engineering. Based on this concept, Vathoopan et al. [39, 69] proposes skills as a means for service orientation in the domain of plant engineering. Here a skill represents a function offered by an automation component and for any discipline or stakeholder involved in the process the function offered by the component is its skill and remains the same throughout the engineering process. They also propose automation components as the service (skill) provider and products as the service (skill) consumer in a service oriented architecture. Such an architecture where components are loosely coupled and integrated based on requested skills of products are shown in Figure 2.5. In this method, each level in the physical system hierarchy offers an interface in the form of skills and they can be coupled based on product requirements from the customer. By modularizing product models based on features, each feature can be mapped on to a skill provided by a physical component in a hierarchical architecture, and thus can support multiple variants of products and their features.

Vathoopan et al. [39] also assert that on provision of universally acceptable models of automation components, a systems engineering process enabling integration of stakeholders and tools is possible in the manufacturing domain. Vathoopan et al. [69] further developed the concept presented in [39], to develop a model based automation systems engineering, using skills and yielding a service oriented hierarchical architecture with code generation in various tools.

Facilitating Personalized Engineering for Personalized Production: The initial engineering of a manufacturing plant can be treated as a green field process. A plant engineering process typically involves design and construction of plants' physical hardware and the software

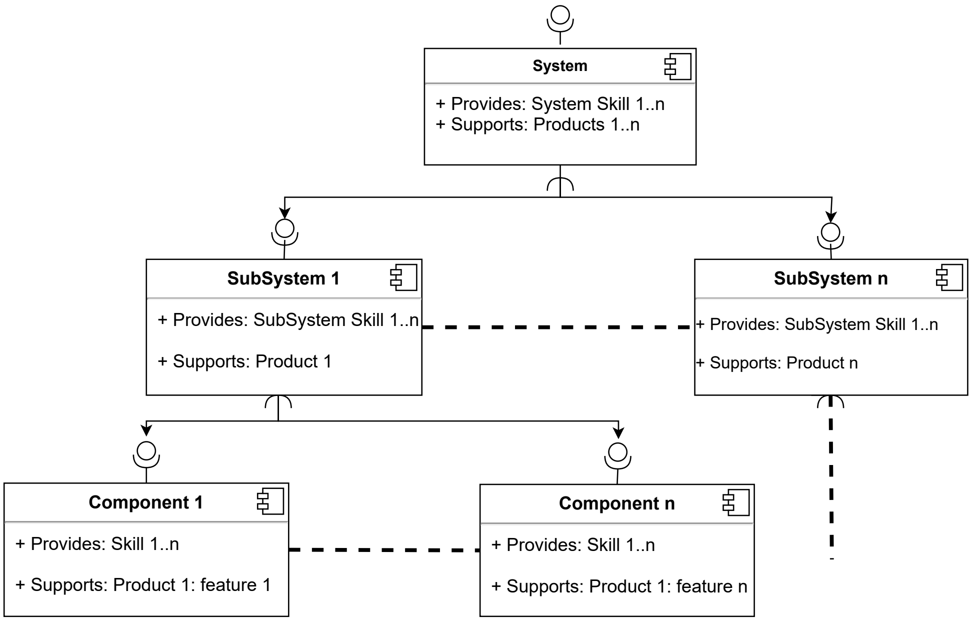

System
+ Provides: System Skill 1..n
+ Supports: Products 1..n
SubSystem 1
+ Provides: SubSystem Skill 1..n
+ Supports: Product 1
SubSystem n
+ Provides: SubSystem Skill 1..n
+ Supports: Product n
Component 1
+ Provides: Skill 1..n
+ Supports: Product 1: feature 1
Component n
+ Provides: Skill 1..n
+ Supports: Product 1: feature n

Figure 2.5: Architecture of a component oriented manufacturing plant (modified from [69]).

that controls the physical hardware. Thus, different disciplines such as mechanical, electrical, design, software, etc., cooperate in the plant engineering process [64]. If the requirement of the customer is for certain types of variants as in the mass production, the plant engineering takes place only once and then it goes to the operational stage, producing these variants of products in mass quantity expecting requirements from the market [42]. The state-of-the-art plant engineering thus has a sequential nature [43] and once commissioned, it keeps operational for next 15-20 years producing the same fixed variants of products.

The future plant requires frequent evolution or reconfiguration such that they are slowly moving towards personalized production in the future. Therefore, the life cycle of a future manufacturing plant will be short and the engineering of such plants possess a sequential and cyclic behaviour as depicted in Figure 2.6. Here it is assumed that a plant already exists and thus the plant engineering can be treated as a brownfield engineering process [64]. In such a process, the customer requirements need to be integrated within the engineering process [43]. The overall plant engineering has a cyclic behaviour, since it is evolved and reconfigured frequently. Every change in customer requirements will require changes in the engineering process as well. In this regard, the engineering process of the FoF can be seen as personalized.

2.2.3 Information Exchange and Communication within Plant Operation

In the FoF, the systems are expected to be modular in nature and they can be rearranged and reconnected to form new factory configurations as explained in the previous section. There can be various types of systems covering various levels of the automation pyramid as shown in Figure 2.3. There can be equipment from different vendors used in different levels. In this

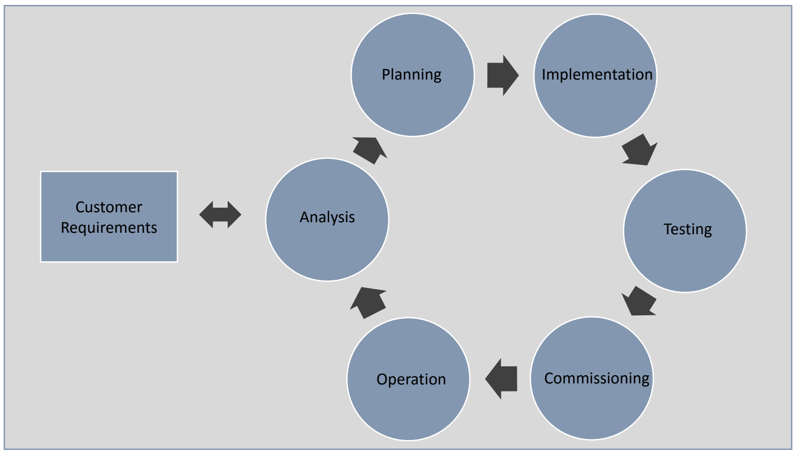


Figure 2.6: Cyclic and sequential nature of plant engineering in a reconfigurable plant.

scenario, it is important that each of these systems can interoperate so that at any point of time, they can exchange information among each other to enact the seamless operation of the plant [48, 49, 44].

Profanter et al. [70] has made a comparison of existing technological solutions for interoperability within the industrial automation domain. Different standard interoperability solutions used in industrial automation such as OPC UA, DDS, ROS, MQTT, etc., are compared. All of these protocols address the problem of interoperability by providing a standardized, open and manufacture independent protocol for communication by using an Ethernet based implementation. Thus, they can replace proprietary field bus protocols since Ethernet offers an open and hardware independent solution without licensing fees. Their basic analysis showed that considering the complex nature of industrial automation systems and multitude of domain specific models employed, MQTT and ROS can be neglected. OPC UA and DDS are compared in detail. A detailed comparison of OPC UA and DDS with information modelling capability modelling specific to industrial automation and also performance showed that OPC UA prevail in the industrial automation domain with the counterpart.

The application of OPC UA has been evaluated in several use-cases within the operation of a manufacturing plant. Schleipen et al. [49] evaluated the application of OPC UA for the implementation and operation of a service based industrial automation system. Merkumians et al. [71] show the use-case of employing OPC UA as a middleware between the control platforms and value added services by using a standard data model for industries. The study from Flat et al. [72] proves the capability of OPC UA to act as an interoperability medium between the human interface devices and the production systems specific for the operation and maintenance of the plant. Vyatkin [8] and Vogel-Heuser et al. [6] identify OPC UA as the interoperability solution for I4.0. Relying on [71, 70, 49, 72, 8, 6] application of OPC UA can be seen as a means for information exchange and communication within the operation of the FoF.

2.3 State-Of-The-Art Review of Industrial Corrective Maintenance

The term maintenance is defined in a production environment as all actions necessary to retain or restore a production item/part/equipment to a defined state [24]. This section reviews the different types of maintenance in a production environment and the importance of improving maintenance, foreseeing the FoF.

2.3.1 Types of Industrial Maintenance

Maintenance in a production environment is mainly of three types in practice [73]. They are elaborated in the following sections and illustrated in Figure 2.7.

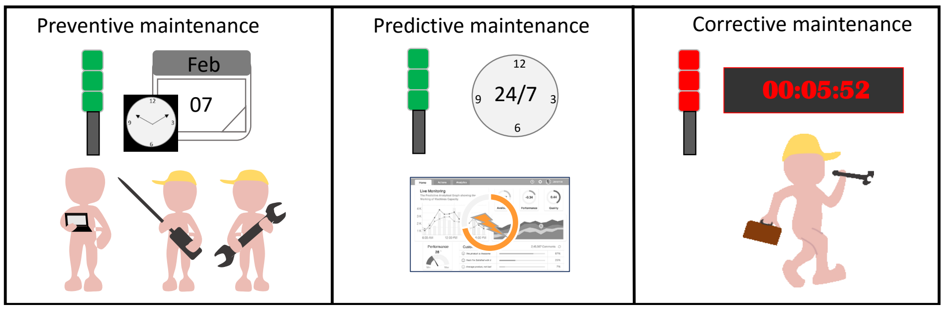


Figure 2.7: Types of maintenance in the manufacturing context.

Preventive maintenance: Preventive maintenance can be defined as all actions carried out on a planned, periodic, and specific schedule to keep an item/equipment in a stated working condition through the process of checking and reconditioning [23]. These actions are precautionary steps undertaken to forestall or lower the probability of failures or an unacceptable level of degradation in later service, rather than correcting them after they occur [24]. Preventive maintenance tasks thus have mainly the following characteristics [74]:

- Tasks are predefined.
- Tasks are carried out in a predefined schedule.
- Tasks are human intensive.

Predictive maintenance: The use of modern measurement and signal processing methods to accurately diagnose an item or equipment condition during operation is known as predictive maintenance. In the context of FoF, predictive maintenance using big data and machine learning technologies is investigated exhaustively for prognostic health management of systems [14]. Predictive maintenance aims to conveniently schedule corrective maintenance, predicting the condition/state of the system by analysing its performance [38]. Along with predictive maintenance technologies, automation technologies are also getting improved such that automated process adjustment and plant reconfiguration technologies evolve. This refers to if a downtime or performance degradation is predicted by the predictive maintenance system, the process can be adjusted with novel automation architecture [44]. Predictive maintenance is normally implemented with machine learning techniques that run 24x7 in the background of a manufacturing process making prognostic data analysis and predict the system health [38]. The tasks of predictive maintenance have the following characteristics:

- Tasks are mostly automated, less human involvement.
- Tasks are predefined for an equipment/item condition.
- Tasks are carried out round the clock.

Corrective maintenance: Maintenance activities carried out by a maintenance personnel, to return items/equipment to a defined state when deficiencies or failures are detected is known as corrective maintenance [23]. Hence, corrective maintenance refers to all activities required to identify and rectify the cause or reduce the severity, if an equipment/machine fails or a potential failure is predicted by a predictive maintenance system. It focuses on bringing a failed equipment back into production in the shortest possible time or other alternative that minimizes production losses while the machine is not productive [75, 76]. The corrective maintenance is carried out, either in a scheduled or unscheduled manner. A scheduled corrective maintenance is a result of either a regular inspection or a prognostic health management system [74]. An unscheduled corrective maintenance is required when an item/equipment breaks or fails during operation. Thus, corrective maintenance is normally applied under a strict time deadline to reduce production losses due to failure [18]. The tasks carried out in a corrective maintenance function have mainly the following characteristics:

- Task cannot be predefined/predicted.
- Tasks are time bound.
- Tasks are scheduled or unscheduled in nature.
- Tasks are human intensive.

2.3.2 Basics of Industrial Corrective Maintenance

Industrial corrective maintenance is applied, after a failure has occurred/ potential failure has identified in an industrial system. Because of the dynamic nature of industrial systems, corrective maintenance occurs mostly as unscheduled. The corrective maintenance in the context of industries includes emergency and breakdown corrective maintenance. A breakdown corrective maintenance is carried out when an equipment fails to function as expected. An emergency corrective maintenance is the one, carried out when an emergency arises from the failure of an equipment with regards to safety or performance [74].

The Table 1.1 in the previous chapter shows, when and where a corrective maintenance is required in industries. The corrective maintenance is normally performed by a maintenance personnel and has a sequence of activity as shown in Figure 1.3 according to [24]. As per 1.3, when a fault is detected, the maintenance personnel locate the fault, then diagnose the fault and carry out the corrective action based on the diagnosis and then checkout.

The corrective action in the state-of-the-art corrective maintenance is classified into five major types [24] as shown in the Figure 2.8 and requires the involvement of a maintenance personnel. They are Fail repair, Salvage, Rebuild, Servicing, Overhaul and Servicing. Fail repair refers to remedial actions required to take a failed system to its operational state. Salvage refers to the actions needed for taking disposed systems back to their defined operational behaviour. Rebuild actions are applied to restore an item to a standard as close as possible to its original state in performance. Overhaul takes a system back to its serviceable state as per maintenance serviceability standard. Servicing results as a side effect of a corrective action performed. For example, corrective action of a tank may lead to leakage in the crank.

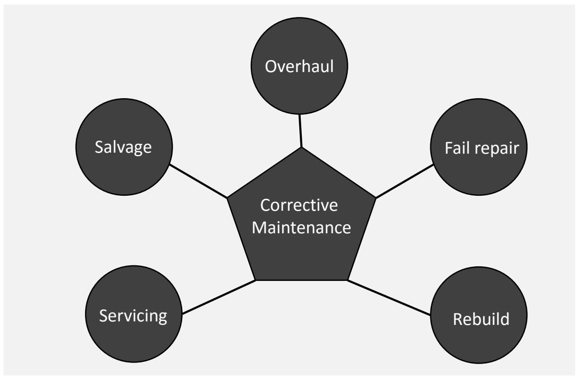


Figure 2.8: Types of corrective actions as shown in [24].

Even though predictive and prognostic techniques allow scheduling corrective maintenance in some cases, the task required in a corrective maintenance function cannot be predicted or pre-planned [35]. Each equipment or item under maintenance has a defined operational/ original/ serviceable state. Based on the type of the failure/breakdown, the maintenance personnel completes the task/sequence required to take the component to the defined operational/original/serviceable state and then checkout. The time between the detection of the fault and checkout of a fault in a system can be interpreted as Mean Time To Repair (MTTR). MTTR is a process indicator in the modern production environment, concerning the relationship between the breakdown and production loss [77].

2.3.3 Important Facts and Figures of Industrial Corrective Maintenance

A large part of the operating budget is constituted by maintenance spending in automated industries [78]. A study from the United States shows that \$300 billion is spent on maintenance of a plant and operations by the US industry and of which 80% is for chronic failure of machines, systems and people [36, 37]. A study by the British ministry shows that it requires around £3000 million annually for maintenance in the UK industries for failure [24]. The average size of a maintenance group in a manufacturing organization varies from 5-10 % of the total operating force. The cost of maintenance can be up to the 25% of the total operating cost [24]. A study from 1968 from the UK showed that better maintenance practices could save approximately £300 million annually [78]. Vathoopan et al. [18] shows that human errors play an important role in elongating a downtime. They state that, by providing proper support for the human, the corrective maintenance can be improved. They also assert that in the context of FoF the complexity of the systems increases and this will affect the human performing maintenance.

2.3.4 Management of Maintenance Activities in Industries

The maintenance activities are managed in two types namely: 1) Centralized maintenance management 2) Decentralized maintenance management.

Centralized maintenance management: Centralized maintenance management is the one in which a fixed number of maintenance personnel are assigned for handling the maintenance of the overall plant. Centralized maintenance management is mainly applied in small and medium scale enterprises as they have constraints related to human and financial resources. Centralized maintenance management employs a minimum number of maintenance personnel and supporting equipment for the management of maintenance activities. However, it assumes that the employed personnel have expert knowledge of the overall production systems [24].

Decentralized maintenance management: Decentralized maintenance management uses dedicated maintenance personnel for distributed areas. This kind of maintenance management also reserves dedicated supporting equipment for the distributed fleet. Thus, it requires more resources in general and is applied mainly in large-scale companies [24].

2.3.5 Importance of Improving Industrial Corrective Maintenance

In the modern context, the term preventive maintenance is slowly being archived in the production environment [38]. Preventive maintenance is applied mainly to enhance capital equipment life, reduce critical equipment breakdown, minimize production losses due to breakdown, and increase safety of maintenance personnel. However, mostly the preventive maintenance programs end up in failure, since their cost is unjustifiable or they take significant time to show the advantages [24]. In case of critical systems, the preventive maintenance is found to be making more production losses than corrective maintenance performed during breakdown, as it exposes equipment to possible damage. It also requires frequent access to equipment and requires access to more resources [35].

The globalization and related market competition has forced the evolution of the manufacturing paradigm in the previous years [7]. According to Lee et al. [38], these changes in the manufacturing paradigm have also effects on the business processes and other functions within the manufacturing companies. The maintenance is also an area, facing challenges concerning these changing manufacturing paradigms. Consequently, Lee at al. [38] assert that maintenance will be more predictive in nature. By leveraging advancements in other areas such as computer science, ICT, etc., Lee et al. [79] propose a strategic change in maintenance by avoiding problems than to face it. The summary of their proposal is depicted in Figure 2.9.

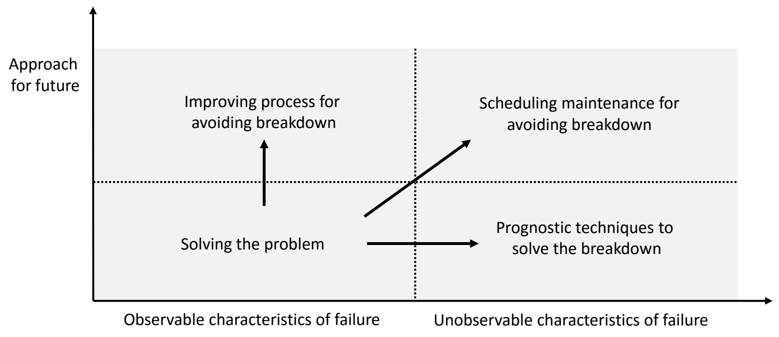

Approach for future
Improving process for avoiding breakdown
Scheduling maintenance for avoiding breakdown
Solving the problem
Prognostic techniques to solve the breakdown
Observable characteristics of failure
Unobservable characteristics of failure

Figure 2.9: Change of maintenance paradigm required for future manufacturing as per [79].

According to Lee et al. [79], by identifying the observable and unobservable characteristics of failure, the state-of-the-art problem solving approach can be shifted to a problem avoiding approach in the future. They propose that the observable characteristics of failure could be used to improve the process and design such that those failure types can be avoided in the future. In case of unobservable failure characteristics such as internal characteristics of a machine which are not observable leading to failure, prognostic techniques can be used to solve the breakdown. The prognostic techniques can be used further to schedule corrective maintenance. According to them, even in case of predictive and prognostic techniques breakdown do occur. However, with predictive and prognostic techniques the necessary maintenance can be conveniently scheduled. Thomas et al. [36] and Komonen et al. [37] propose that the evidence collected during a breakdown should be extensively used for avoiding further breakdown in the future. According to Thomas et al. [36] and Komonen et al. [37] predictive maintenance should be applied more towards improving operation rather than using to identify wear and tear.

Voegl Heuser et al. [80], describe fault tolerance and self-reconfiguration as one of the features of FoF. They also analyse the state-of-the-art approaches for fault handling. According to them, the current approaches aim to reduce the increase in operational cost of a plant caused by the downtime of the production resources. In a state-of-the-art production environment, fixing a fault requires manual intervention and is often carried out with a restart of the process, which is time consuming and costly. They propose two approaches for fault handling in a reconfigurable manufacturing system. First is to replace the faulty element with a virtual element where possible, second is using a redundant system.

Keddis et al. [44] proposes a similar approach as shown in Figure 2.10 by preceding with redundant systems (or other systems offering the same functionality) and self-configuring machines based on the production recipe. The figure depicts a standard workflow and an error-generating step (Step-2). From Step-2, depending on the type of error, error-handling mechanisms are included in the production recipe. For example, if the error is <Type1>, a self-handling mechanism reconfigures the system and a redundant machine performs the Step-2. If the error persists, the product is discarded. If the error is of <Type2>, a manual solving time is expected, if not the product is discarded. Both of these approaches describe handling error and as a part of the modern production strategy and thus contributes to reduce the financial burden of breakdown. However, employing redundant systems or virtual elements as in [80, 44] require additional resources and effort.

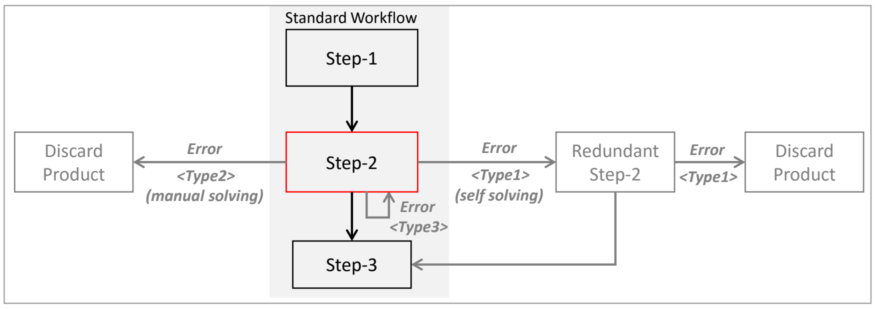


Figure 2.10: Automatic error handling integrated as part of production flow; adopted from [44].

There are tremendous efforts in the research community to improve industrial maintenance in general [38, 36, 37, 44, 80]. Summarizing the results of [38, 36, 37] it can be asserted that the focus of the research is mostly on predictive maintenance. Researches on predictive maintenance aim to predict any potential failure and hence to conveniently schedule corrective maintenance. Thus, the corrective maintenance is relevant even in presence of predictive maintenance [18]. In addition, there are efforts to make fault tolerant systems within industries [80, 44]. Different studies [28, 14] clarify that, although every effort is taken to make the systems reliable by applying preventive and predictive techniques, they do fail frequently. Consequently, remedial action has to be taken, to take the production system back to operation termed as corrective maintenance in general. The corrective maintenance is thus essential even in the context of FoF.

The state-of-the-art industrial corrective maintenance activities are mostly unscheduled. Unpredictable maintenance needs are handled in each corrective maintenance function. In many cases, it requires urgent and prompt actions in order to maintain the production schedules [81]. Analysis of the facts and figures of state-of-the-art industrial corrective maintenance indicates that the human error and MTTR have to be reduced in future industrial corrective maintenance. The human resources have to be managed better compared to the state of the art, to achieve resource and cost efficiency in corrective maintenance. Thus, novel methodologies and approaches are necessary in the future factories' corrective maintenance. The focus of this thesis is hence on improving the state-of-the-art industrial corrective maintenance foreseeing the FoF.

2.4 Improving Industrial Corrective Maintenance by Applying Self-Diagnosis

Based on the described problem in Section 1.2 of the previous chapter, this section reviews methodologies which improve the industrial corrective maintenance in detail.

2.4.1 Fundamentals of Self-Diagnosis

Self-diagnosis is referred to as the capability of a system to observe its functionality and diagnose any fault in it, without using an external mechanism [82]. The state-of-the-art self-diagnosis methodologies combine fault detection, localisation and diagnosis of a system [30]. Self-diagnosis is applied across different domains such as consumer electronics, industrial systems, automotive systems, etc [82, 83, 84]. Consequently, there are several methods for creating self-diagnosis.

Iserman [30] conducted a survey of existing self-diagnosis methodologies to find their applicability in the automotive domain. He lists several methodologies for fault detection based on models such as limit checking, signal model based, process model based, etc. He identifies classification based methods and inference based methods for fault diagnosis. He asserts that when prior knowledge on causalities of fault symptoms can be derived inference based diagnosis can be applied, and when not different classification approaches like statistical, neural network based, fuzzy clusters, etc., can be applied.

Isermann [30] shows examples of classification based diagnosis models for components such as actuators used in the automotive domain. Even though the methods for creating fault detection models and diagnosis models are given in this work, the models are created manually and require detailed knowledge, heuristics, resources and time for development. Classification based approaches for self-diagnosis have been extensively evaluated further [85, 86], and shows acceptable results. Statistical approaches were also evaluated later, showing competent results [26, 27]. However, the main drawback of these approaches [85, 86, 26, 27] is their high effort for development. In addition, the solutions are problem specific and not reusable.

Iserman et al. [87] further describe inference based self-diagnosis models. According to him, there are features specific to the equipment/item/part and their ideal states. Any violation from this state is normally identified as a fault [30]. There are different methods for identifying or detecting a fault. Normally a fault is detected with the help of a measured variable by instruments and observed variables and states by maintenance personnel [30]. Since the fault detection and diagnosis requires analytical methods, a knowledge base is created where ideal models of features exist. The creation of the knowledge base is a manual process, the complexity of which depends on the type of machines and their complexity.

Fault tree based self-diagnosis models are generally employed when prior knowledge on causalities of fault symptoms are available. Collecting this prior-knowledge generally requires heuristics of maintenance personnel within the context of industries [83]. Several researchers agree on the efficiency of fault tree based self-diagnosis in assisting humans performing corrective maintenance within the context of industries [30, 83, 84, 88]. Fault tree based approaches combine fault diagnosis and localization by hierarchical modelling of sources of faults as shown in Figure 2.11. Hence, a fault tree based approach reduces the chance of human errors [30]. The main drawback of the fault tree based approach is that they are built in an application specific manner [89]. As shown in Figure 2.11, the diagnosis of a system fault requires manual modelling of its tree structure along with the definition of fault in the lowest component. For this reason, they are not applicable if any changes are applied in the production process. Second drawback is the cost of developing such models.

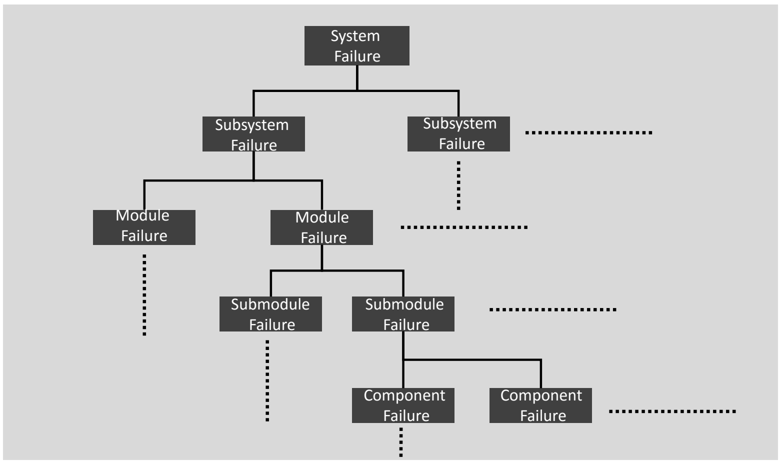
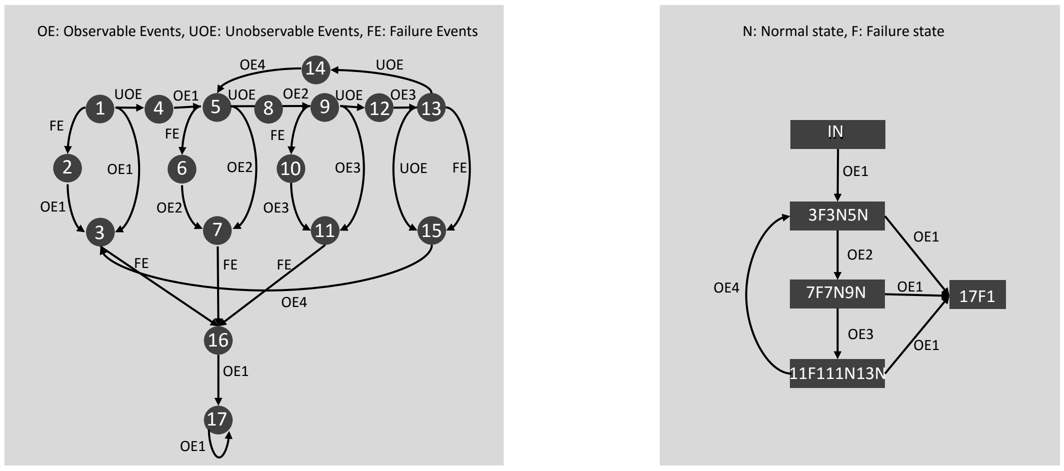


Figure 2.11: A fault tree model showing propagation of a fault in a system (modified from [84]).

Sampath et al. [90] proposed the construction of an observable event based diagnoser model for discrete event based systems' diagnosis. This approach combines fault localization and diagnosis within the diagnoser model, with prior knowledge of causalities. The diagnoser model is created manually based on the discrete behaviour of the system and their causalities to the unobservable fault events. An example of the diagnoser model as shown in [90] is depicted in Figure 2.12. The figure illustrates diagnosing fault in a discrete system based on observable events. The Figure 2.12(a) depicts the event propagation model in the system, where OE refers to Observable Events, FE refers to Failure Events and UOE refers to unobservable events. The Figure 2.12(b) depicts the specific diagnoser built for this system based on observable events, where N refers to Normal state and F refers to failure state. The labelling of the state is used for the diagnosis. This work has been further extended by many researchers [83, 91, 92], whose evaluations show positive results. However, these approaches [90, 83, 91, 92] also need high effort for creating the diagnoser models.

Considering the distributed nature of industrial systems Niggemann and Lohweg [15] show the importance of modelling self-diagnosis in a distributed manner. Rather than by using a


OE: Observable Events, UOE: Unobservable Events, FE: Failure Events
N: Normal state, F: Failure state
IN
3F3N5N
7F7N9N
11F111N13N
17F1
OE1
OE2
OE3
OE4
UOE
FE

(a) System event propagation model. (b) System diagnosis model.

Figure 2.12: An example of diagnosis model as shown in [90] showing its application dependency.

central observer, in distributed self-diagnosing systems, each distributed unit has its own diagnosis model and access to the diagnosis relevant data [82]. Niggemann and Lohweg describe the different methodologies of self-diagnosis applicable to distributed industrial systems. Their approach show the importance of improvement in classification based self-diagnosis and clarify the efficiency of inference based models within industries.

2.4.2 Self-Diagnosis and Corrective Maintenance

The Section 2.3.5, clarifies the importance of improving industrial corrective maintenance. Dhillon [24] finds, improving the performance of humans and hence reducing the MTTR can improve the corrective maintenance. As per definition [24], corrective maintenance involves five sequential steps namely: fault identification; fault localization; fault diagnosis; corrective action; and checkout. According to Dhillon [24] the first three steps in the corrective maintenance, i.e., fault identification, fault localization, and fault diagnosis are the most time taking steps, and the time required largely depends on the skill of the person performing maintenance. He suggests that achieving efficiency in these three steps will reduce the MTTR and thus improve maintenance effectiveness.

There were previous efforts [83, 93, 30, 92, 25] to improve the efficiency of maintenance personnel in the production environment by implementing self-diagnosis within corrective maintenance. Self-diagnosis integrates the first three steps in the corrective maintenance function namely fault detection, localization and diagnosis [18]. Self-diagnosis in any system is implemented as a software module, which continuously monitors the operation of a resource, detects, localizes and diagnoses any fault within that resource [87]. Self-diagnosis thus acts as a human assistive feature for corrective maintenance in a production environment [83, 93, 15, 92].

2.4.3 Importance of Applying Visual Assistive Models with Self-Diagnosis

Even though the automation systems are flexible in a FoF, the most flexible entity inside a future factory is the human itself. The human workers will be faced with a multitude of jobs like strategic decision making for reconfiguration, monitoring operation, and doing corrective maintenance etc. The challenge lies in these jobs when the complexity of systems increases [45].

Considering the complexity of systems in a FoF environment, one of the core areas of research is to apply interaction technologies and metaphors from consumer industries in the industrial domain. The main objective of these researches [94, 95] are to identify means and methodologies for interaction within the FoF environment. Researchers have identified visual models in augmented reality and virtual reality as potential means for interaction in future complex factory environments. The use of consumer devices have also found to be evident in the future environment as they are tuned to meet the consumer requirements [94, 95].

Previous works [94, 95, 55] show that visual technology applications help handling the complexity of operation and maintenance in the industrial environments. Figure 2.13 shows an example of using augmented reality based visual models for corrective maintenance as shown in [94]. In the figure, a visual model of the system is augmented on a real system aiming to reduce the effort of its corrective maintenance.

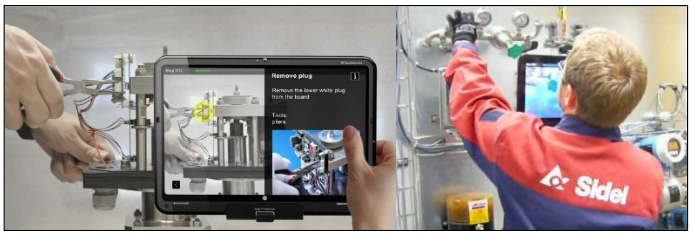


Figure 2.13: Example of applying visual assistive technology in maintenance (modified from [94]); an augmented reality tablet displays the maintenance tasks and a human performs it.

The enablement of self-diagnosis aims, reduction in the effort of human performing corrective maintenance. A recent review on self-diagnosis within the context of industries reveals the use of visual models and consumer devices as medium of interaction between humans and machines [27]. According to [27], application of visual models assists the humans in performing the corrective maintenance. The application of visual technologies have been found to be beneficial in reducing the complexity of corrective maintenance applications [94, 55]. However, the visual models in these approaches [27, 94, 55] are application specific and not reusable.

2.5 Scope of the Research and Questions Addressed

The objectives of this thesis, mainly aim at improving the cost and resource efficiency of corrective maintenance function. Foreseeing the solutions to be applied in a FoF environment, the fundamental characteristics and elements of the FoF are analysed. The review of the fundamentals of FoF reveals that the future systems will be flexible and reconfigurable in nature and also possess human assistive features. The future factories should hold cognitive capabilities, intelligence and seamless interoperability.

As it was found that, the maintenance of a production system has strong dependencies to the engineering and operation of a production system, the state-of-the-art plant engineering and operation influential to the corrective maintenance are also reviewed. The studies on engineering of FoF summarize that the future plant engineering features modularization, component orientation and service (skill) orientation. The domain specific and stakeholder specific tools of the future, interoperate and generate seamlessly exchangeable engineering data. As the communication and information exchange between operation and maintenance platforms is relevant for corrective maintenance, a review of information and communication exchange technologies for FoF were also performed. This analysis revealed OPC UA as the choice for operational information exchange and communication within the industrial manufacturing domain.

Further analysing the state of the art and research trend in corrective maintenance, it was clear that the state-of-the-art industrial corrective maintenance has to be revamped for the FoF. Though different studies reveal the advantages of self-diagnosis in improving corrective maintenance by reducing MTTR and human errors, it was also clear that enabling self-diagnosis on manufacturing systems requires a lot of resources and effort. The review of the applicability of different diagnosis approaches shows that they are developed for specific problems using specific technologies and mostly are not reusable.

By identifying the reduction in human error and MTTR as a must for revamping the future corrective maintenance, this thesis aims enabling self-diagnosis in future factories in a cost efficient and reusable manner. By acknowledging the benefits of visual assistive technologies in the corrective maintenance, this thesis further investigates visual models for integrating reusable self-diagnosis models within future corrective maintenance. This thesis also aims to accomplish the proposed characteristics of FoF in their corrective maintenance function.

Within the scope of this thesis, the following research questions are addressed:

1. **Is it possible to create reusable models for self-diagnosis in production systems? What are the prerequisites for it?**
   Acknowledging the application specific behaviour of different self-diagnosis approaches, this question focuses on methodologies for creating reusable models for self-diagnosis in production systems and the prerequisites for it.
2. **How to realize self-diagnosis of automated production systems in a cost efficient manner? Is it possible to leverage their engineering and operational aspects for achieving cost efficiency in self-diagnosis realization?**
   Literature analysis reveals the high cost and resource utilization for developing self-diagnosis

in general. Hence, this question tries to identify methodologies for developing self-diagnosis in a cost efficient manner. The possibility of reusing the engineering and operational data of production systems for developing self-diagnosis is also examined under this question.

3. **How to add flexible and reconfigurable characteristics to the self-diagnosis feature of production systems?**
   The future automation systems are said to be flexible and reconfigurable in nature. consequently, this question addresses means and methodologies for adding flexible and reconfigurable characteristics to their self-diagnosis.
4. **How to effectively integrate visual assistive features for corrective maintenance function with reusable self-diagnosis models?**
   Researches identify the benefits of visual models and assistive technologies in industrial corrective maintenance. This question examines models and features required in visual assistive technologies for corrective maintenance, hence they can be integrated with the reusable self-diagnosis models of automated production systems.
5. **How to manage the maintenance personnel allocation, leveraging the self-diagnosis and visual assistive features of the automated production systems?**
   An analysis of the literature shows humans as an important element of FoF. This question tries to identify the responsibilities of a maintenance personnel in a factory with self-diagnosing production systems.

The research questions are addressed in Chapters 4-7 as shown in Table 2.1.

Table 2.1: Research questions addressed and allocated chapters.

	Chapter 4	**Chapter 5**	**Chapter 6**	**Chapter 7**
Research Question 1	✓	✓		
Research Question 2	✓	✓	✓	✓
Research Question 3		✓		✓
Research Question 4			✓	✓
Research Question 5			✓	✓

Chapter 3

Requirements for Enabling Self-Diagnosis in Future Corrective Maintenance

This thesis hypothesizes that efficient realization of self-diagnosis along with visual assistive features in production systems will improve the industrial corrective maintenance in the future. This chapter identifies the requirements for achieving the same using the methodologies of requirements engineering. The application of requirements engineering promises to derive the users perspectives, functional specifications and technical characteristics of a system from its elicited requirements [96, 97, 98]. Thus, the application of requirements engineering guarantees that the system under consideration meets the needs and expectations of its users. This thesis uses the elicited requirements to further refine the scope of the research and subsequently to derive the research methodologies.

This chapter is divided in four sections. Section 3.1 describes the fundamentals of requirements engineering. The stakeholders and the stated requirements of the system are introduced in Section 3.3. Section 3.4 describes the use-cases and the elicited requirements of the system. Subsequently, Section 3.5 concludes this chapter.

3.1 Requirements Engineering as a Means to Ensure Industrial Applicability of the Research Results

This thesis is partly developed within the scope of the research projects OPAK [99] and DEVEKOS [100], funded by the German Federal Ministry for Economic Affairs and Energy (BMWi). These projects integrate academic and industrial partners, envisioning the industrial applicability of the research results. Therefore, the results of this thesis are also foreseen to be transferable to the industries. Hence, methodologies of requirements engineering are used to formally elicit the requirements of the system under consideration in this thesis. Requirements are used as a means to convey the technical aspects and functionalities of the system among the stakeholders. The requirements are traced through the further development of this thesis, foreseeing that the results of this thesis meet the stakeholders' needs.

Within the research projects OPAK and DEVEKOS, the production resources are assumed as a composition of modular CPPS based automation components. The projects primarily examine the methodologies for engineering modular production resources of the future, consuming the services of the automation components. These projects presume that the manufacturers of CPPS based automation components can distribute the digitized engineering models of their components along/prior to their delivery to the consumer. Consequently, the consumers can leverage the digitized engineering models available from the manufacturers of the CPPS based automation components, for the cost efficient engineering of their automation systems.

This thesis examines means and methods for cost and resource efficient realization of self-diagnosis in industrial automation systems. The partners from the projects anticipate that the concept for engineering automation systems applied in the projects is also applicable for the realization of self-diagnosis. The component manufacturers can distribute the self-diagnosis models of CPPS based automation components along/prior to their delivery to the consumer. The consumer can make use of the self-diagnosis models of the components to reduce the cost, and effort for realizing self-diagnosis and visual assistive features in their automation systems.

Thus, this thesis presumes two systems under consideration: 1) A CPPS based automation component 2) An automation system composed of CPPS based automation components. The technical specifications and functionalities of the self-diagnosis and visual assistive features of these two systems have to be derived using the principles of requirements engineering.

3.2 Defining the Desired Practice of Requirements Engineering

Requirements engineering practice in the industrial environment varies from project to project and company to company [96]. The requirements engineering commonly integrates several activities such as requirements elicitation, analysis, negotiation, specification and validation [101, 102]. The requirements elicitation itself include several stages such as stakeholder identification, understanding the customers' needs, clarifying requirements, etc [96, 98]. In the initial analysis, it was found that only some of the aspects of the industrial requirements engineering practice is applicable in this thesis. The sequences of activities of requirements engineering applied in this thesis are described below.

The process of requirements engineering applied in this thesis starts by, identifying the stakeholders of the system under consideration. According to Westfall [97], the stakeholders of a system are mainly categorized into three types. The first are the acquirers of the software product or system; the second are the suppliers of the software product or system; and the third one are the other stakeholders. The acquirers can be further divided into two major groups; the customers who request, purchase and pay for the software product and the users who actually use the product. The suppliers have further internal stakeholders such as developers, advisers, project groups that are involved in developing the system, etc. The other stakeholders may change depending on the type of the product and project. Examples of other stakeholders are legal or contract management, upper management, government or regulatory agencies, etc [97].

The core activities of the requirements engineering starts by collecting expectations of the acquirers of the system. The expectations of the acquirers are otherwise termed as stated requirements [96]. The stated requirements can be of different types in a project namely, business requirements, user requirements, product requirements, environmental requirements and unknowable requirements [96, 98]. Business requirements are used to specify the customer's business goals and corresponding bounds. These are the initiating reasons for developing new systems or software of any kind. When the system involves user interactions, user requirements are used to derive the user's needs for the system or software. Product requirements represent the requirements of the products/services offered by the system. Environmental requirements concern the physical setting, social and cultural conditions of the system and the setting in which the system or software will be used. Unknowable requirements are those, which are not known at the beginning of a system development, and are highlighted only as the system evolves [96].

The stated requirements are then analysed to derive the real requirements. There are different techniques and means for requirements analysis, such as requirement workshops, high level data flow diagrams, use-case diagrams, etc. Use-cases help to specify the requirements from a users point of view and to elicit the hidden requirements from the stakeholders. In addition, they can be used in the further development of a system [103]. Hence, this thesis employs use-case diagrams to elicit the real requirements from the stated requirements. The elicited real requirements are later used consistently throughout the development of this thesis.

The sequence of activities of requirements engineering applied in this thesis are as follows:

1. Identify the stakeholders and derive the stated requirements of the systems.
2. Elicit the real requirements of the systems by analysing the use-case scenarios.

3.3 Stakeholders and Stated Requirements of the Systems

The first step of requirements engineering is to identify the overall stakeholders of the system under consideration [97]. Subsequently from the overall stakeholders, the acquirers have to be identified and their needs and expectations have to be collected.

3.3.1 Identifying the Stakeholders

The stakeholders of the systems under consideration in this thesis, are identified by discussion with partners from the projects OPAK and DEVEKOS. The overall stakeholders of the systems foreseeing the realization and application of self-diagnosis and visual assistive features in their corrective maintenance are depicted in Figure 3.1. The systems under consideration are shown in the innermost ellipse marked as (a). The ellipse encapsulating the systems marked as (b) depicts the acquirers of the systems. The ellipse marked as (c) shows the suppliers of the systems. The outermost ellipse marked as (d) shows the other stakeholders of the systems.

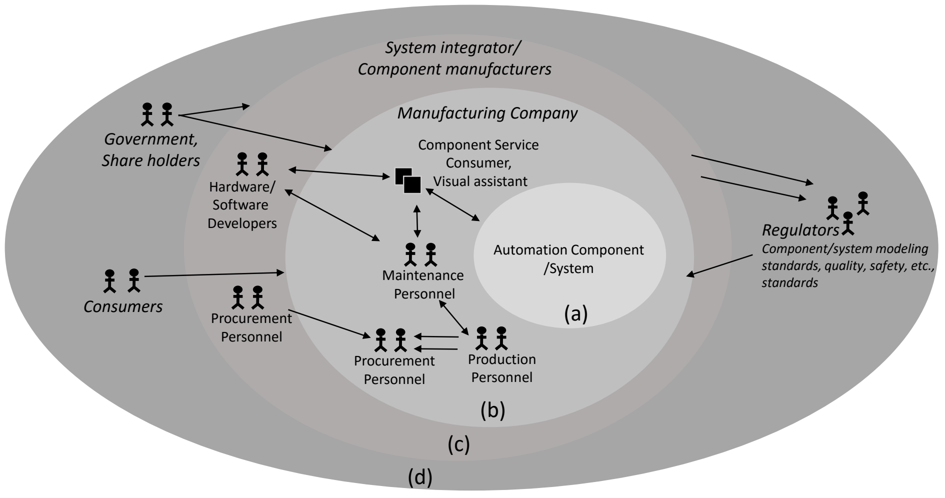


Figure 3.1: Systems under consideration with acquirers, suppliers and other stakeholder (from innermost ellipse to outermost ellipse).

From the figure, the primary acquirers of the systems are identified as the manufacturing company. A manufacturing company employs a CPPS component based automation system to automate their manufacturing process. The definition of a CPPS automation component asserts that the CPPS automation components have characteristics of a system. They have modular features, they can function independently and thus can also be applied as a single unit within a manufacturing plant [104]. In this sense the automation components and systems coexist in a manufacturing plant. Thus, the CPPS component manufacturer and the system integrator are identified as the suppliers to the manufacturing company. A system integrator is a company, who builds the production resources (automation systems) for a manufacturing company. Considering the automation systems to be composed of automation components, the system integrator acts as an acquirer of the automation components. Thus, system integrator is considered as a secondary acquirer.

The primary acquirer (manufacturing company) includes the maintenance personnel, production personnel, procurement personnel, component/system service consumer and visual assistant. The component/system service consumer is the control software module, which consumes the services of the automation components. The visual assistant is a software module, which assists the maintenance personnel with visual assistive feature for carrying out the corrective maintenance function. The maintenance personnel are the indirect users of the systems through the visual assistant. The maintenance personnel coordinate with the production personnel to schedule and execute corrective maintenance functions. Thus, the production personnel are indirect and passive users of the systems. The procurement personnel are the customers of the systems under consideration. The procurement personnel decide on the acquisition, based on the review of the system by the production personnel and the maintenance personnel.

The supplier of the systems can be either the component manufacturer or the system integrator. From the component manufacturer/system integrator, the stakeholders interacting with the automation component/system are the hardware/software developers, and procurement personnel. The hardware/software developers from the component manufacturer/system integrator interact with the maintenance personnel concerning their systems. The hardware/software developers from the component manufacturer/system integrator are the ones, who develop the automation system/component hardware and the corresponding service consumer and visual assistant software modules. The stakeholders within the system integrator also serve the additional role of secondary acquirer.

The other stakeholders such as the government, or shareholders might also influence the activities in a manufacturing company affecting the procurement personnel in a negative manner. The consumers of the products of the manufacturing company have a direct influence on the automation systems and the manufacturing company. The regulators such as component modelling standard, quality, safety, etc., standards used within the manufacturing company influence the component manufactures and system integrator negatively.

3.3.2 Stated Requirements

The stated requirements of the systems are created by interviewing the partners within the projects having the role of acquirers (manufacturing company and the system integrator).

Business Requirements: The initiation of the systems are triggered by the basic business goals of the manufacturing company or the system integrator. The system integrator plans to leverage the self-diagnosis feature of a CPPS based automation component to facilitate self-diagnosis in a component based automation system. The manufacturing company intends to employ the automation systems with self-diagnosis and visual assistive features for the corrective maintenance of FoF. The business requirements are listed below:

1. The application of self-diagnosis and visual assistive features shall decrease the downtime and the production loss in FoF.
2. The self-diagnosis and visual assistive features of the systems shall have re-configuration and flexible characteristics, such that these can also be reconfigured according to produc-

tion reconfiguration/s.

3. The self-diagnosis and visual assistive features shall reduce human involvement in corrective maintenance. By reducing human involvement, human error can be reduced and also human resources can be efficiently employed.
4. The facilitation of the self-diagnosis and visual assistive features shall have cost and time efficiency. Hence, the cost efficiency of corrective maintenance can be achieved.

User Requirements: The expectations of the manufacturing company/system integrator on the usage of the self-diagnosis feature within the corrective maintenance of future systems are listed below:

1. Less effort shall be required in composing self-diagnosis feature of automation components to facilitate self-diagnosis in automation systems.
2. The systems shall handle complexity, since the FoF is envisioned to be complex in nature.
3. The usage of self-diagnosis feature in automation components should be intuitive and human assistive. Thus, the facilitation self-diagnosis in future automation systems should reduce human effort in corrective maintenance.
4. The future corrective maintenance systems shall use existing/intuitive user interfaces. Therefore, the learning curve required for any new interface/software can be reduced.

Product Requirements: Product requirements evolve from the characteristics of FoF elaborated in Section 2.1 of the previous chapter. These are listed below:

1. The self-diagnosis aspects from the component manufacturer shall have interoperability and exchangeability. Hence, they can interoperate and exchange information with the component/system service consumer and the visual assistant module.
2. The self-diagnosis shall have loosely coupled and modular architecture, such that they have flexibility and reconfigurability.
3. The self-diagnosis of the systems shall exchange information with the production modules or systems: The maintenance systems have dependencies on production systems and information exchange will help improving production based on corrective maintenance.
4. The self-diagnosis of the automation system shall not induce any safety threat or performance issues to the production systems.

Environmental Requirements: Environmental requirements are derived from the system integrator and the manufacturing company and are listed below:

1. The automated production systems employed in the manufacturing company shall satisfy the requirements of FoF.
2. The development shall be performed in the standard bounds recommended within the industrial automation domain.
3. The humans shall act as strategic decision makers in the corrective maintenance function.

3.4 Use-case Analysis and Elicited Requirements

At this point, the use-case scenarios of the systems under consideration can be constructed. Use-cases are one of the different techniques used in requirements analysis for better understanding the customers' expectations and needs [96]. Use-cases help to derive the real requirements from the user expectations or stated requirements in terms of the systems functionality. This finally leads to defining the specifications and features of the system under development. Use-cases provide a semantic link from the user expectations to the most detailed view of the system [96].

3.4.1 Use-cases of the Systems

The use-cases of the systems foreseeing the enablement of self-diagnosis and visual assistive features in their corrective maintenance are shown in Figure 3.2. The use-cases above the dashed line within the automation component/system, occur during the operation phase of the automation component/system. The use-cases below the dashed line occurs during the initial design/reconfiguration phase of the automation component/system.

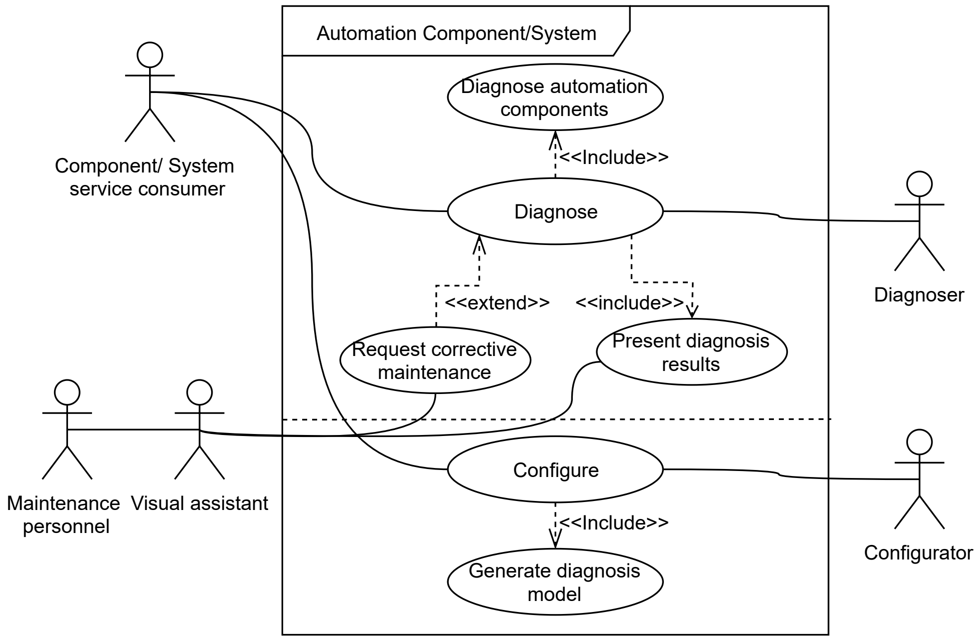

Automation Component/System
Diagnose automation components
<<Include>>
Diagnose
<<extend>>
<<include>>
Request corrective maintenance
Present diagnosis results
Configure
<<Include>>
Generate diagnosis model
Component/ System service consumer
Diagnoser
Maintenance personnel
Visual assistant
Configurator

Figure 3.2: Use-case analysis of self-diagnosis and visual assistive features of the automation systems in the factories of the future.

Use-cases are prepared by identifying actors of the systems under consideration. The actors represent the role played by external entities that reside outside the functional system but interact with it [103]. The actor can be human or non-human such as hardware, software, etc., based on the type of the system. The actor can be a requester, who requests some functionality from the system or a provider, who provides some functionality to the system.

For defining the actors of the systems, the stated requirements were further analysed as functionalities requested and provided from the systems. Accordingly, the requesters identified are the component/system service consumer, the visual assistant and the maintenance personnel. Two software components were defined as the providers. The first software component is a Diagnoser, which provides a self-diagnosis feature to the automation component. The second software component is a Configurator, which provides a configuration feature to the automation system. The functionalities required for the self-diagnosis and visual assistive features are provided by these two software components.

For naming the use-cases, the notation from Nasr et al. [103] is used. Accordingly, the use-cases in this thesis are named as The <System name> is requested [by the <actor name>] to perform the <Use-case name>. The system name/s within the scope of this thesis are the " CPPS based automation component" and the "component based automation system". The different use-cases within this use-case analysis are described below.

Diagnose: This use-case occurs each time the service consumer of the automation component/system consumes a service from the component/system. Hence, it occurs in the operation phase of the systems. The "Diagnose" use-case of an automation system includes the "Diagnose" use-case of its constituent components. This use-case is described in Table 3.1.

Table 3.1: The Component/System service consumer requests the Automation Component/System to perform Diagnose.

Name	Diagnose
Description	The automation component/system offers self-diagnosis feature to the service consumer of the automation component/system.
Actors	Component service consumer, Diagnoser.
Used use-cases	Nil
Preconditions	Self-diagnosis models of the automation component/system are available prior to their commissioning/operation.
Postconditions	Diagnosis results of the automation component/system are available.
Basic course of actions	1. Detect fault in an automation component/system. 2. Derive localization of the fault in an automation component/system. 3. Derive causalities of the fault in an automation component/system.

Present Diagnosis Results: "Present diagnosis results" use-case is an included use-case of "Diagnose". It occurs every time the "Diagnose" use-case occurs. If there is a failure, the result shows the causality, otherwise the result shows the healthy status. This use-case is consumed by the visual assistant and thus also by the maintenance personnel. It is described in Table 3.2.

Table 3.2: The Component/System service consumer requests the Automation Component/System to perform Present diagnosis results.

Name	Present Diagnosis Results
Description	The diagnosis results produced by the Diagnoser have to be displayed in the visual assistant to be consumed by maintenance personnel.
Actors	Component/system service consumer, Diagnoser, Visual Assistant, Maintenance personnel.
Used use-cases	Nil
Preconditions	Self-diagnosis of the component/system is completed and diagnosis results are available.
Postconditions	Diagnosis results are transformed to a visual human assistive model.
Basic course of actions	1. Notify detection of a fault in an automation component/system. 2. Visualize location of the fault in an automation component/system. 3. Display diagnosis results in a natural language.

Configure: This “Configure” use-case occurs during the initial configuration/reconfiguration phase of automation components/system. It is elaborated in Table 3.3.

Table 3.3: The Component/System service consumer requests the Automation Component/System to perform Configure.

Name	Configure
Description	The component manufacturers/system integrator allows configuration of their component/system. The engineering data of the component/system are provided accordingly.
Actors	Component service consumer, Configurator.
Used use-cases	Generate Diagnosis Model
Preconditions	The component manufacturer/system integrator provide configuration options and modular engineering data of their components/system.
Postconditions	The engineering data of a component/system based on their configuration are available.
Basic course of actions	1. Record the configuration data of a component/system. 2. Produce the engineering data of a configured component/system.

Generate Diagnosis Model: “Generate diagnosis model” is an included use-case within the “Configure” use-case. The manufacturing company/system integrator requires an automatic generation of the diagnosis model, each time an automation component/system is configured/reconfigured. This use-case is described in Table 3.4.

Request Corrective Maintenance: The “Request Corrective Maintenance” is an extended

Table 3.4: The Component/System service consumer requests the Automation Component/System to perform Generate Diagnosis Model.

Name	Generate Diagnosis Model
Description	Each time a configuration occurs in the automation component/system, the self-diagnosis models are generated based on the configuration data.
Actors	Component/system service consumer, Configurator.
Used use-cases	Nil
Preconditions	The component manufacturer/system integrator provide configuration options and modular diagnosis models of their components/system.
Postconditions	The diagnosis model of the reconfigured component/system is generated.
Basic course of actions	1. Identify the variations in the engineering data of a configured component/system. 2. Generate the diagnosis model based on the variations in the engineering data of the automation component/system.

use-case from “Diagnose” of the automation system. When a fault is detected within the “Diagnose” use-case the “ Request corrective maintenance” of the system is automatically triggered by the automation system. This use-case is consumed by the visual assistant and thus also by the maintenance personnel. This use-case is described in Table 3.5.

3.4.2 Eliciting the Requirements

The requirements for enabling self-diagnosis and visual assistive features in the corrective maintenance of the systems are elicited by analysing the use-cases and the stated requirements. The analysis reveals that the automation components and systems are expected to be modular and loosely coupled in the future. The maintenance personnel are required to act as the strategic decision makers. The visual assistive and self-diagnosis features of the automation components/systems are envisioned to assist them.

Additionally, the analysis clarifies that the self-diagnosis features of the systems are envisioned to not only integrate the fault detection and its localization but also derive its causalities. The visual assistive feature is required to notify the detection of fault, visualize the location of the fault and display the diagnosis results in a natural language. Further, the automation components/systems are expected to schedule their corrective maintenance action if they fail and also recommend the necessary actions. The automation components and systems are required to record their configuration data, generate corresponding engineering data and identify variations in the engineering data for different configurations. It is envisioned that the systems reuse their engineering data and generate their self-diagnosis models based on this engineering data.

Table 3.5: The Component/System service consumer requests the Automation Component/System to perform Request Corrective Maintenance.

Name	Request Corrective Maintenance
Description	The manufacturing company foresees the self-diagnosis of the automation systems along with the visual assistant applied for their corrective maintenance. Thus, whenever a fault is detected, the service of a maintenance personnel is requested through the visual assistant.
Actors	Component service consumer, Diagnoser, Visual assistant, maintenance personnel.
Used use-cases	Nil
Preconditions	The self-diagnosing automation component/system can interoperate with the visual assistant.
Postconditions	The corrective maintenance of the automation system is triggered.
Basic course of actions	1. Notify the detection of a fault and display its diagnosis result. 2. Schedule the corrective maintenance of the faulty automation component/system. 3. Recommend corrective action for the detected fault.

Further, the analysis derives the requirement of using the recommended standards within industrial automation for modelling and visualizing self-diagnosis of the systems. In addition, the self-diagnosis models of the automation components are envisioned to be distributed along/prior to their delivery. The analysis also clarifies that the self-diagnosis feature is required to operate along with the production systems without affecting their performance. Further, it reveals the requirement of using standard and vendor neutral interfaces available in the industrial automation domain.

3.5 Conclusion

This chapter presented the requirements for enabling self-diagnosis and visual assistive features in the corrective maintenance of future production systems. By applying the methodologies of requirements engineering, it is envisioned that the research results meet the needs and expectations of its users. In addition, based on the requirements the research methodologies applied in thesis are refined as follows:

1. First, the methodology for efficient realization of self-diagnosis in automation components is derived.
2. Next, the methodology for efficient realization of self-diagnosis in component based au-

tomation systems is defined.

3. Finally, the methodology for improving the application of visual assistive and self-diagnosis features in the corrective maintenance of a production system is addressed.

The requirements elaborated in Section 3.4.2 are traced in the further development of this thesis.

Chapter 4

Modelling Self-Diagnosis of Modular Industrial Automation Components

Self-diagnosis is a key feature in many consumer devices, such as printers, washing machines, etc., in and around our daily life. The self-diagnosis feature of these devices has been found to be quite efficient in reducing the human effort for the corrective maintenance of such devices [90]. This thesis hypothesizes that, implementing self-diagnosis and visual assistive features in the production resources will improve their corrective maintenance. Self-diagnosis feature has already been implemented in industrial automation systems. However, the previous experiences show that self-diagnosis implementation in industrial automation systems are not efficient, considering the cost and effort required [36, 89, 24].

The previous chapter defines, a methodology for efficient realization of self-diagnosis in automation components as an initial requirement for deriving the overall methodology of this thesis. Consequently, this chapter examines a methodology for cost efficient realization of self-diagnosis in automation components. Thus, Section 4.1 of this chapter describes the prerequisites for modelling self-diagnosis in automation components. The model of a skill, which acts as a facilitator for implementing self-diagnosis is introduced in Section 4.2. Later, Section 4.3 describes the types of faults, which serve as the point of entry for modelling self-diagnosis in skill of an automation component. Different aspects of reusing engineering data for realizing self-diagnosis are elaborated in Section 4.4. Subsequently, Section 4.5 concludes this chapter.

4.1 Prerequisites for Modelling Self-Diagnosis of Automation Components

Self-diagnosis has been applied in multiple domains, such as consumer electronics, industrial systems, automotive systems, etc. [90, 30, 89]. Sampath et al. [90] showed an example of modelling self-diagnosis in a copier machine, considering it as a discrete event based system. They detect faults, based on the observable events from the system model. The fault diagnosis is modelled, based on the model of the internal physical components and their logical interaction within the copying process. Another approach for modelling self-diagnosis is explained by Isermann [87, 30], for components in the automotive domain. He showed a method to detect internal faults of a component by analysing the characteristics of its process models using a knowledge base. The fault diagnosis is modelled, based on the characteristic changes in the actuators, sensors and controllers executing the concerned process. Zibaei et al. [89] present the example of a cyber physical system (CPS) diagnosis, based on the fault tree of that system. The fault detection and diagnosis is modelled by associating the logical and physical behaviour of the components of the system with the plausible faults of the system.

In literature, there seems to be no general definition of the prerequisites for modelling the self-diagnosis. After analysing the previous works on self-diagnosis described above [90, 30, 89], the prerequisites for modelling self-diagnosis can be inferred as: the model of its 1) physical behaviour 2) logical behaviour and 3) the interaction of logical and physical behaviour within the system. The logical behaviour model specifies how the system produces outputs corresponding to the logical inputs it receives, hence the input-output relationship of the system. The physical behaviour model specifies how the physical resources within the system process the logical inputs, and produce the required physical outputs of the system. The physical behaviour model also defines the physical dependencies, using which the physical resources function.

The automation components within the context of this thesis refers to CPPS based automation components. CPPS based automation components are those automation components, which have a Programmable Logic Controller (PLC) integrated within, and hence function/control independently without an external control entity [104]. CPPS incorporate necessary logical and physical entities to offer an automated process or part of the process inside a production environment [18]. The prerequisites for modelling self-diagnosis in the CPPS based automation components can be derived by mapping the general prerequisites on to the CPPS based automation components. The following sections describe the prerequisites for modelling self-diagnosis in the CPPS based automation components.

4.1.1 Prerequisite Associated with the Skill Model of a Component

For modelling the self-diagnosis, the interaction between the logical and physical behaviour model of a component is required. There are recent efforts [105, 16, 19] in the industrial automation domain to define the skills of CPPS based automation components. Skill is defined as the capability of an automation component to execute a process or part of it. Skill can be considered as the sum of all properties of a component, and can be made executable via a service [106, 105, 16, 19]. This thesis asserts that the model of a skill can be used to define the interaction between the logical and physical behaviour models of an automation component.

A sample model of an automation component, where the skill is used as a means for modelling the interaction between its logical and physical behaviour models is shown in Figure 4.1. In this model, the automation component has two sub-components namely: a software component and a hardware component. The software subcomponent implements the logical behaviour and the hardware subcomponent implements the physical behaviour. The skill is executable as a service offered by the component and it has a protocol: It receives a “Request Skill” input and produces “Response Skill” output. The service interfaces of the skill integrate the software subcomponent and the hardware subcomponent to implement its protocol. For the component to produce the “Response Skill”, after receiving the “Request Skill”, the interaction between the logical and physical behaviour model of a component has to occur.

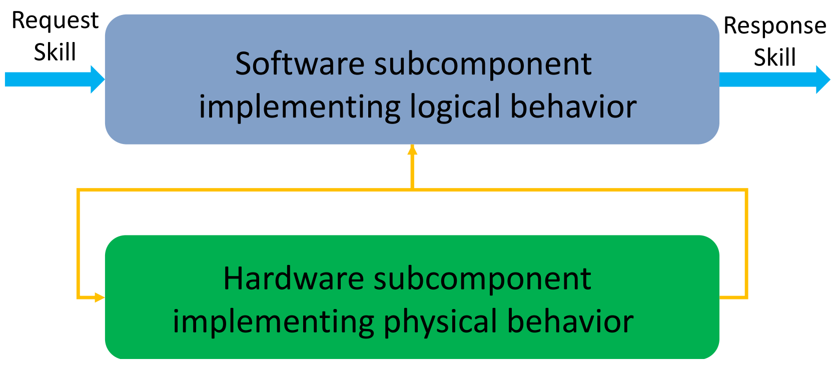

Request Skill
Software subcomponent implementing logical behavior
Response Skill
Hardware subcomponent implementing physical behavior

Figure 4.1: Skill service interfaces integrating the hardware and software subcomponents of a CPPS based automation component.

4.1.2 Prerequisite Associated with the Behaviour Model of a Component

The prerequisites for modelling the self-diagnosis mandate that the physical behaviour model of the component is defined. This thesis proposes that, if the offered functionality of the automation component can be defined as a skill the physical resources executing the skill can be attributed to the skill. The physical resources executing the skill can be defined as the hardware subcomponent defined in the previous section. For demonstrating such a model, a Single Input Single Output (SISO) component, providing a single skill is taken as an example. The hardware subcomponent and its association to the skill, for a SISO is depicted in Figure 4.2. The hardware subcomponent of such a component has an actuator and sensor, which interface with the software subcomponent implementing the skill of an automation component. The actuator makes the necessary physical effect in the physical world, receiving the control signal from the PLC. The sensor senses the physical effect, and sends the measured output signal back to the PLC. The hardware subcomponent thus defines the physical behaviour of the component.

For modelling the self-diagnosis, the logic behaviour of the component is also necessary. This

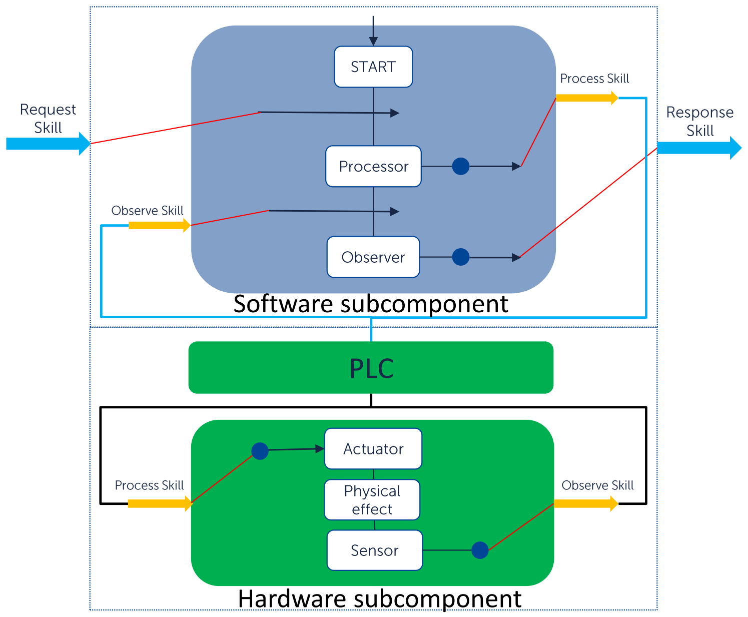


Figure 4.2: Software and hardware subcomponents implementing the logical and physical behaviours of a CPPS based automation component.

thesis proposes the logical behaviour model to be defined as the software subcomponent defined in the previous section. The example of such a logic behaviour model is depicted in Figure 4.2. This model is based on the structure of a SISO automation component with an actuator and sensor. The logic behaviour model is modelled as an automata, which has two states namely: Processor and Observer. The Processor can send Process Skill through the Actuator and the Observer can receive Observe Skill from the Sensor. Thus, the logical behaviour model interacts with the physical behaviour model. The logical behaviour model also interacts with the service interfaces of the skill, as it processes the "Request Skill" and generates the "Response Skill".

Therefore, the overall model of the skill of an automation component integrates the physical and logical behaviour models within an automation component. The skill model also acts as a service interface of an automation component. In the literature, a complete model of the skill is not available; only the service model of a skill is available [105, 16, 19]. This thesis proposes the attributes of a skill introduced in Section 4.1.1, as a foundation for developing the complete model of a skill. Consequently, this thesis also asserts that, on the provision of such a skill model, the self-diagnosis can be modelled on the skill.

According to Isermann [30], a fault in a system can be defined as a deviation from the ideal or expected behaviour of the system. Isermann [87] also defines the self-diagnosis model, as a combination of fault detection, localization and diagnosis. Based on [30, 87], within the context of this thesis, a fault can be defined as a deviation from the expected behaviour of a skill. Consequently, the fault can be diagnosed by analysing the logical and physical behaviour models of the skill.

4.2 Implementing Self-Diagnosis of Automation Components Using Model of a Skill

The last section describes the characteristics of a skill model and the suitability of a skill to act as a facilitator for self-diagnosis in automation components. Self-diagnosis is normally implemented as a monitor running parallel to the system operation, to detect the fault and deduce the diagnosis results accordingly [89]. Thus, modelling the self-diagnosis of skills, mandates the means for implementing the skill as a first step. The characteristics of the skill model proposed in this thesis require means for modelling the logical, physical, service model of a skill and their interactions.

Dorofeev et al. [105], describes means for implementing the service model of a skill with a domain specific model within industrial automation. They show that abstracting the behaviour of the skills with a unified model within industrial automation helps to use skills intuitively in a service oriented architecture. The literature analysis of state-of-the-art automation systems [8, 63] shows the increasing digitization, existence of multi domain tools and corresponding domain specific models. These tools and different domain specific models realize the overall behaviour of automation systems, including their logical and physical behaviour models. Literature also reveals several means for modelling the interaction between domain specific models within automation systems [63, 107].

Fully justified by the results of [105] and relying on [8, 63, 107], this thesis proposes the skill model introduced in this thesis, to be implemented with the following means: 1) multiple domain specific models specifying the logical behaviour, physical behaviour, and service model of the skill 2) means for modelling the interaction between domain specific models. The generic model of a skill, according to the concepts proposed in this thesis, is depicted in Figure 4.3.

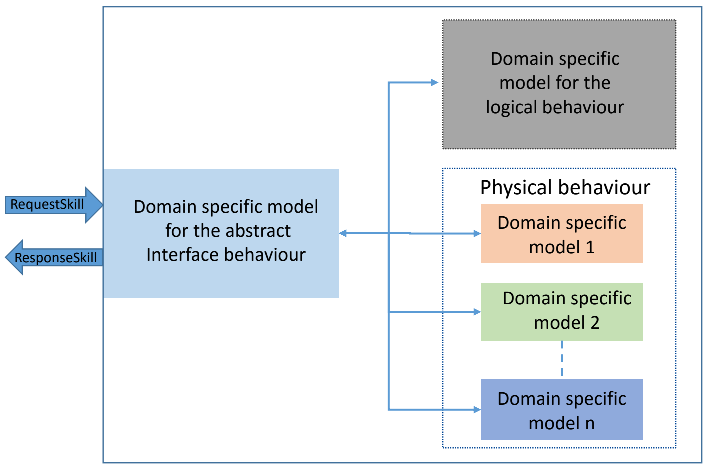


Figure 4.3: Generic Model of a skill as a facilitator of self-diagnosis in automation components. The arrows indicate interrelation among different models.

The figure shows the service model and the logical behaviour model of the skill implemented in domain specific formats. The physical behaviour of the automation systems, generally comprises multiple models. Hence, multiple domain specific models are employed to depict the physical behaviour. The interrelation among different models are shown with the arrows.

4.3 Identifying Plausible Faults for Diagnosing Skill of an Automation Component

The entry point for modelling the fault diagnosis of a system is identifying the probable faults within the system. In the context of industrial manufacturing, faults can be classified into two: process related or resource related [44]. The process related faults occur within the process, and the resource related faults occur from the resources applied for executing the process. Process related faults are not detected during the production. The resource related faults are detected during the production, and normally lead to a halt in the production [44]. Therefore, this thesis examines only the resource related faults.

Within the context of this thesis, the resource related faults can be allocated to the CPPS based automation components or systems. Based on the concept of diagnosing skill of an automation component, this thesis classifies the resource related faults further into software and hardware related faults. Referring back to the SISO model of an automation component in Section 4.1.2, the ideal model or behaviour of a skill defines a flow from “Request Skill” to “Response Skill”. The fault within a skill can be defined as when the component does not produce a “Response Skill” event after it received a “Request Skill” event. That is, a deviation from the ideal or expected behaviour of a skill. The fault in a skill can be due to software reasons which are termed as software related faults, or due to issues in the hardware resources applied, which are termed as hardware related faults. The classification of the plausible faults can be used as the foundation for modelling the diagnosis of the fault.

4.3.1 Software Related Faults

This thesis proposes using the skill as a software interface of automation components. The skill acts as a service provided by the automation component. Hence, the industrial automation system can be engineered using a service oriented approach employing skills of automation components. The skills define its interface behaviour model, and the interface behaviour model abstract the overall behaviour of the skill [105, 108]. Based on this concept, the consumer of the skill does not necessarily need to have in-depth knowledge of the component providing the skill. However, a consumer is expected to have a detailed knowledge of how to utilize the interfaces of the skills of an automation component and the functional behaviour of the component. Software related faults are defined as those types of errors which occur due to the wrong utilization of the skill services of an automation component. Based on the model of a skill introduced in the previous section, two types of software faults are identified.

Type 1 Fault: Analysing the generic model of an automation component as shown in Figure 4.1, the communication protocol of a skill can be modelled as an interface automata as shown in Figure 4.4.

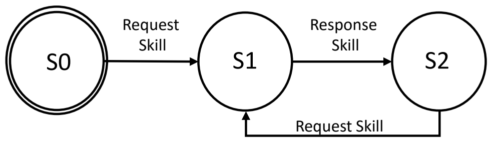


Figure 4.4: Communication protocol of a skill. Type 1 Fault occurs when the consumer of a skill breaks the communication protocol of a skill.

The figure can be interpreted as follows. The skill is initially in the state S0. After receiving the “Request Skill” event, the automation component processes the “Request Skill” event by using its hardware resources and makes a transition to the S1 state. The hardware resources produce the “Response Skill” event on processing the Request Skill, which takes the skill to the state S2. From S2, if it receives the “Request Skill” event, it goes back to the S1 state. Based on this model, it can be asserted that the “Request Skill” event cannot be processed in the S1 state or in transition between S1 and S2 states. If the automation component receives a “Request Skill” event either in S1 state or between S1 and S2, it will be neglected. If a consumer sends a “Request Skill” in S1 or between S1 and S2 states, this can be defined as Type 1 of software related fault and as a result “Response Skill” cannot be produced.

Type 2 Fault: Fault of Type 2 is applicable for automation components that provide more than one skill for external consumption, but processed by a single hardware resource. In this case, the interface behaviour of a skill is bound to a behaviour model, since only a single skill can be processed at a time. Examples of such behaviour models are shown in [109] and is depicted in Figure 4.5. The component offers two skills to the consumers namely Skill 1 & Skill 2. The component has two input events namely “Request Skill 1” and “Request Skill 2” and two output events namely “Response Skill 1” and “Response Skill 2”. In this case, the “Request Skill 1” cannot be processed in S1, S2, S3 and in transition between these states. Similarly, “Request Skill 2” cannot be processed in S0, S1 and S2. If the component receives a “Request Skill 1” or “Request Skill 2” in any of these cases, this can be defined as a software fault of Type 2, and as a result their “Response Skill” cannot be produced.

4.3.2 Hardware Related Faults

For identifying the hardware related faults, the example of the SISO component shown in Figure 4.2 is considered. As shown in Figure 4.2, whenever a “Request Skill” is received, the

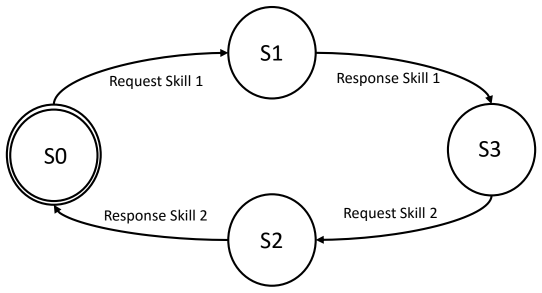


Figure 4.5: Example showing interface behaviour of two skills bound to a functional behaviour model. Type 2 fault occurs when the consumer of a skill breaks the behaviour constraints of a skill.

actuator is the component responsible for making the physical effect in the process. The sensor observes the physical effect and produces the Observe Skill signal which triggers the “Response Skill”. Thus, on the occurrence of a hardware related fault, this can be observed with the “Response Skill” interface of the skill. The hardware faults in SISO components can be of two types 1) actuator related fault and 2) sensor related fault. Of these two types, only the actuator related fault is mostly taken into the diagnosis scope, because the actuator related fault is observable through the sensor employed [30]. For detecting the fault related to the sensor, it requires additional or redundant sensors.

Within the scope of this thesis, only the actuator related fault is considered and the sensor related fault is neglected. It is assumed that the sensors are working or have redundant means. The actuator in an automation component is physically driven based on the sources, such as pneumatic, hydraulics, mechanical, electrical, piezo-electric, etc. Therefore, any issues on these physical sources can lead to an actuator related fault, which can be observed by a sensor. Hence, the hardware related faults may change with variants of components. If an automation component receives “Request Skill” which does not cause any software related fault, nonetheless it cannot produce the “Response Skill” this can be defined as a hardware related fault.

4.4 Reusing Engineering Data for Modelling Self-Diagnosis of Automation Components

There exists two methods for developing self-diagnosis, namely inference based method and classification based method [30]. Inference based method is applied when prior knowledge of the faults and their causalities concerning a system are available. Classification based method is applied when the prior knowledge of the faults and their causalities are not available [83, 90, 87]. A generic problem identified, to both the methods introduced above are their high initial development effort and system specific nature [83, 90, 30, 89]. Nevertheless, the inference based method with prior modelling of faults and their causalities have found to be efficient in terms of their performance in many cases [83, 90, 30]. Fully justified by the performance related benefits of inference based method, this thesis proposes applying inference based approach for developing self-diagnosis in automation components.

From [90, 87] it is clear that creating system specific diagnosis models is a challenge when it requires cost efficiency. Zibaei et al. [89] and Feischmann [27] show that, for achieving efficiency in terms of cost and effort on realizing self-diagnosis, it is necessary to handle variants of automation systems, and create reusable and generic solutions.

In the industrial automation domain, there exist variants even in the level of CPPS based components. This can be illustrated with the SISO automation component introduced before. In a SISO component, there exists an actuator and a sensor. The SISO component can be reconfigured to have several variants of it. For example, the actuator can be of pneumatic, electric or mechanical or some other type. The sensor can be of different types such as optical, pressure, proximity, etc. For each actuator or sensor, the physical behaviour of the component can differ and hence may result in variation of its logical behaviour. An illustration of the variants in case of a SISO component is shown in Figure 4.6

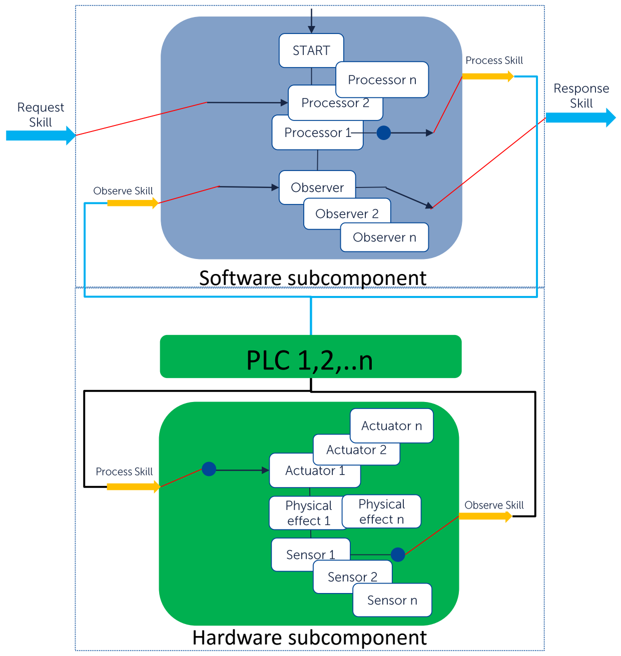


Figure 4.6: Types of variants in a SISO generic automation component.

The figure depicts the actuators and sensors as type 1 to n. Correspondingly, the skill logical behaviour (automata) changes. The processor and observer state in the logical behaviour can be of type 1 to n (n variants). This clarifies that, the skill logical behaviour changes for every change in the hardware. Apart from the actuator and sensor, the changes in the PLC may also lead to changes in the skill logical behaviour, as vendors use different standards for implementing the logic. As diagnosis models heavily depend on the logical and physical behaviour models of the skills, this will lead to the requirement of separate diagnosis models for each variant.

Considering the issue of cost effectiveness in self-diagnosis implementation, this thesis asserts that there should be a methodology to handle the variants while developing self-diagnosis.

4.4.1 Handling Variants of Automation Components

Approaches on handling variants of components whilst engineering have been in literature for quite some time [110, 111, 112]. Many researchers [110, 111, 112] agree on inputting predefined variation points in the engineering model, with criterion for variation such as customer requirements as a solution for handling variants while engineering. The skill model introduced in this thesis employs several domain specific models such as logical model, pneumatic model, electric model, geometrical model, kinematic model, etc. It is envisioned that these domain specific models change, whenever any change (variation) occurs in an automation component. Considering the proposed concept of enabling self-diagnosis on skills it can be inferred that, if variation points can be defined on the self-diagnosis model based on the domain specific models of skills, the diagnosis model can be developed efficiently. This is depicted in Figure 4.7.

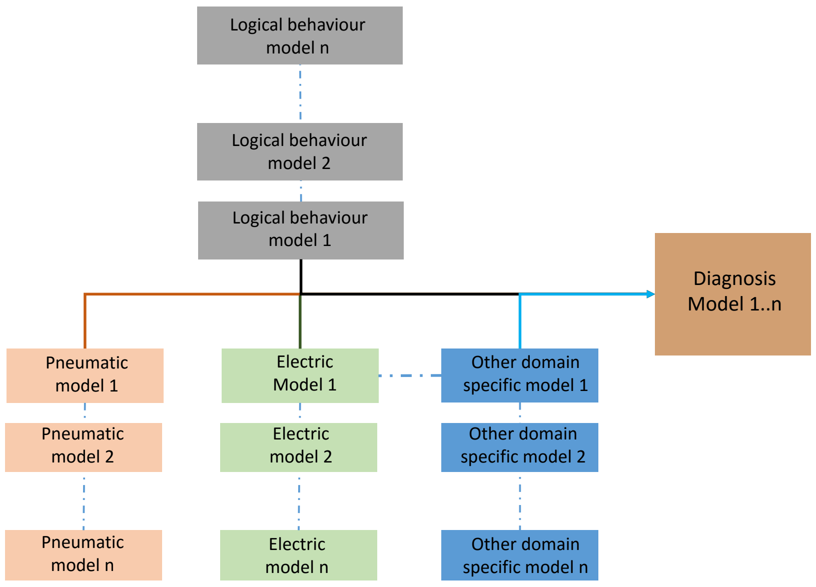

Logical behaviour model n
Logical behaviour model 2
Logical behaviour model 1
Diagnosis Model 1..n
Pneumatic model 1
Electric Model 1
Other domain specific model 1
Pneumatic model 2
Electric model 2
Other domain specific model 2
Pneumatic model n
Electric model n
Other domain specific model n

Figure 4.7: Concept for handling variants in self-diagnosis by reusing engineering data as input for the diagnosis model. Arrows in different colours indicate the interoperability required between the domain specific models.

Sampath et al. [90] and Isermann [30] show examples of inference based diagnosis method by explicit modelling of faults. They identify that when the logical and physical behaviour models of a system are available, the causalities of its fault can be attributed to its logical and physical behaviour models. Relying on [90, 30], this thesis proposes explicit modelling of faults in automation components and attributing the fault causalities to their logical and physical behaviour models. This thesis also proposes that these causalities can be derived during the engineering phase, based on different domain specific models of the automation component.

4.4.2 Diagnosing Software Faults of Automation Components

Within the scope of this work, software related faults are classified into two types: Type 1 and Type 2. Type 1 fault occurs, when the consumer of the automation component breaks the protocol of the skill itself. The Type 2 fault occurs when the consumer of the automation component breaks the behaviour constraints of the skill. The diagnosis of the software faults can be done, if the corresponding constraints can be checked/ monitored against the execution of the skill. From this definition it can be inferred that, the diagnosis model of a software related fault require the following models as variables:

1. The consumer model of the skills of a component.
2. The model inferring the communication protocol and behaviour constraints of a skill.
3. The logical behaviour of a skill.
4. The physical (execution) behaviour model of the skill.

Based on the above analysis, this work proposes the software fault diagnosis model to be a four variable model as depicted in Figure 4.8. The software fault diagnosis model reuses the consumer model, physical behaviour model, the interface behaviour model and the logical behaviour model of the skill. The consumer model along with the interface behaviour model is supposed to provide the actual execution behaviour (consumption behaviour) of the skill. The logical behaviour model provides the behavioural constraints of the skill. The physical behaviour model provides the mapping of the ideal physical behaviour of the skill onto a time domain.

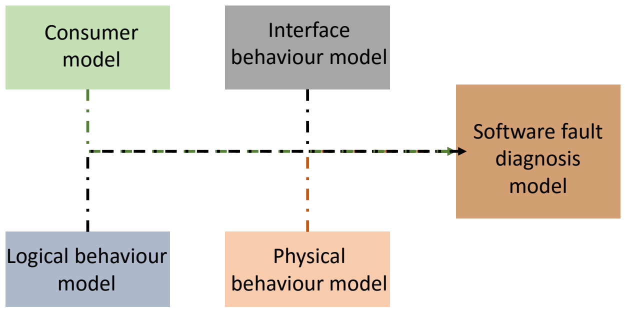


Figure 4.8: Engineering models required as inputs for diagnosing software fault; the consumer model along with the interface behaviour model provide the actual execution behaviour of the skill.

The logic sequence for the diagnosis is given in Algorithm 1. As a variable model, the algorithm inputs the skill consumer model, the ideal logical model of the skill and the ideal physical behaviour of the skill mapped onto the time domain (T). The output of the algorithm shows, if the software fault has occurred and of which causality.

4.4.3 Diagnosing Hardware Faults of Automation Components

There exist several approaches in the literature for diagnosing the hardware fault. The hardware faults can be diagnosed by attributing the causality of the failure to the applied hardware

Algorithm 1: Algorithm for software fault diagnosis.

```
Input  : Skill consumer model, ideal interface behaviour model of the skill, ideal
         physical behaviour of the skill mapped onto the time domain (T)
Output: Software fault type 1 or 2
while Time==T do
    Generate interface automata of the ideal behaviour of the skill (A);
    Generate interface automata of the application model of the skill (B);
    if (A-B == 0) && (AXB) == [RequestSkill, ResponseSkill] then
        Return No Error;
    else
        if (A-B == 0) && (AXB) == [RequestSkill, NULL] then
            "Request Skill" is called before "Response Skill" event;
        end
        if (A-B != 0) && (AXB) == [ResponseSkill] then
            Hard fault;
        else
            Return null;
        end
    end
end
```

sources such as pneumatic, mechanical, etc [30, 89]. For diagnosing the hardware faults, different approaches from literature, applicable to the automation components are proposed.

Limit checking: This approach employs limit checking of the dedicated sensors for diagnosis. According to Isermann [30] this approach brings competitive results, as the physical constraints are verified for the skill execution. This thesis proposes, reusing the physical constraints model such as pneumatic model, electric model, etc., for the limit checking based diagnosis. The diagnosis model thus depends on the consumer model, the interface behaviour model and multiple domain specific models defining physical constraints depending on the hardware employed. A schematic representation of the approach is depicted in Figure 4.9 and the applicable algorithm is given in Algorithm 2. The algorithm inputs the skill consumer model, physical constraints from the domain specific models, sensor inputs, the ideal physical behaviour of the skill mapped onto the time domain (T). It produces a variable output, based on the physical constraints from the domain specific models and the sensor inputs.

Applying available observable signals: This approach does not employ dedicated sensors. It leverages the observable signals [90, 92] from the system for creating system specific diagnosis

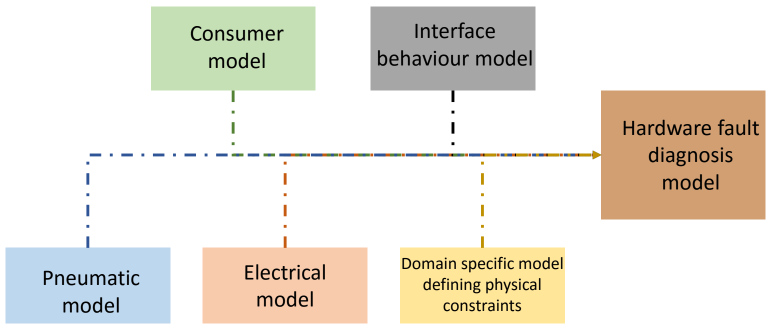

Consumer model
Interface behaviour model
Hardware fault diagnosis model
Pneumatic model
Electrical model
Domain specific model defining physical constraints

Figure 4.9: Engineering models required as input for diagnosing hardware fault.

Algorithm 2: Algorithm for hardware fault diagnosis.

```
Input  : Skill consumer model, physical constraints from the domain specific models,
         sensor Inputs, the ideal physical behaviour of the skill mapped onto the time
         domain (T)
Output: Hard fault ascription on to the physical constraints
while $Time==T$ do
    Collect skill response and the sensor values if $!Response\ Skill$ then
        if $Sensor\ 1 > Value\ 1$ then
            Return Hard Fault 1;
        end
        if $Sensor\ 2 > Value\ 1$ then
            Return Hard Fault 2;
        end
    else
        Return null;
    end
end
```

models. This thesis proposes temporal analysis of the execution of the skills for diagnosing the hardware faults by using observable signals. The temporal analysis of skills based on observable entities can be of two types: 1) based on the trend of skill execution for the last n occurrences 2) based on the slope of responses of the consecutive execution of the skills. The analysis of both of these temporal characteristics can change in variants of components. The temporal characteristics can be limit checked against the ideal time for skill execution to derive the diagnosis. This approach hence, reuses the domain specific models as similar to the software diagnosis model depicted in the Figure 4.9

The applicable sequence of logic is shown in Algorithm 3. The algorithm inputs the consumer model along with the interface behaviour model and the ideal physical behaviour of the skill mapped onto the time domain time (T). The algorithm outputs the type of hardware faults.

Algorithm 3: Algorithm for hardware fault diagnosis based on temporal analysis.

```
Input  : The Consumer model of the skill, the ideal physical behaviour of the skill
         mapped onto the time domain (T)
Output: Hard fault ascription on to the physical constraints
while Time==T do
    Calculate slope of the consecutive occurrences of skills;
    Create trend of skill behavior for the last n occurences;
    if Trend of skill behavior is normal and slope of consecutive responses is > defined
      value then
        Return Hard fault type 1;
    end
    if Trend is increasing and slope of consecutive occurrences is normal then
        Return Hard Fault type 2;
    else
        Return null;
    end
end
```

Modelling fault in the physical simulation model: This approach uses the explicit modelling of faults, within the physical simulation model as shown in [18]. The classification of types of faults (which are not observable) and their causalities with the physical constraints are modelled as a part of the physical simulation model. This approach thus reuses the same domain specific models as shown in Figure 4.8. The applied algorithm uses the principle of limit checking. However, the algorithm uses the human input to get the fault classified (not machine observable) and then derives the observable characteristics out of it. Algorithm 4 depicts the flow of logic.

4.5 Conclusion

This chapter described the means and methodologies for modelling the self-diagnosis of CPPS based automation components. The chapter logically derives the general prerequisites for modelling the self-diagnosis and then analyses the same in the scope of CPPS based automation components. The analysis clarified the concept of leveraging the model of a skill to facilitate modelling self-diagnosis of the automation components. Thus, the approach introduces a skill oriented modelling of self-diagnosis, instead of modelling the self-diagnosis of components in a monolithic manner.

Algorithm 4: Algorithm for hardware fault diagnosis based using fault injection on simulation models.

```
Input  : The consumer model of the skill, Human observed fault
Output: Hard fault ascription on to the physical constraints
while Time==T do
    Map the human observed fault onto the error classification in the simulation model;
    if Type of Error == Modelled error then
        Return Hard fault type and machine observable characteristics;
    end
end
```

As an entry point for diagnosis, different types of faults plausible to an automation component designed in a CPPS architecture are derived. Methodologies and algorithms for modelling the self-diagnosis of different types of faults are presented. The presented solution addresses the challenge of cost efficient modelling of self-diagnosis in variants of the automation components by reusing their engineering data.

It is envisioned that the component manufacturers model the self-diagnosis of their components using the means and methodology presented in this thesis. Consequently, the self-diagnosis models of component based automation systems can be developed by leveraging the self-diagnosis models of components they employ.

Chapter 5

Modelling Self-Diagnosis of Component Based Automation Systems

This chapter examines the methodology for realizing self-diagnosis in a component based automation system, on the provision of self-diagnosis models of automation components. Hence, this methodology is envisioned to be applied at the system integrator or the manufacturing companies, as they realize the component based automation systems. Considering the challenge of reducing the cost and effort for realizing self-diagnosis, as pointed out in Chapter 1, this chapter is organized in five sections.

Section 5.1 identifies the prerequisites for realizing self-diagnosis in future automation systems, considering their reconfigurable and flexible architecture. Section 5.2 and Section 5.3 describe the aspects for facilitating the reconfigurable characteristics to the self-diagnosis models of future automation systems. Later, Section 5.4 explains the methodology for achieving cost and resource efficiency in the realization of self-diagnosis feature of the automation systems. Finally, Section 5.5 concludes this chapter.

5.1 Prerequisites for Modelling Self-Diagnosis of Future Automation Systems

The state-of-the-art self-diagnosis solutions of automated systems do not feature reconfigurability; they require re-implementing the self-diagnosis each time a system is reconfigured [89, 27]. The development methodologies of current industrial self-diagnosis solutions apply heuristics of maintenance personnel concerned with the deployed automation systems [24, 30]. Presuming the FoF to be frequently reconfigured [3], it can be inferred that the development of future self-diagnosis solutions will require application of more human resources. Consequently, it can be confirmed that the current development methodologies of self-diagnosis solutions will not be applicable for the FoF. Therefore, this thesis asserts that the future self-diagnosis solutions require development methodologies addressing the reconfigurable and flexible nature of the FoF.

Many researchers [113, 108, 114, 105] agree on the CPPS based, hierarchical and layered architecture of the FoF. Brandenbourger et al. [16] and Dorofeev et al. [105] endorse the application of skills (as a service) for intuitively engineering such a system by their experience. Based on [113, 108, 114, 105], this thesis presumes the layered, hierarchical and skill oriented architecture of the future automation systems. Figure 5.1 shows the example architecture of a future automation system, within the context of this thesis. For simplified illustration, this example depicts only two layers in the automation system; a more complex example of a layered architecture can be seen in [114].

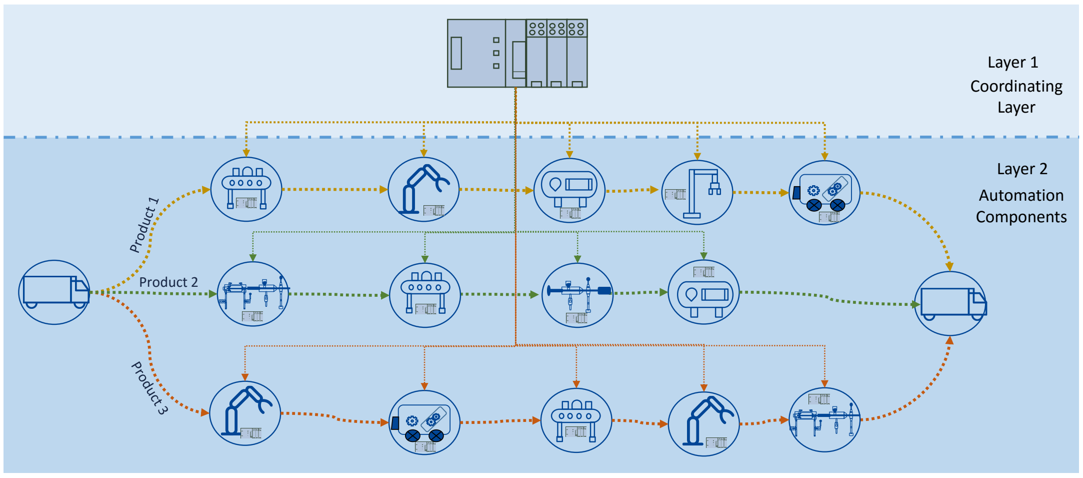


Figure 5.1: Layered architecture in a future automation system; the system has reconfiguration feature based on product variants 1, 2 and 3.

The Layer 1 of the system in the figure is the coordinating layer, where the process workflow (application logic) is modelled. Layer 2 is a group of automation components, where the application logic is executed. The workflow of the process and the physical architecture of the automation system change based on the production requirements of the manufacturing company. For example, the workflow for Product 1 is not the same as that of Product 2 or Product 3. The interconnections of components in Layer 2 also change based on the product variants.

According to [105], in a skill-based architecture the Layer 1 can be seen as a consumer of the skills provided by the components in Layer 2. Layer 1 implements a skill-based workflow and establishes remote connection with the skill interfaces (software interfaces) of the automation components in Layer 2. The components in Layer 1, along with the components in Layer 2 form the physical hierarchical architecture of the system. Thus, in automation systems with hierarchical skill oriented architecture, the physical and logical behaviour of the automation systems can be seen as dynamic in nature, depending on the production requirements.

The Section 4.1 from the last chapter clarifies the general prerequisites for modelling self-diagnosis as the logical, physical behaviour models and the interaction between them in a system. Accordingly, it can be inferred that, the realization of self-diagnosis in a layered, hierarchical and skill oriented future automation system needs the following prerequisites:

1. The model of the skill-based workflow of the process, which defines the logical behaviour of the system and its interaction with the hierarchical physical systems.
2. The layered physical architecture of the automation system, which processes the logical behaviour of the system, and hence the physical behaviour of the system.

5.2 Analysing Fault Tree for Reconfigurable Self-Diagnosis Models

Realizing self-diagnosis on the automation system requires fault detection, localization and diagnosis enabled in the automation system as a whole. The self-diagnosis models as shown in [83, 90, 30] apply monolithic approaches, and are not applicable to flexible and reconfigurable systems. Hence, these approaches [83, 90, 30] cannot be applied for the reconfigurable automation systems presumed in the context of this thesis.

Zibaei et al. [89] show the possibility of creating a fault tree based diagnosis model for a reconfigurable cyber physical system (CPS). Zibaei et al. [89] assume that the fault detection is enabled until the last child element of the CPS. They model the CPS with a four variable and reconfigurable model. They show that the fault propagation and thus the self-diagnosis can be realized using a variable fault tree of the CPS. Their approach requires the hierarchy of the system to be known, so that the causalities can be perceived and the overall fault propagation can be implemented using a fault tree.

Relying on the findings of [89], this thesis proposes that a fault tree based approach can also be applied to the FoF. Applying the concept of [89], the fault detection in an automation system can be perceived as a propagation of fault detection from the employed components in the automation system. The localization of fault corresponds to the components' physical location in the automation system's hierarchy. The diagnosis result of the automation system can be as a propagation of self-diagnosis results from the employed components in an automation system.

5.3 Analysing Planning Models for Fault-Tree Based Reconfigurable Self-Diagnosis

For gathering the prerequisites for realizing self-diagnosis in CPPS component based automation systems of the future, an analysis of the engineering of automation systems was conducted.

Several works [115, 63, 116] agree on the sequential nature of the engineering process of automation systems. Estevez et al. [115] identify: planning; analysis; design & construction; and programming as the phases in automation systems engineering. According to Drath et al. [63] the automation systems engineering consists of 8 stages, namely: product design; plant and process planning; mechanical engineering; electrical engineering; communication systems engineering; PLC programming; virtual commissioning; and commissioning. Schmidt et al. [116] describe the automation systems engineering to have five phases namely: analysis; basic engineering; functional engineering; system integration; and then commissioning. An analysis of [115, 63, 116] shows that the prerequisites for realizing self-diagnosis (workflow of the process and the physical architecture of the automation system) are defined in the early phases of engineering such as planning, analysis, and functional engineering.

Himmler [20] shows three main phases in a function based automation systems engineering process namely: plant configuration; detailed engineering; and offer generation. He proposes the workflow of the process flow and the physical architecture of the automation system to be completed in the plant configuration phase, based on the requirements from the customer. Vathoopan et al. [117] extend the results of [20], to define the phases in a skill-based automation systems engineering. They endorse three phases in a skill-based automation system engineering, namely: planning; model generation & construction; and commissioning [117]. In the planning phase, the functional requirements of the automation system, the architecture of the resources required and the workflow of the processes are defined. In the model generation & construction phase, the different software models are generated and the physical construction is carried out. In the commissioning phase, the constructed system is verified against the user requirements and commissioned.

Within the scope of this thesis, a skill-based automation system composed of CPPS based automation components is foreseen in the future. The planning model of a skill-based automation system, based on the results of [117] is depicted in Figure 5.2. The skill-based workflow can be seen as a component of Layer 1, which is coordinating the skills executed by the components in Layer 2. The planning model also includes the physical system hierarchy, with a coordinating PLC in Layer 1 and the CPPS based automation components in Layer 2. The skill-based workflow of the process changes from product to product. The applied automation components change as the skills required by the process change. Thus, the prerequisites for realizing self-diagnosis on the automation system can be elicited from the skill-based planning model of the automation system.

The previous section introduced a fault tree as the means to realize self-diagnosis in a component based and reconfigurable automation system. Consequently, this thesis proposes that the fault tree of the automation system can be derived from the skill-based planning model of the automation system shown in Figure 5.2. The self-diagnosis model of the automation system

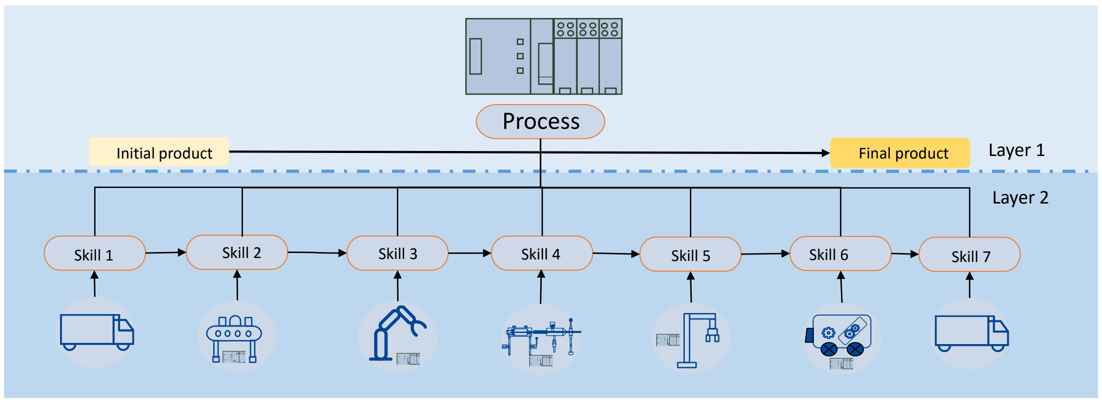


Figure 5.2: Planning model of a skill-based automation system: Coordinating process model and the components offering skills in a hierarchy.

is foreseen as a Layer 1 component in the fault tree. The self-diagnosis model of the automation system is expected to aggregate the propagation of fault diagnosis from the automation components in Layer 2.

5.4 Generating Fault-Tree Based Self-Diagnosis Models from Planning Models

To address the challenges of reducing the cost and effort of realizing self-diagnosis [83, 36, 89, 24], this thesis proposes, generating the self-diagnosis models of future automation systems from their planning models. The planning model consists of the model of the workflow of the process and the physical hierarchy of the automation system. For deriving the self-diagnosis model of an automation system from its planning model, this thesis assumes the following conditions to be satisfied:

1. The skill models of the automation components enclose their self-diagnosis models.
2. The self-diagnosis models of the automation components are exchangeable and interoperable.
3. The planning model of the automation system is exchangeable and machine-readable.

Consequently, the realization of self-diagnosis of an automation system is foreseen as a generative process as shown in Figure 5.3.

The process of generation as shown in Figure 5.3, mandates the self-diagnosis models of automation components to be managed in a single (execution) environment. Additionally, the self-diagnosis models of automation components have to interoperate with the application (logic) model of the automation system. The logic models of the automation systems are generally implemented in control platforms/tools [118]. Hence, this thesis proposes generating and managing the self-diagnosis model of the automation system, in a control platform/tool.

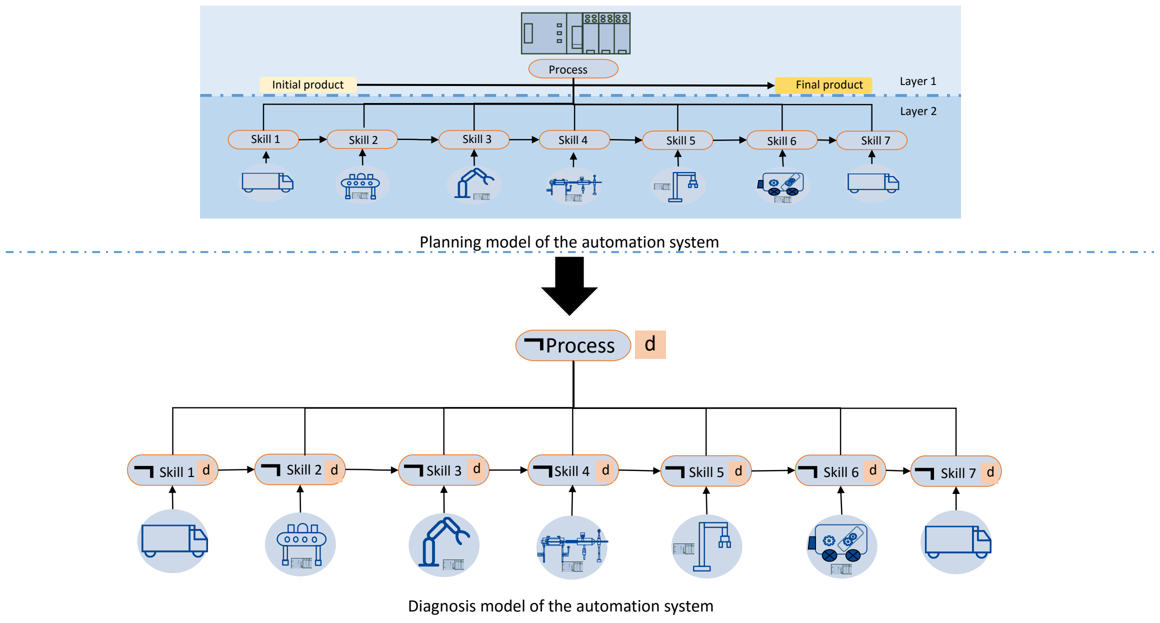


Figure 5.3: Concept of generating fault tree based self-diagnosis in a component based automation system from its planning model. The negation symbol indicates a fault and d indicates its diagnosis.

The generative approach leverages the self-diagnosis models of skills in the applied automation components of Layer 2. The detection and localization of fault in Layer 1 (on the automation system) can be seen as the propagation of fault detection and localization from the skills of components in Layer 2. Similarly, the diagnosis in the automation system (Layer 1) combines the diagnosis results from the skills of automation components in Layer 2.

The generic fault tree model of the automation system, composed of the self-diagnosis models of the skills of the automation components is shown in Figure 5.4. The figure depicts an application (logic) model (Process P) executing on a resource (Rs). The process P is composed of skills 1 to n, executed on resources R1 to Rn. The automation components in a system with more than one hierarchical layer, can be attached to the fault tree of the immediate upper system component in the system fault tree. The skills of the components in the lower layers of the hierarchical system propagate its fault detection, localization and diagnosis to the immediate upper system component. Consequently, the automation system composes the fault detection, localization and diagnosis of the skills of the underlying components.

5.4.1 Deriving the Detection and Localization of Fault in an Automation System

The detection of fault in an automation system can be derived from the application model (process model P) executed on the system. The Process P is composed of one or more skills

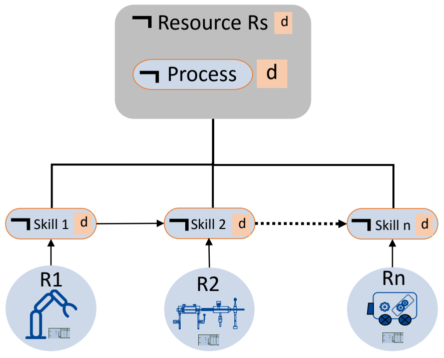


Figure 5.4: Definition of fault and diagnosis in a process as a composition of skills and the resource where process is executed.

executed by the automation components. If a Process P is composed of Skills S1, S2, ... Sn and P is running on a system Rs as shown in Figure 5.4 , the detection of fault in the process P is denoted as in Equation 5.1.

$$\neg P = \neg S1 \vee \neg S2 \ \vee ..... \ \neg Sn \ \ \vee \neg Rs \tag{5.1}$$

The fault in an automation system is caused by a fault in the skills it composes or due to a fault in the resource where the process itself is executed. In order to define a fault within the resource where the process is executing it requires that the self-diagnosis model of the resource Rs is exchangeable and is interoperable.

The fault detection further yields the localization of the fault within an automation system. The resources where the skills are executed are attributed to the skills. Hence, the detection of fault also provides the corresponding resource (component) and its location in the physical hierarchy of the automation system.

5.4.2 Deriving the Diagnosis of Fault in an Automation System

Similar to the definition of a fault, the self-diagnosis in an automation system is defined for the Process P, as shown in Equation 5.2. The diagnosis of the Process P, P(d) is a composition of the skills it composes and the resource (Rs) where it executes.

$$P(d) = S1(d) \wedge S2(d) \wedge ..... \ Sn(d) \wedge Rs(d) \tag{5.2}$$

5.5 Conclusion

This chapter describes the methodology for realizing self-diagnosis of a component based automation system, by leveraging the self-diagnosis models of the employed automation components.

Considering the future automation systems to be frequently reconfigurable in nature, a generative approach, using their planning model is proposed for realizing the self-diagnosis model of an automation system. Thus, the proposed solution is envisioned to reduce cost and effort for realizing the self-diagnosis model of a component based automation system.

This thesis proposes the application of this methodology, at a system integrator or a manufacturing company, who deploys a component based automation system. The proposed solution presumes the planning model of an automation system to be exchangeable in nature. The solution also assumes that each skill of automation components incorporates an exchangeable and interoperable self-diagnosis model of that skill. Consequently, the self-diagnosis model of the component based automation system can be generated in the control platform/tool of the manufacturing company.

Chapter 6

Improving Self-Diagnosing Automation Systems' Realization and Application

Integrating the concepts from Chapter 4 and Chapter 5, the methodology of realizing a self-diagnosing automation system can be summarized as follows. The automation component manufacturers model self-diagnosis on the skills of their components. The self-diagnosis models of the components are made available in an exchangeable format to the end users, such as a manufacturing company or a system integrator. The system integrator or the manufacturing company derives the self-diagnosis model of their component based automation system, using the planning model of their automation system.

This thesis proposes applying self-diagnosis for the corrective maintenance of future automation systems. Consequently, a reduction in MTTR, cost and utilization of resources are envisioned within the corrective maintenance of future automation systems. This chapter introduces methodologies for improving the realization and application of self-diagnosis within FoF. The required standards within the realization of self-diagnosing automation systems are elaborated in Section 6.1. Section 6.2 describes the involved stakeholders and their deployment within the system development process. The aspects for applying self-diagnosis in the industrial corrective maintenance are described in Section 6.3. Later, Section 6.4 concludes this chapter.

6.1 Application of Standards for Improving the Realization of Self-Diagnosis

Standardization is reported as one of the fundamental requirements of the FoF [8, 6]. Standardization describes a process of unification, especially in terminology, capabilities of personnel, technology and organizational processes [119, 120]. According to Jiang et al. [121] standardization acts as the key for innovation, since it trims the technology down and narrows the challenges to a transparent and open path. Standardization triggers opportunities in a globalized economy, as they enable transparency and comparability of the entities [122]. For example, when property such as quality is transparent, products or services can be compared with one another.

For the providers of the products or services, the standards permit greater efficiency in development and processing, as the capabilities and properties of their products or services are unified. They can easily achieve growth, when quality can be reproduced over time and in various locations. In a standardized work environment, the technical knowledge and innovations can be distributed. For the customers, the standardized products or services are of low risk in quality or investment, because they can be compared with one another. The customers get more freedom to choose their products, with a foreknowledge of the properties such as quality of a product or service [122, 123].

According to Reichwald [124], within the industrial or service sector, there exist different aspects of standardization. They are service standardization, technical systems standardization and process standardization. These have a high impact on the commercial success of the organization. Standardizing services helps to avoid unambiguous communication. Standardization of technical systems allows exchange among actors in a specific service market. Standardization of a process is required to avoid erroneous behaviour when services have to be composed.

6.1.1 Importance of Applying Available Industrial Automation Standards

The literature on the application of standards in industrial automation systems were further analysed within the scope of this thesis. Several studies [6, 63, 43, 8] identify that, the custom standards or models from manufacturers necessitates extra learning effort at the end users. They also identify that the custom standards or models create deadlocks while developing automation systems. According to the findings, the application of available standards or standardization of existing entities within the industrial automation systems can solve this problem.

This thesis proposes leveraging the self-diagnosis models of automation components to compose the self-diagnosis models in component based automation systems. The proposed solution assumes that the component manufacturers provide the self-diagnosis models of their components in an exchangeable format. Hence, it is necessary that the self-diagnosis models of automation components of different manufacturers are interpretable by their consumers. In addition, it requires the interoperability of self-diagnosing automation components with the automation system, such that the self-diagnosis continuously monitors the automation systems' operation.

By relying on the findings of [8, 6, 63, 43], this work proposes the development of self-diagnosis models of automation components in available exchangeable standards within the industrial automation domain. Consequently, the consumers of automation components (system integrator) can use the tools supporting the standards for generating the self-diagnosis models of the automation system. If the planning models are also available in an available exchangeable standard, the self-diagnosis model of the overall system can be managed in a single tool. This work also proposes employing the available interoperability standards within the industrial automation domain between the control model and the self-diagnosis model of the automation system, so that diagnosis models can monitor the control model.

6.1.2 Proposed Standards for Improving the Self-Diagnosis Models of Automation Components

The approach for developing self-diagnosis models in automation components has been illustrated in Chapter 4. The approach leverages the model of skill of an automation component. The plausible types of faults in the skill of an automation component are defined. Subsequently, a methodology for realizing the self-diagnosis of the plausible fault types in the skills, reusing the domain specific engineering models of an automation component is proposed.

Recently the naming conventions and granularity of skills of automation components/systems are being standardized under German Association of Engineers (VDI) 2860 [125]. For example, "Grip" and "Move" are lowest granularity skills. Additionally, the interface behaviour model of a skill is getting standardized by German Association of Mechanical Engineers (VDMA) under the Service Oriented Architectures and Realtime Control (SOArc) specification [126]. This thesis proposes, applying both of these standards, as they unify the semantic interpretation and interface behaviour of the skill. With unified semantics for the skills, the self-diagnosis models can be defined for types of skills. Unified interface behaviour model facilitates reuse of the diagnosis models for the fault types introduced in Section 4.3.

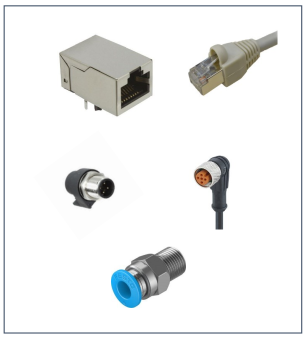
Within the context of this thesis, the interrelation between different domain specific models within the model of a skill is used for deriving its diagnosis model. This thesis proposes, application of available standards for modelling the domain specific engineering models, hence they can be interpreted in an unified manner by the consumer of the components. Additionally, the interrelations among different models have to be defined in a standard manner. For example, the interrelation between the self-diagnosis model and the logical behaviour model of a skill. This thesis foresees standardised means for modelling the interrelations among different domain specific models as the foundation for automatically deriving diagnosis models of variants of components.

The generic model of the skill introduced in Section 4.1.1 facilitates the reuse of engineering data for realizing the self-diagnosis models. Hence, it reduces the effort of modelling the self-diagnosis of components and their variants. Therefore, to increase the efficiency of realizing the self-diagnosis models, this thesis also proposes the standardization of generic model of the skill introduced in this thesis.

6.1.3 Proposed Standards for Improved Generation of Self-Diagnosis Models of Automation Systems

This thesis proposes generating the self-diagnosis models of automation components from their planning model. The planning model proposed in this thesis, includes the process model composed of skills and the hierarchy of automation components executing the skills. The self-diagnosis models are generated based on the following: 1) the association between the process model and the components serving the skill, and 2) physical architecture of the automation systems composed of the constituent components.

In literature, standardised means for modelling skill-based planning models of automation systems are not available. Hence, this thesis proposes developing and standardizing means for modelling skill-based planning, which incorporates the process model and the hierarchy of an automation system. This thesis foresees the process model to have means representing the association between the process model and the components executing the skill. For representing the architecture of the system, this thesis foresees means for modelling the physical architecture of the system using standardized connectors as shown in Figure 6.1. Figure 6.1(a) shows examples of standard connectors in the industrial automation domain such as pneumatic (e.g.:- R1/8), electrical (e.g.:-RJ 45, M13), etc. The composition of a system applying some of the standard connectors of components is shown in Figure 6.1(b).


(a) Example of standard connectors

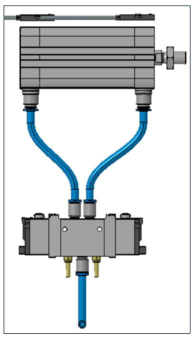

(b) Application of some of the connectors

Figure 6.1: Example of different domain specific connectors and some of their application in automation systems, modified from [127].

6.2 Deployment of Different Stakeholders in the System Development

The development approach for self-diagnosis models proposed in this thesis, combines three known methods from the software engineering domain. They are: 1) component based development; 2) service orientation; and 3) model driven engineering with code generation.

Under the scope of this study, a component is interpreted according to IEC 61987 [128] which defines the data structure for elements of industrial process measurement and control. Accordingly, a component is “that supports partial or fully automated operation of industrial processes”. A component (automation component) can have a mechatronic structure [129] and can have multiple software and hardware components. Within the scope of this thesis, service refers to skill and is applied in two different perspectives: 1) the automation systems are engineered in a skill-based manner resulting in a service oriented architecture; and 2) the diagnosis is carried out on the skills offered by the component. The model driven engineering with code generation is applied in the overall generation of fault tree based self-diagnosis of automation systems.

The service oriented engineering of component based automation system has been found complex and error prone in a study by Brandenbourger et al. [16]. They find the obligation of having a methodology for continuous data and model management, for reducing complexity and errors in such a software intensive development process. As a solution they propose a three stakeholder engineering process as follows:

It defines a standardization consortium as the first stakeholder in the engineering process. The standardization consortium provides a metamodel including all the necessaries for modelling different aspects of an automation component such as mechanical part, electrical part, control part, etc. The authors suggest that the metamodel is then consumed by the second stakeholder (component manufacturers) to model their automation components or systems. Based on the metamodel provided by the standardization consortium, the component manufacturers model their specific components along with their skills (services). The component manufacturers deliver their hardware components along with the standardized model of the component, to the third stakeholders (system integrator) who build the automated manufacturing plant. The system integrator can follow a component based, service oriented and model based systems engineering process to build the plant.

Brandenbourger et al. [16] underline the key advantage in their approach as the third stakeholders (system integrator) do not require in depth knowledge of the automation components. The second stakeholder, the component manufacturer who holds the in-depth knowledge of the components, provides the detailed mechatronic models of their components, along with skill interfaces. The system integrator makes use of the skill interfaces of the components to compose an automation system in a service-oriented manner. While reconfiguring any plant, the manufacturing plant or system integrator can reuse the component models wherever applicable and follow a model-based systems engineering approach.

Fully justified by the findings of Brandenbourger et al. [16], this thesis proposes to apply the three stakeholder engineering process for the development of self-diagnosis models within the FoF. The deployment of stakeholders in a future corrective maintenance system development and their tasks based on [16] are depicted in Figure 6.2. The approach envisions the entities necessary for self-diagnosis of a component modelled by the component manufacturer who hold the in-depth knowledge of their components and their failure scenarios. The model of an automation component from the manufacturer contains its engineering models, self-diagnosis models and corresponding software interfaces for engineering and diagnosis. The standardization consortium provides the metamodel, which is required for modelling the entities necessary for engineering, diagnosis, etc., of an automation component. The system integrator can make use of automation component models, for the realization of the engineering and self-diagnosis models of the automation system.

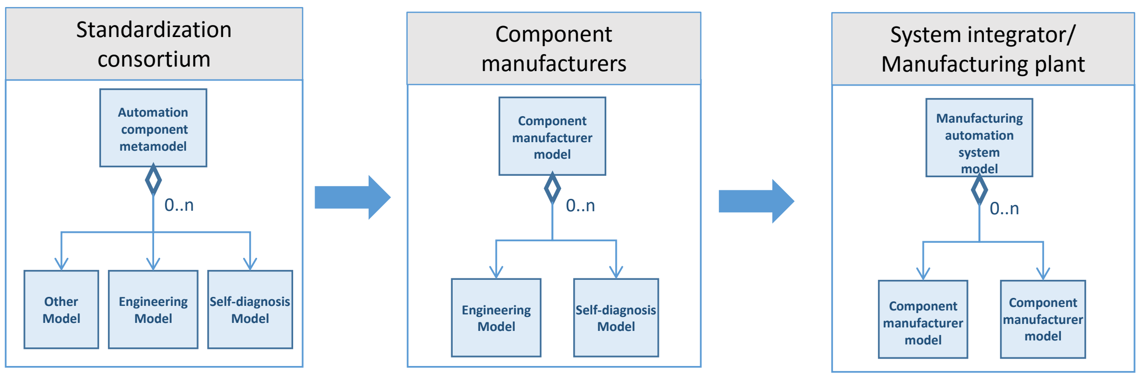

Standardization consortium
Automation component metamodel
0..n
Other Model
Engineering Model
Self-diagnosis Model
Component manufacturers
Component manufacturer model
0..n
Engineering Model
Self-diagnosis Model
System integrator/ Manufacturing plant
Manufacturing automation system model
0..n
Component manufacturer model
Component manufacturer model

Figure 6.2: Tasks of different stakeholders in developing self-diagnosing automation systems.

6.3 Self-Diagnosing Automation Systems and Corrective Maintenance

The methodologies for development of self-diagnosis models of industrial automation systems exist in Literature [83, 130]. However, a thorough search of the literature yielded no related article on methodology for performing corrective maintenance of self-diagnosing automation systems. Therefore, this section makes a proposal for application of the developed self-diagnosis system in the corrective maintenance of future automation systems.

6.3.1 Taking Humans in the Loop with a Visual Interface

The first and foremost approach to be defined is the role of maintenance personnel in the corrective maintenance of future automation systems. The state-of-the-art corrective maintenance consists of a sequence of activity as shown in Figure 1.3, which include fault detection, localization, diagnosis, corrective action and the checkout activities. In the state-of-the-art industrial automation systems, the fault detection is mostly enabled on their control software [80, 44]. On detecting the fault the production stops, then the maintenance personnel carry out the rest of the activities within the corrective maintenance sequence. When the maintenance personnel checkout the maintenance function, the production resumes.

A self-diagnosing automation system performs the first three activities in the corrective maintenance sequence, namely: fault detection; fault localization; and fault diagnosis. The maintenance personnel carry out the rest of the activities in the sequence, namely: corrective action; and checkout. Thus the maintenance personnel has to interpret the self-diagnosis result from the automation system, then perform the corrective action and then intimate the production to resume by checking out. This necessitates the maintenance personnel to interact with the self-diagnosing automation system and with the production process.

There exist several studies on human-machine interaction within the context of the FoF. Norman [131] finds that an organized presentation of information or data is necessary in future human interface mediums. He proposes visual mediums such as smart consumer devices, augmented reality, etc., as the human-machine interfaces of the future. Shredoff [132] shows that applying user interfaces and interaction techniques from the same domain reduces the learning curve and complexity in software intensive future automation systems. Studies of [94, 95] show that, the application of smart consumer devices and augmented reality improves the performance of operators in the manufacturing plant.

Relying on [131, 132, 94, 95] this thesis proposes employing a visual interface for the interaction between the maintenance personnel, the self-diagnosing automation systems and the production process. The visual interface acts as the medium for taking the maintenance personnel in a corrective maintenance loop. The visual interface provides the necessaries for presenting the self-diagnosis results as an input to the maintenance personnel who perform corrective maintenance. In addition, it provides means for transmitting the human output such as the checkout signal to the production process. A depiction of the simplified architecture of the overall system and application scenario is depicted in Figure 6.3.

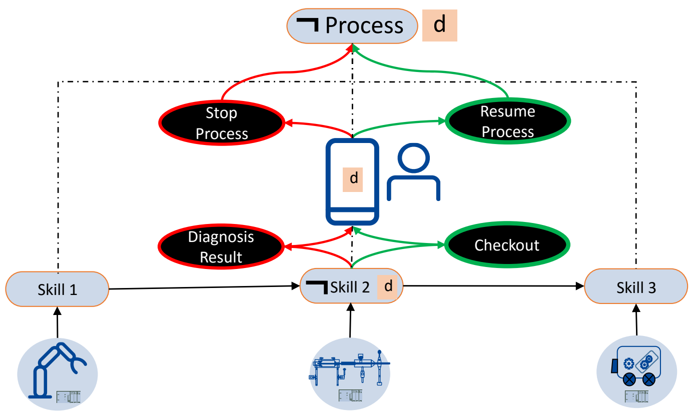


Figure 6.3: Example of human-machine collaboration in corrective maintenance. On detecting fault a in skill, a consumer device aids the maintenance personnel for corrective maintenance and facilitates a human machine interface.

The figure shows a process composed of three skills 1, 2 and 3. On identification of a fault in any of the skills for example in skill 2, based on the criticality, the production stops. The user interface immediately presents the diagnosis result to the maintenance personnel. The maintenance personnel carry out the corrective action for skill 2, and then signal checkout, on which the production resumes. Thus, the human is treated as part of the corrective maintenance system of the future automation systems.

6.3.2 Leveraging Humans as the Strategic Decision Makers

The literature analysis on corrective maintenance presented in Section 2.3 shows that, most of the human effort in a corrective maintenance sequence is applied until the fault diagnosis activity. Similarly, most of the human errors in a corrective maintenance sequence also occur until the fault diagnosis activity. As soon as a fault is detected, a self-diagnosing automation system produces the fault diagnosis result. Hence, it can be asserted that, the application of self-diagnosing automation systems will result in the reduction of the human effort for corrective maintenance. This thesis proposes the self-diagnosis and thus the corrective maintenance to be carried out on the services (skills) of automation components/systems, rather than considering the component/system as a whole. Consequently, this thesis foresees that the complexity and hence the possibility of human error reduces in the corrective maintenance of FoF.

Many studies on the FoF [54, 5] identify humans as the strategic decision makers within the FoF. Accordingly, this work proposes employing maintenance personnel as strategic decision makers in the FoF. Different studies [24, 74] show that data collected from maintenance can improve the production. The maintenance personnel in the FoF can identify potential data (evidence), relevant for avoiding problems such as problems related to bad design, or programming. These evidences and the cognitive skills of the maintenance personnel thus can be used for improving production. In addition, on the provision of interoperability between the corrective maintenance visual interface and the inventory tools, these evidences can also be utilized for improving the inventory.

With plausible reduction in the skills required for corrective maintenance, this thesis proposes employment of minimum number of maintenance personnel within the FoF. The maintenance personnel should have the required skill set for performing corrective action and expertise in the production process within the FoF.

6.4 Conclusion

By identifying lack of methodologies for developing and applying self-diagnosis in the industrial automation domain, this chapter introduced potential methodologies applicable for developing and applying self-diagnosis in future automation systems. As a first step, the available standards and the required extension of standards necessary for improving the development of the self-diagnosis models are presented. Secondly, a three stakeholder sequential deployment of stakeholders is proposed for maintaining consistency in the development and reducing errors. As a final step, a methodology for applying self-diagnosis in the corrective maintenance of future automation systems is proposed, by taking the human in the loop of corrective maintenance sequence. The approach also leverages humans as a strategic decision maker. Overall application methodology not only reduces the complexity and human error but also improves MTTR and resource utilization. The application methodology also proposes means for improving production through corrective maintenance.

Chapter 7

Realizing the Self-Diagnosing Automation Systems of Future

This chapter describes the implementation of the proposed solution using specific tools and technologies of the FoF. The selection of tools and technologies are made considering the following methodologies proposed within the context of this thesis:

1. The self-diagnosis models of automation components reuse their engineering data.
2. The self-diagnosis models in component based automation systems can be generated automatically from their planning models.
3. The humans are integrated within the corrective maintenance of future self-diagnosing automation systems with a visual interface.

Accordingly, this chapter is organized in four sections. Section 7.1 introduces the technology that enables reuse of engineering data for realizing self-diagnosis. The tool that bridges the planning phase of an automation system with the maintenance phase of an automation system is elaborated in Section 7.2. Subsequently, Section 7.3 introduces other important tools and technologies used within the context of this thesis. Section 7.4 concludes this chapter.

7.1 AutomationML for Modelling Self-Diagnosis by Reusing the Engineering Data

Description languages have been in place for quite some time. One of the first application examples of description languages in the industrial automation domain was for field devices and their configuration [133]. The state-of-the-art field devices have different communication interfaces and their device specific configuration. The field device manufacturers describe their device configuration with description languages such as Electronic Device Description Language (EDDL). The device manufacturers supply the description along with the devices, such that the software tools who use the devices can interpret the specific configuration of the field devices [133, 134]. The concept of device description has been extended to several other phases in the industrial automation domain such as for systems engineering (SysML) [135], for product description (STEP XML) [136], for engineering data exchange (AML) [63], etc.

The proposed development methodology within the context of this thesis raises the requirement of a description language under the following circumstances:

- The component manufacturers reuse different domain specific engineering models for modelling the self-diagnosis.
- The component manufacturers deliver the self-diagnosis models to their consumers such as system integrator.
- The system integrator can interpret the self-diagnosis models of the automation components they employ.
- The system integrator generate the self-diagnosis model of their automation system using the planning model of the automation system.

Accordingly, the following characteristics have been identified for a description language to be used for the modelling purpose within the context of this thesis:

1. Machine-readable; hence, they can be exported and imported in different tools employed at different stakeholders.
2. Neutral, manufacturer independent and unified format for exchange; therefore, they can be employed seamlessly.
3. Capability to model skills and skill-based production planning.
4. Capability to model different disciplinary aspects such as geometry, kinematic, logical, diagnosis, etc.
5. Support for existing standardized data exchange formats within the industrial automation domain.
6. Means for modelling inter relations among different disciplinary models.
7. Means for modelling physical composition of component based automation systems.
8. Capability to model logical composition of processes out of skills.
9. Capability to model physical and logical interfaces of components.
10. Support of proper syntax and semantics; such that consistency can be maintained.
11. Text based format; such that versions can be controlled.

7.1.1 Comparison of Existing Description Languages

Based on the characteristics listed in the previous section, the technology solutions available in the market such as AADL (Architecture Analysis and Description Language) [137], EDDL, SysML (Systems Modelling Language) and AML have been compared. In the initial stages of the comparison, it was found that, AADL and EDDL do not hold most of the characteristics listed above [138]. A detailed comparison of the rest of the technology solutions namely, AML and SysML have been carried out later. The results of the comparison are shown in Table 7.1. Based on the comparison, it was found that AML provides most of the listed characteristics and brings better features considering the future directions of this thesis. Therefore, AML is chosen for the purpose of modelling within the context of this thesis.

7.1.2 AutomationML and Its Features

AML is the result of a study conducted by Daimler research, aiming reduction in the cost of engineering automation systems [139]. In the study it was identified that, lack of means for transferring the data between different tools used, was accounting for most of the cost of engineering automation systems. AML was proposed as a solution to this problem by using it as a standard for data transfer between different tools. AML is an open, neutral, XML based and standard data format and is available for free to use [139].

AML is a mark-up language and inherits all the basic properties of XML. It offers marking up in documents, tags with attribute value pairs and the organization of tags in trees. It can be used for multitude of applications such as serialization and semantic mark-up of web pages. It can also be used as a metalanguage for marking up other objects from software. It stores data in plain text format, which provides software and hardware independent ways of storing, transportation and sharing data. Thus, it supports data sharing, data transport platform changes and data variability. It can be read by people, computers, voice machines, news feeds, etc.

AML itself does not propose a new language. Instead, it integrates different disciplinary related standard exchangeable formats within industrial manufacturing. Thus, it can be ap-

Table 7.1: Comparison of description languages for modelling self-diagnosing automation components.

Characteristics required for the description language	**AuomationML**	**SysML**
Machine readable	Yes	Yes
Neutral, manufacturer independent and unified format	Yes	Yes
Capability to model skill and skill-based engineering of automation systems	Yes	No
Capability to model different disciplinary aspects	Yes	No
Modelling inter relations among different disciplinary models	Yes	No
Model physical structure of a component	Yes	Yes
Model physical and logical interfaces of components	Yes	No
Support of proper syntax and semantics	Yes	Yes
Version controllability	Yes	Yes

plied throughout the plant engineering process [63]. It can represent plant structure, geometry, kinematics, logic description, relation between objects, network related data, etc. AML uses Computer Aided Engineering Exchange (CAEX) as the base format. CAEX is an IEC 62424 standard format for exchanging plant structure and relations [140, 141]. Further, the state of the art in AML proposes COLLADA [142] for geometry and kinematic related data exchanges and PLCopenXML [143] for logic data exchange. Communication aspects have been addressed within the base format CAEX. Altogether, AML is standardized as IEC 72714.

The base structure of AML is shown in Figure 7.1. It depicts the usage of CAEX in AML to neutralize different other disciplinary models such as PLCopenXML, COLLADA, etc.

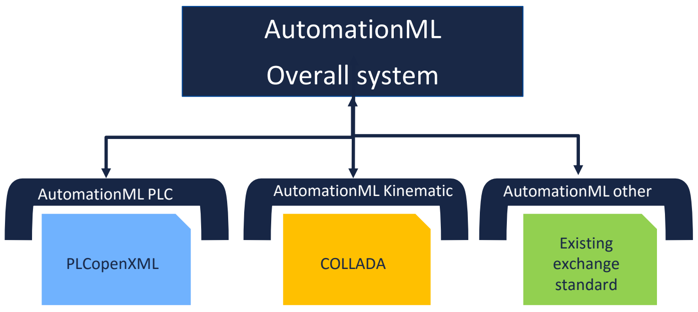
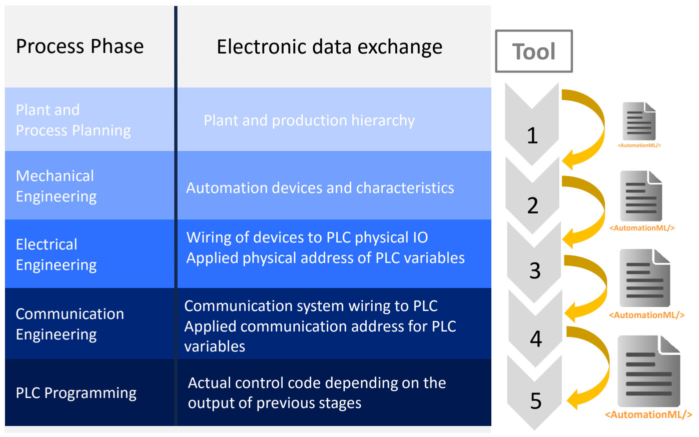


Figure 7.1: Structure of AutomationML.

The basic application scenario of AML as a data exchange format within the automation systems engineering process is depicted in Figure 7.2. The figure depicts different tools employed in a conventional plant engineering process. Initially, the plant and production hierarchy is defined within the tool employed in plant and process planning. This data is transferred to the tools employed in mechanical engineering, where the basic characteristics of the automation devices are defined. This sequence continues until the PLC programming tool.

AML defines specifications for representing different industry relevant concepts such as plant



Process Phase	Electronic data exchange
Plant and Process Planning	Plant and production hierarchy
Mechanical Engineering	Automation devices and characteristics
Electrical Engineering	Wiring of devices to PLC physical IO Applied physical address of PLC variables
Communication Engineering	Communication system wiring to PLC Applied communication address for PLC variables
PLC Programming	Actual control code depending on the output of previous stages

Figure 7.2: Application scenario of AutomationML.

topology, geometry, kinematic, behaviour, references and relations. The base format of AML, the CAEX has its basic elements namely *RoleClass*, *Interfaces*, *SystemUnitClass* and *InstanceHierarchy*. AML provides the semantic layer on top of each CAEX elements to apply them within the industrial automation domain. This include the following:

- *RoleClassLib*: A CAEX *RoleClass* is semantically enriched within AML. For example, a *RoleClass* "Robot" explains semantically a CAEX object as a Robot. The *RoleClasses* can be organized in libraries known as *RoleClassLib*.

- *InterfaceClassLib*: *Interfaces* are used to model the relation between different CAEX objects and domain specific models used within AML such as PLCopenXML, COLLADA, etc. There are two types of *Interfaces* namely the *InternalInterfaces* and *ExternalInterfaces*. The *InternalInterfaces* are generally applied for modelling topology elements such as ports, connectors, etc. *ExternalInterfaces* are generally employed for relation between a CAEX object and an external domain specific model such as PLCopenXML.

- *InternalElements*: *InternalElements* represent child elements of a CAEX Object. *InternalElements* with assigned *RoleclassLib* element can be used to model for example the hierarchical elements of a Robot, such as an arm.

- *AttributeLib*: Each CAEX element can have an attribute field. *AttributeLib* defines standard attributes of objects used within the industrial automation domain.

- *InternalLinks*: Are applicable, when it is required to relate two *Interfaces*. Within AutomationML *InternalLinks* can also be specified depending on the type of *Interfaces*.

- *SystemUnitClassLib*: This provides means to model classes of objects within AML. For example, if there exist a Robot of class Gantry Type or Robot from company X, this is modelled as a *SystemUnitClass*. A *SystemUnitClass* can hold other elements such as *RoleClasses*, *Interfaces* and *InternalElements* to model the overall aspect of in an industrial system such as a Robot.

- *InstanceHierarchy*: These are used to store the project data or overall system data.

7.1.3 Modelling Automation Components' Inter-model Relations, Connectors and Skills in AutomationML

The methodology for realizing self-diagnosis within this thesis reuses different engineering models. In order to facilitate the reuse of engineering models, it is necessary to model the engineering data of automation components as the first step. AML by definition supports different existing standards such as PLCopenXML, COLLADA for domain specific modelling of different entities within an automation component. It also allows extending the standards to include more, where necessary.

Hence, this thesis examines those engineering aspects of an automation system, which are reusable for the development of its self-diagnosis models. This includes:

1. Modelling domain specific connectors of an automation component.
2. Modelling interrelations among different models within an automation component.
3. Modelling skills of automation components.

The important aspects of AML applied in the implementation of this thesis are described below.

Modelling different domain specific connectors of an automation component: For modelling different domain specific connectors of an automation component, the concept of using the *RoleClass Connector* is proposed. The *Connector* allows modelling of external interfaces of automation components, which are required when connecting components with any other entities within a production plant. The *Connector* acts as a high-level external interface for a component and can have models within, where necessary.

A *Connector* connects the different internal domain specific models and represents the interfacing aspects of the domain specific models. The concept of *connectors* can be applied to different domain specific aspects like electric, pneumatic, mechanical, etc. For example, the pneumatic inlet, electric input and the mechanical attachment point of a pneumatic linear actuator can be modelled with a *connector.* Detailed models of different domain specific connectors are out of scope of this thesis.

Modelling interrelations among models within an automation component: For modelling the inter-dependencies of different domain specific models within an automation component, the standardized aspects necessary for modelling interrelations is proposed. Two different entities were identified for modelling of internal inter-dependencies. First aspect is, model-to-model inter-dependency. For example in a pneumatic linear actuator, the pneumatic inlets are piloted by an electrical signal and the electrical signals are triggered from a control program. The second aspect is, the connection between the connectors and the models. In order to model these aspects, the initial concept for standardizing *InternalLinks* within an automation component based on the type (Model-to-Model or Connector-to-Model *InternalLinks*) is proposed.

Modelling skill of a component: The generic model of a skill is introduced in Chapter 4. This include the following:

1. The logical behaviour of a skill.
2. Multiple domain specific models specifying the physical behaviour of a skill.
3. The abstract interface behaviour model of a skill so that they can be employed in a service oriented architecture.
4. The interrelations between the logical behaviour model and the resources applied.

Figure 7.3 shows the class diagram of the skill model within AML applicable to an automation component. The skill itself can be modelled with a *RoleClass* “SkillModel”. Based on the concept of using the skill as a service interface of automation components, the *Skill-Model* can have a *Connector* named *ComponentSkillConnector*. Further, different domain specific models can be associated with the *SkillModel*, with *InternalLinks*.

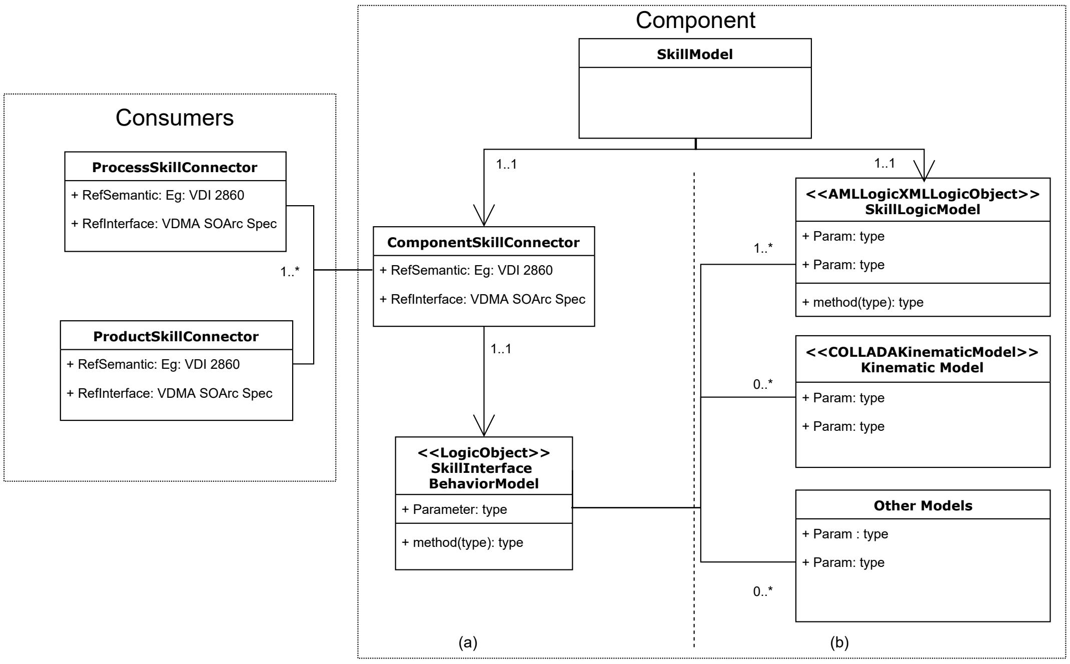

Component
SkillModel
Consumers
ProcessSkillConnector
+ RefSemantic: Eg: VDI 2860
+ RefInterface: VDMA SOArc Spec
ProductSkillConnector
+ RefSemantic: Eg: VDI 2860
+ RefInterface: VDMA SOArc Spec
1..*
1..1
ComponentSkillConnector
+ RefSemantic: Eg: VDI 2860
+ RefInterface: VDMA SOArc Spec
1..1
<<LogicObject>> SkillInterface BehaviorModel
+ Parameter: type
+ method(type): type
1..1
<<AMLLogicXMLLogicObject>> SkillLogicModel
+ Param: type
+ Param: type
+ method(type): type
1..*
<<COLLADAKinematicModel>> Kinematic Model
+ Param: type
+ Param: type
0..*
Other Models
+ Param : type
+ Param: type
0..*
(a)
(b)

Figure 7.3: Class diagram of skill model of a component in AutomationML. (a) Association of *ComponentSkillConnector* with its consumers. (b) Its capability to integrate domain specific models.

The implementation of the *ComponentSkillConnector* as a *RoleClass* is depicted in Figure 7.4. It can have attribute fields necessary to implement the naming convention standards such as VDI 2860 [125]. Further, it contains *ExternalInterfaces* and *Attribute* fields necessary to implement standards for interface behaviour models such as the VDMA SOArc standard [126]. The *SkillInterfaceBehavior* can be used to refer an externally defined interface behaviour model. The *RoleClass* can have 0 to *n* *SkillSignalInterfaces* and *SkillParameterInterfaces* based on the interface standard. It should have a minimum a *ResourceToProcessInterface* and *ResourceToProductInterface* so that they can be connected to a *ProcessSkillConnecctor* and *ProductSkillConnector* respectively. The association of a *ComponentSkillConnector* with its consumer such as *ProcessSkillConnector* is depicted in (a) side of Figure 7.3.

Apart from that, the *ComponentSkillconnector* can be internally connected to other disciplinary models using standards for *InternalLinks* mentioned in the previous section. For example, using *InternalLinks* the *ComponentSkillConnector* can be connected to a logical behaviour model implemented in PLCopenXML or any other standard supported by AML or can be integrated to AML. This is shown in (b) side of Figure 7.3.

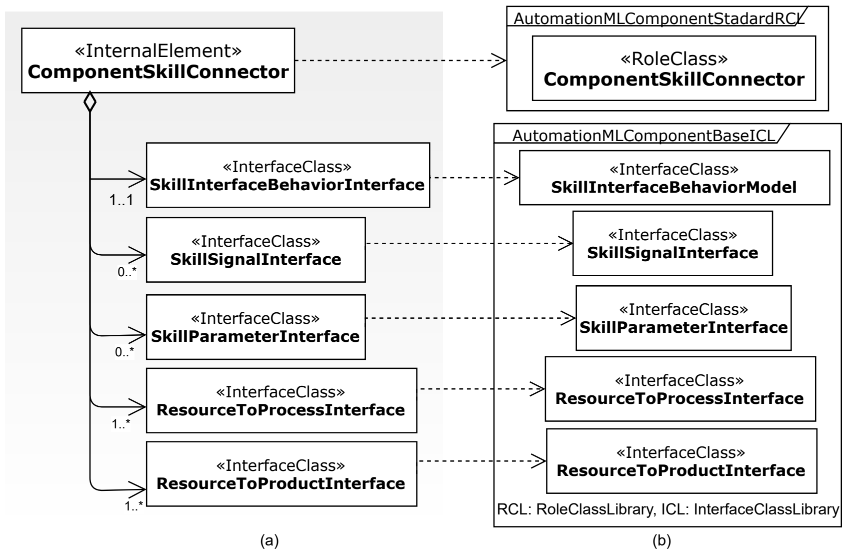


Figure 7.4: *ComponentSkillConnector* in AutomationML. (a) The constituents of the *ComponentSkillConnector*. (b) The proposed standard library elements required in AutomationML.

7.1.4 AutomationML for Reusing Engineering Models for Self-Diagnosis

The methodology for developing the self-diagnosis model of the automation components reuses domain specific engineering models. Hence, the variants can be managed effectively, and efficiency can be achieved in development. The engineering model of an automation component, which offers standardized skill to its consumer, is depicted in Figure 7.5.

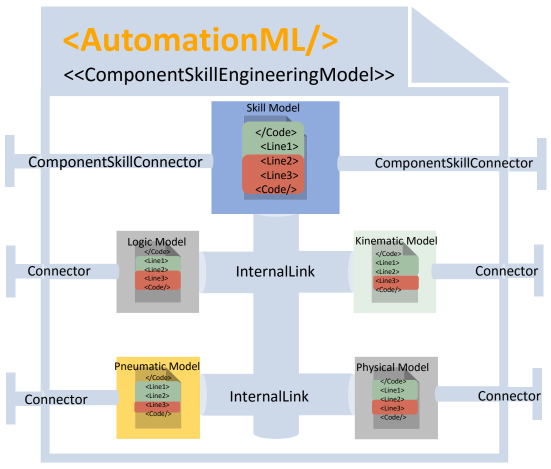


Figure 7.5: Engineering model of an automation component offering standardized skill in AML.

The figure depicts the following capabilities of AutomationML as a modelling language.

- It can hold different domain specific models required for engineering of a component, implemented with XML based standards in industrial automation.
- AML neutralizes the domain specific model and converts them to universally understandable aspects within AML.

- Different domain specific external interfaces can be modelled with the help of *Connectors*.
- Standard model of a skill can be implemented within an automation component and can be connected to different domain specific models with *InternalLinks*.

The concept applied in the engineering model of an automation component can also be applied for modelling its self-diagnosis model. The overall aspects of a skill diagnosis model is depicted in Figure 7.6. The self-diagnosis model can be implemented in an industrial standard available within AML or extend the standard where necessary. The different domain specific models can be neutralized and connected internally with AML. The service interface necessary for diagnosis is modelled with a *DiagnosisConnector*. *DiagnosisConnector* can be used as an interface for consuming the self-diagnosis aspect of the skill. External interfaces of other domain specific models are generalized as a *Connector* as they are not relevant for realization of self-diagnosis models. Similar to a *ComponentSkillConnector*, the *DiagnosisConnector* also defines

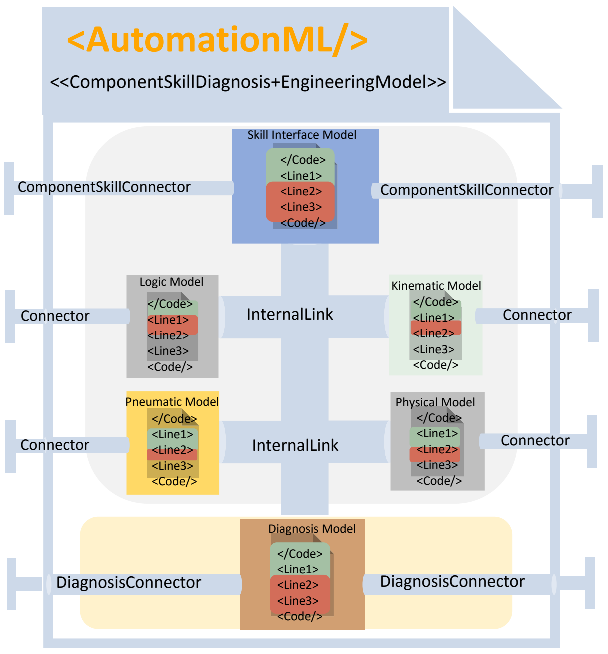


Figure 7.6: Diagnosis model reusing the engineering aspects in AML. The models in grey background are the engineering models; the model in yellow background is the diagnosis model.

its interface behaviour model, so that the diagnosis models can be used in a unified manner from anywhere. The interface behaviour model of a *DiagnosisConnector* defined according to [144] is shown in Figure 7.7.

The interface behaviour model of a *DiagnosisConnector* makes the initial transition on receiving “RequestSkill” signal. On receiving the “ResponseSkill”, if the time constraints are not satisfied it makes the next transition “FailureSignal” and subsequently the “DiagnoseSkill”. When it does not receive the “ResponseSkill”, and times out after “RequestSkill”, it makes the transition to “FailureSignal” and subsequently to the “DiagnoseSkill”. The *DiagnosisConnector* can be implemented using the similar concept and models applied in the *ComponentSkillConnector*. The *DiagnosisConnector* is connected to the Diagnosis model internally with ConnectorToModelInternalLinks as defined in the previous section.

For the overall development of the models of self-diagnosis in AML as described above, the deployment of stakeholders are envisioned as shown in Figure 6.2. The concepts proposed in this thesis for modelling the self-diagnosis aspect of a component have been presented to the AML consortium for review and standardization. Thus, this work proposes AML consortium as the first stakeholder in the process who provide the standard metamodel including necessary aspects for modelling the engineering and diagnosis aspects of an automation component. The automation component manufacturer can make use of the metamodel from the AML consortium for modelling the engineering and diagnosis aspects of their specific components and distribute it to the system integrator or the manufacturing company.

7.1.5 AutomationML for Deducing Fault Tree from Planning Model

AML has been evaluated previously for modelling and exchanging planning data of industrial automation systems [63, 43, 115]. Identifying the data exchange problem in the automotive domain, Drath et al. [63] proposed intermediate modelling language (IML) for AML. They proposed that, different graphical planning models employed in the automotive domain can be transformed to IML format, hence they can be exchanged seamlessly. Their work showed that the graphic elements in Gantt chart, Pert chart, timing diagram and activity on node diagrams can be transformed into AMLIML and the AMLIML models can be imported in control engineering tools supporting IEC 61131 standard.

This concept was extended later to support a schema for AMLIML known as *AMLLogicXML*. *AMLLogicXML* is an XML based logic format standardized under AML part 4 [117]. *AMLLogicXML* foresees that any logic related aspect can be represented in AMLLogicXML and thus can be exchanged seamlessly. This work proposes applying the same concept in the development of self-diagnosis of automation systems, where it requires the planning model to be reused. Based on the concept elaborated above, the process models of a skill-based automation system has to

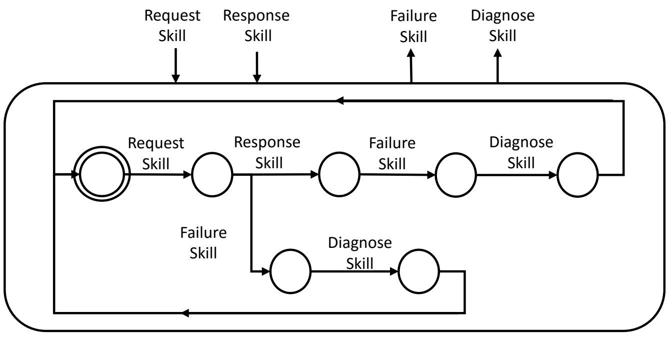


Figure 7.7: Interface behaviour model of a *DiagnosisConnector*, defined based on [144].

be represented in *AMLLogicXML* and the physical hierarchy within AML.

7.2 SystemPlanner between Planning and Maintenance Phases of Automation Systems

SystemPlanner is a prototype implemented for the planning of a skill-based automation system. The tool was developed, by analysing the literature and state of the art in industrial automation, which revealed lack of a tool for skill-based planning of an automation system [117]. The basic aspects of planning of a skill-based automation system is introduced in Chapter 5. These include process planning based on skills and physical composition of automation systems by using the connectors of automation components. The *SystemPlanner* employs the AML component models as shown in Figure 7.6 for planning of the automation system.

An illustration of the PPR based [19] planning methodology applied in the *SystemPlanner*, with two reusable components is shown in Figure 7.8. The planning starts with the product modelling. The initial product is first converted to the mid product, and then to the final product with the help of processes. The processes are provided by the skills of the components. With a common understanding of the semantics of the skills, the planning of a system can be performed by ordering the skills required for the product transformation and mapping these skills on to the provided components. By employing CPPS based automation components, each skill in the process plan can find a physical counterpart, on which the skill can be executed.

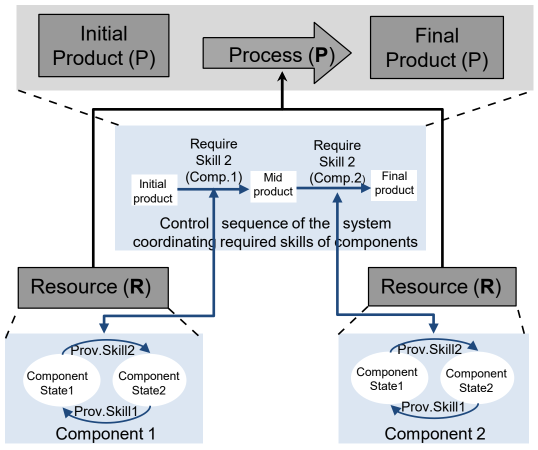


Figure 7.8: The methodology of planning applied in the *SystemPlanner* (modified from [117]). The elements in the light blue background depict a skill-based automation system. The elements in the grey background indicate the basics of the PPR concept.

The current implementation of the *SystemPlanner* does not include provision for modelling the products. It provides only process and resource aspects of the PPR concept [19]. Figure 7.9 shows the screen shot of the current implementation of the tool. *SystemPlanner* employs an AML metamodel as the backbone. The AML metamodel provides a library of components with *ComponentSkillConnectors* and other domain specific connectors, and a library of process skill elements with *ProcessSkillConnectors*.

An analysis of the existing graphical process modelling languages supported by *AMLLogic-XML* [117] showed that, they do not have the capability to notate a skill-based process. By identifying the potential of UML activity diagram for notating a skill-based process [117], the *SystemPlanner* implements a workspace based on it for the planning of the process. The skills are mapped onto the activity of the UML activity diagram. The workspace for planning is shown in (a) side of Figure 7.9.

For the physical composition of the automation system, *SystemPlanner* provides a 3D workspace, where the automation components appear with domain specific connectors displayed as snapping points. There exist different graphical snap point representations for different types of connectors. The snap points are used to compose the physical architecture of automation systems. The 3D workspace is shown in (b) side of Figure 7.9.

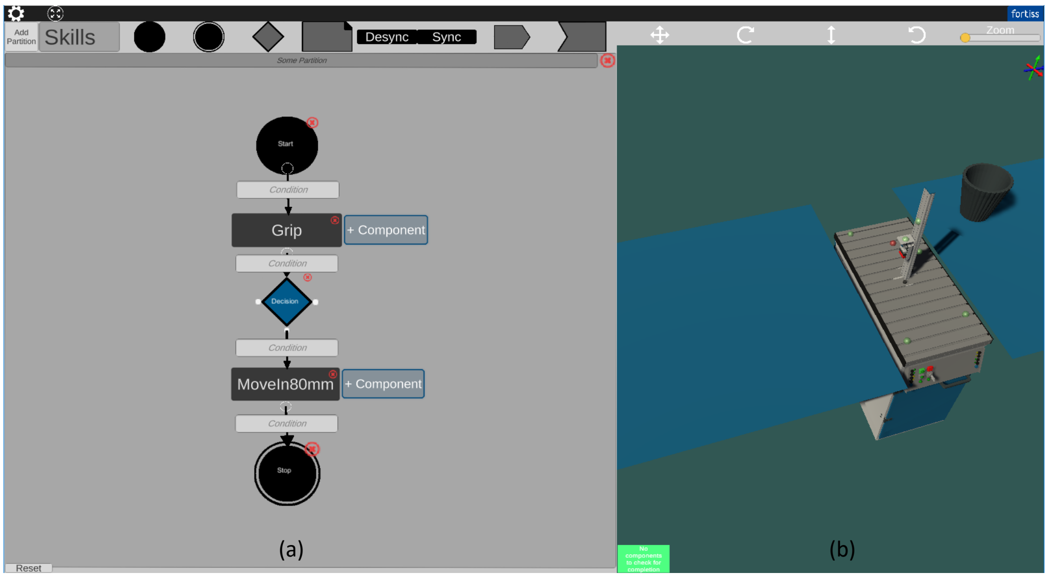


Figure 7.9: User interface of the *SystemPlanner*. (a) Shows the workspace for skill-based process planning; (b) shows the workspace for physical system composition.

The *SystemPlanner* converts the graphical planning models to an AML *InstanceHierarchy*. The AML *InstanceHierarchy* contains the hierarchical structure of the automation system along with the process model. The graphical elements of UML activity diagram are transformed to a standard *AMLLogicXML* file. The hierarchical information of the composition of the physical configuration of the automation system is represented within the AML *InstanceHierarchy*. The output from the *SystemPlanner* is a standard AML file, which can be used by any tools supporting import of AML. The output of the *SystemPlanner* integrates all the entities inside an automation component model implemented in AML, of which the core models are the engineering models of the component. Apart from the engineering models, the automation component model contains also the diagnosis models offered by the component. Under the scope of this thesis, only the diagnosis models are relevant.

An abstract model of the output of the *SystemPlanner* relevant for realizing the self-diagnosis of an automation system is shown in Figure 7.10. As shown in the figure, the Process Model is connected with the skills provided by the component with *InternalLinks* each skill has a diagnosis model. The Process Model is implemented as an *InternalElement*, providing an *ExternalInterface* to implement the logic behaviour of the process. The Process Model uses the *RoleClass* “Process” from AutomationML standard *BaseRoleClassLibarary* and the Resource Model uses the *RoleClass* “Resource” from the *BaseRoleClassLibarary*. The component models are developed based on the standard modelling recommendations for modelling automation components. Thus, the *SystemPlanner* provides a standard AML file with physical hierarchy and the logical behaviour of the automation system as its output. Hence, on the provision of AML support in the tool where self-diagnosis models are realized, the planning models from *SystemPlanner* can be directly interpreted and reused.

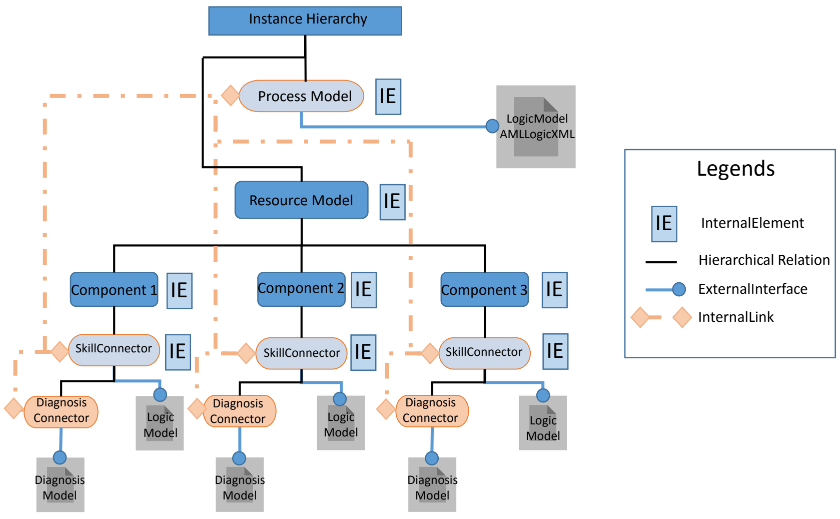


Figure 7.10: Abstract representation of an AutomationML *InstanceHierarchy* generated from the graphical planning process in *SystemPlanner*.

7.3 Using Eclipse 4diac for IEC 61499 Based Distributed Self-Diagnosis Models

There exist mainly two standards namely IEC 61131-3 [143] and IEC 61499 [145] for the control of automation systems foreseeing the FoF. IEC 61131-3 is the standard of control in the state-of-the-art industrial automation systems which implements a centralized control architecture. IEC 61131-3 addressed the problem of portability of PLC programming languages, by introducing the concept of unified and standard programming languages across vendors. However, as it implements a centralized and tightly coupled control architecture based on a central PLC, the configuration of PLCs are not portable across vendors [146].

IEC 61499 was introduced intending to bring portability, interoperability, configurability, reconfiguration, and distribution within industrial automation systems [146]. IEC 61499 allows using the programming languages of IEC 61131-3 for implementing the control algorithms and follows an event driven control architecture. IEC 61499 specifies a reference architecture model for distributed modular automation systems with a management interface foreseeing a component based distributed architecture.

The characteristics of the self-diagnosis models, proposed in this thesis can be summarized as follows. The CPPS automation components are enabled with their self-diagnosis models. The diagnosis algorithm of a component is triggered on identifying a fault event within the component. The self-diagnosis model of the automation system is proposed to be implemented as a fault tree composing the self-diagnosing automation components. The fault tree based self-diagnosis of the automation system is triggered by the fault events and diagnosis events from the applied components. Thus, the self-diagnosis models have characteristics of a distributed, event-based system. Additionally, this thesis proposes the self-diagnosis models to be implemented in an existing standard in the industrial automation domain. The interoperability of the executing control program of the automation systems, and the human interface systems with the self-diagnosis models are also foreseen.

This thesis proposes the self-diagnosis models to be implemented in the standard IEC 61499, since it provides the characteristics required for self-diagnosis models. The capability of IEC 61499 to coexist with the most predominant existing standard IEC 61131-3 [146] is also considered. The open source implementation of IEC 61499 standard Eclipse 4diac is applied for the realization of self-diagnosis models within the scope of this thesis. Eclipse 4diac provides a development environment based on the Eclipse modelling platform called 4diac IDE and a C++ based run-time environment named 4diac run-time environment (forte) [146].

7.3.1 Modelling Self-Diagnosis of Automation Components

The models for diagnosis proposed in this thesis (described in Chapter 4), use different approaches such as limit checking, matching of automata, temporal analysis, etc. IEC 61499 provides *BasicFBType* (Basic Function Block Type) which allows implementing custom algorithms in a standardized and exchangeable format. The proposed algorithms of this thesis can be implemented using the *BasicFBType* of IEC 61499.

The proposed approach of modelling self-diagnosing algorithms reuses engineering models. The IEC 61499 *BasicFBType* has different data types as input. The solution proposes these input data types to be fed from domain specific models within the AML component model. Hence, the inputs of *BasicFBType* can be changed automatically in case of variants of automation components. Changing the diagnosis models of variants automatically requires managing the AML components in a repository and individual domain specific tools committing their changes to the repository. The changes in the repository can be identified using version-controlling mechanisms. These changes can be used to alter the input events and data fields of the *BasicFBType* [108] implementing the algorithm. Automation of such a process is out of scope of this thesis.

7.3.2 Generating Self-Diagnosis of Automation Systems

There do not exist many tools in the market that support AML. One of the key reasons for that is the classic application of AML as an engineering data exchange format as shown in [43]. As an engineering data exchange format, AML is applied in the plant engineering process of a manufacturing company (Figure 7.2). Unless the engineering process is standardized, the data exchanged during engineering can vary in different companies. Hence, most of the use cases of AML in the state of the art and in literature is specific for the application or some manufacturing company, which is not universally applicable [147, 148].

On the availability of a standardized model for automation components, the support of AML can be implemented in a unified manner. Additionally, different tools can interpret these models in a unified manner. For the implementation of the solution proposed in this thesis, it necessitates the AML support for the tool realizing the self-diagnosis models. Consequently, an AML importer for 4diac IDE is implemented using the standardization aspects proposed in this thesis for modelling the automation components. The principle of the implemented importer uses the fundamentals of model transformation. The importer is implemented as an Eclipse Plugin [149] using the CAEX workbench [140]. The standardized model of automation components in AML are interpreted using the CAEX workbench, and are transformed to the IEC 61499 standard elements within the 4diac IDE.

Within the context of this thesis, the input AML applicable for the importer is the output AML produced by the *SystemPlanner*. The principle of the model transformation applied in the importer, based on the output of *SystemPlanner* is shown in Figure 7.11. On the assumption that, the logic models and self-diagnosis models of the skills of individual automation components are available in IEC 61499 standard models, they can be directly imported to the workspace of Eclipse 4diac. IEC 61499 provides *SubAppType* (Subapplication Type) for organising *BasicFBType* and other function block types in a standard and exchangeable format [108]. This thesis uses *SubAppType* to group the skill model and the different self-diagnosis algorithms of a skill.

The Process Model implemented in AMLLogicXML is transformed to a *BasicFBType* [108] in 4diac IDE. The generation of the connections [108] between the ProcessModel and the individual Skill of automation components are based on the InternalLinks between the ProcessModel and

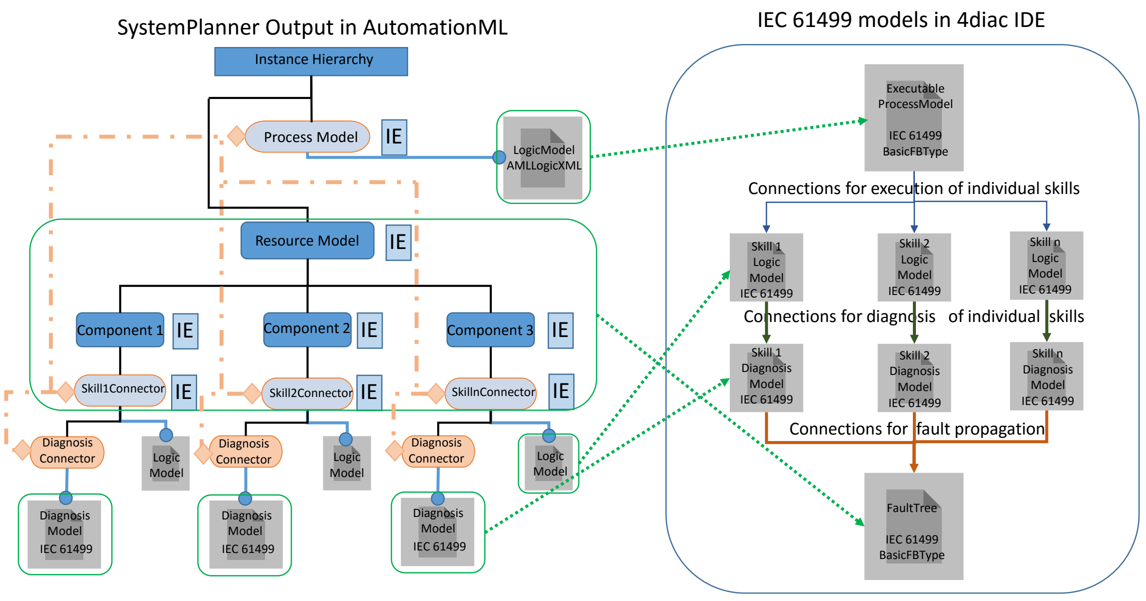

SystemPlanner Output in AutomationML
Instance Hierarchy
Process Model
IE
LogicModel AMLLogicXML
Resource Model
Component 1
Component 2
Component 3
Skill1Connector
Skill2Connector
SkillnConnector
Diagnosis Connector
Logic Model
Diagnosis Model IEC 61499
IEC 61499 models in 4diac IDE
Executable ProcessModel IEC 61499 BasicFBType
Connections for execution of individual skills
Skill 1 Logic Model IEC 61499
Skill 2 Logic Model IEC 61499
Skill n Logic Model IEC 61499
Connections for diagnosis of individual skills
Skill 1 Diagnosis Model IEC 61499
Skill 2 Diagnosis Model IEC 61499
Skill n Diagnosis Model IEC 61499
Connections for fault propagation
FaultTree IEC 61499 BasicFBType

Figure 7.11: Principle of generating IEC 61499 standard self-diagnosis models in 4diac IDE from SystemPlanner generated AutomationML instance hierarchy shown in Figure 7.10.

the *ComponentSkillConnector*. The generation of the connections between the ProcessModel and the DiagnosisModel of the components uses the *InternalLinks* between the *ComponentSkill-Connector* and the *DiagnosisConnector*. Finally, for generating the fault tree of the automation system, the hierarchical relationship between the process and corresponding resource model is used. The overall self-diagnosis model is organised in an IEC 61499 standard application and can be executed in the run-time environment (forte) of 4diac.

7.3.3 Using OPC UA for Interoperability among Models within Eclipse 4diac

The proposed solution, as elaborated in 6.3 mandates interoperability between different levels of the implementation of the self-diagnosis models. The first and foremost requirement is the interoperability between the executing Process Model and the self-diagnosis models. This interoperability facilitates the self-diagnosis models to monitor the functionality of the automation system in the context of the executing Process model. Secondly, the self-diagnosing automation components need to interoperate with the fault tree of the automation system to derive the self-diagnosis model of the overall automation system.

Eclipse 4diac provides inherent support for enabling interoperability with several means, such as MQTT, OPC, OPC UA, etc [150]. Several studies [70, 151] recommend application of OPC UA in the industrial automation domain, considering its modelling capability and performance. Relying on these results, this thesis applies OPC UA for enabling interoperability in different levels of the implementation of the self-diagnosis models.

7.3.4 Node-RED for Developing the Visual Interface for Diagnosis Models

This thesis proposes consumer devices as the interface between the maintenance personnel and the self-diagnosing future automation systems. Eclipse 4diac, does not inherently support integration of visual interfaces for such purposes. Since the self-diagnosis models are realized in Eclipse 4diac, it requires technology solutions which can interface the 4diac IDE easily with a consumer device based visual interface. Thus, the development environment should hold capabilities for enabling interoperability between the 4diac IDE and consumer devices. Additionally, it should also provide means for implementing the user interfaces and interaction techniques from the industrial automation domain.

Consequently, this thesis applies Node-RED [152] for the implementation of consumer device based visual interface for the corrective maintenance. Node-RED is a web-based tool for connecting distributed hardware by providing a flow based programming environment. It provides a browser based flow-editing environment implemented in JavaScript using Node.js. framework [152]. The selection of Node-RED for implementing the visual interface for corrective maintenance application is made based on the following characteristics Node-Red:

1. It provides an event based execution environment and portability to many platforms.
2. It has a distributed component based architecture.
3. It allows configuration and management of other interoperable hardware systems, within the development environment.
4. It provides a library of graphic elements for user interfaces common in industries.

7.4 Conclusion

This chapter elaborated implementation of the proposed solution using specific tools and technologies. This thesis envisions the application of these tools in a sequence as shown in Figure 7.12 by a system integrator or a manufacturing company. Whenever the system integrator or a manufacturing company configure/reconfigure their automation system, the tools are applied in this sequence.

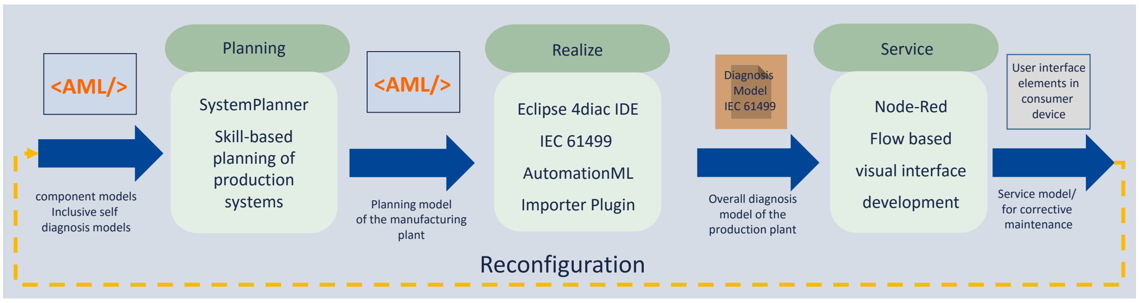

<AML/>
component models Inclusive self diagnosis models
Planning
SystemPlanner
Skill-based planning of production systems
<AML/>
Planning model of the manufacturing plant
Realize
Eclipse 4diac IDE
IEC 61499
AutomationML
Importer Plugin
Diagnosis Model IEC 61499
Overall diagnosis model of the production plant
Service
Node-Red
Flow based
visual interface
development
User interface elements in consumer device
Service model/ for corrective maintenance
Reconfiguration

Figure 7.12: Sequence of tools applied and model transformation involved in the implementation.

The AML component models (including their self-diagnosis models) from the component manufacturers are consumed by the *SystemPlanner*, which is used for the planning of the automation system. Initially, the *SystemPlanner* transforms the AML component models to visual elements within the *SystemPlanner* workspace. Subsequently, the visual planning models from the *SystemPlanner* are transformed to an AML *InstanceHierarchy.* This AML model is consumed by the AML importer of Eclipse 4diac IDE, which realizes the self-diagnosis model. The AML importer transforms the AML output of the *SystemPlanner* to an IEC 61499 standard diagnosis model within the 4diac IDE. The self-diagnosis models realized in the Eclipse 4diac IDE are further transformed to visual elements within Node-RED for their service phase.

Based on this sequence, the self-diagnosis model of the automation system is generated automatically with the Eclipse 4diac IDE. Hence, the self-diagnosis models can be seen as a by-product of the configuration/reconfiguration of the automation system.

Chapter 8

Evaluation and Discussion

Identifying the perpetual increase in cost and resource consumption for the corrective maintenance of industrial automation systems, this thesis proposes integrating self-diagnosis in the corrective maintenance of future automation systems. The future automation systems are assumed as a composition of CPPS based automation components. Based on this assumption, a methodology for cost efficient realization of self-diagnosis in CPPS component based automation systems, by reusing their engineering data is proposed. Foreseeing the future automation systems as frequently reconfigurable in nature, a methodology for enabling flexible and reconfigurable characteristics to the self-diagnosis feature is also proposed.

With a visual human-machine interface for self-diagnosing automation systems, a human-machine collaborative environment is proposed for the corrective maintenance of FoF. Consequently, it is envisioned that the future automation systems can be maintained with minimum resources and cost. Thus, this thesis contributes to the improvement of corrective maintenance within the context of FoF.

This chapter evaluates the proposed solution, with two application examples and discusses the results. The first application example, a lab scale pick and place module, is used to evaluate the overall concept of self-diagnosis based corrective maintenance introduced in this thesis. The second application example, an industrial assembly demonstrator, is used to evaluate the scalability of the approach to an industrial environment.

Thus, this chapter is organized in seven sections. The pick and place module is introduced in Section 8.1. Section 8.2 describes the self-diagnosis models of the components of the pick and place module. Section 8.3 elaborates the planning process of the pick and place module. The realization and execution of self-diagnosis in the pick and place module in explained in Section 8.4. Subsequently, the evaluation of corrective maintenance of the pick and place module with self-diagnosis is described in Section 8.5. Later, Section 8.6 evaluates the industrial scalability of the approach. Finally, Section 8.7 discusses the results.

8.1 Evaluating the Overall Approach with a Lab Scale Pick and Place Module

For the evaluation of the overall concept of self-diagnosis based corrective maintenance introduced in this thesis, a lab scale pick and place module is used. The pick and place module is a result of planning the automated assembly of a product as shown in Figure 8.1. The product is obtained by the marriage of two submodules; the bottom cylindrical housing and the top temperature gauge.

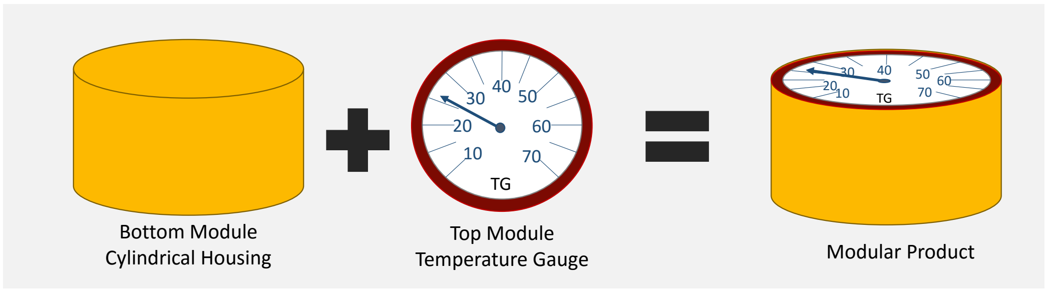


Figure 8.1: Temperature gauge with cylindrical housing forming a modular product.

The process of marriage of the bottom module with the top module requires picking and placing the top module (temperature gauge) from the storage unit of the manufacturing plant to the top of the bottom cylindrical housing as shown in Figure 8.2. The slide, where the top module is kept, is the storage unit of the manufacturing plant. The bottom module (shown in the conveyor belt) is supplied by the conveyor belt to a defined position. The top module has to be picked and placed from the slide on to the bottom module to obtain the (assembled) completed product.

The concept of skill-based engineering [117] asserts that, for a specific process any resources providing the skills required by that process can be employed. The skills required for the pick and place process can be conceptually satisfied by many resources such as a robot, a human operator or any other resources offering the skills required to complete the pick and place process. However, the planning process of the product transformation as shown in Figure 8.2 with plant specific constraints yields the pick and place module as the solution.

The overall schematic representation of the resulting pick and place module is also depicted in Figure 8.2. The pick and place module in its original form from Festo Didactic [153] does not have a modular CPPS component based architecture. The CPPS architecture of the automation components are defined as one of the prerequisites for enabling self-diagnosis feature in an automation component within the scope of this thesis. Hence, for the demonstration of the proposed solution, the components of the pick and place module are modified to a modular, CPPS architecture. The CPPS components of the pick and place module are named as CPPSDGSL-80, CPPSDGSL-50 and CPPSVASB-15-1/8.

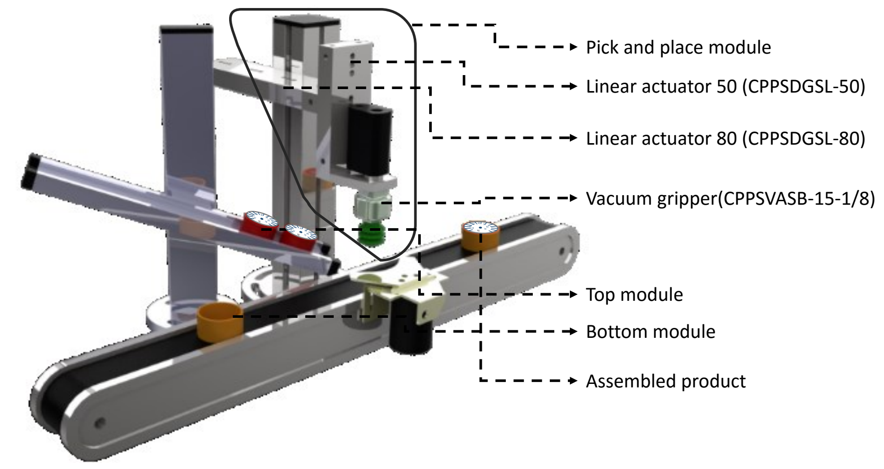

Pick and place module
Linear actuator 50 (CPPSDGSL-50)
Linear actuator 80 (CPPSDGSL-80)
Vacuum gripper(CPPSVASB-15-1/8)
Top module
Bottom module
Assembled product

Figure 8.2: The pick and place module (marked inside the boundary) as a solution for picking and placing temperature gauge on top of the cylindrical housing module (modified from [108]).

For evaluating the overall approach proposed in this thesis, the rest of the chapter elaborate the following:

1. Modelling the self-diagnosis of the automation components of the pick and place module in AML.
2. The planning process of the pick and place module using the tool *SystemPlanner*.
3. Generating the self-diagnosis models of the pick and place module in Eclipse 4diac IDE based on the output model of the *SystemPlanner*.
4. Corrective maintenance of the self-diagnosing pick and place module with a visual human-machine interface.

8.2 Modelling the Self-Diagnosis of Components of the Pick and Place Module

This thesis proposes that the modelling of self-diagnosis of an automation component is facilitated by the skill model of the component. The skill model proposed in this thesis, is derived from the modular CPPS architecture of the automation components. It is clarified that, with the provision of such a skill model, the self-diagnosis of a component can be implemented on the skill they provide.

The modular CPPS architecture of the automation components used in the pick and place module are shown in Figure 8.3. The components have their software, hardware subcomponents and the skills (services) they provide as their software interface. The interface behaviour of the skill implemented according to VDMA SOArc [126, 105] integrates the software and hardware subcomponents of the components.

The interface behaviour model of the skill introduced in [105] has several interfaces applicable

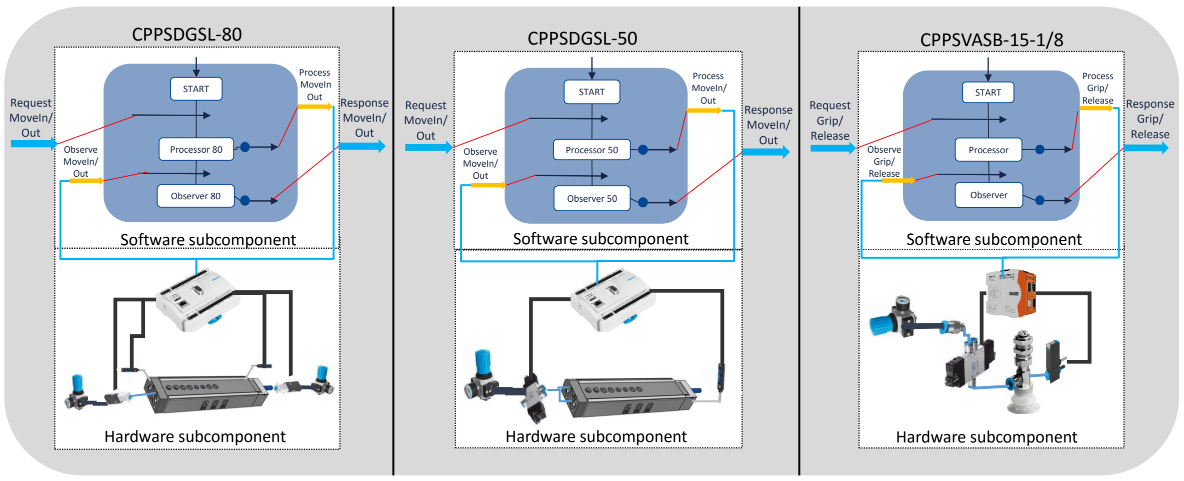


Figure 8.3: CPPS based automation components of the pick and place module.

for the control of a component, which are not relevant under the scope of this thesis. An analysis of this model showed that “Start Skill” and “Idle State” of this model is equivalent to “Request Skill” and “Response Skill” of this thesis as proposed in Section 4.3. Hence, the interfaces of the skills are represented with “Request Skill” and “Response Skill” within the scope of this thesis.

8.2.1 Modelling the Self-Diagnosis of CPPSDGSL-80 and 50 as Variants

The CPPSDGSL-80 and CPPSDGSL-50 have identical functionality of moving a payload linearly. Hence, they are modelled as variants of the linear actuator series CPPSDGSL. The CPPSDGSL-80/50 provide two skills “MoveIn” and “MoveOut” whose interface behaviour models integrate the hardware and software subcomponents of the component. The CPPSDGSL-80/50 have an integrated PLC Festo CECC-LK [154], on which the skills are executed.

The key differing characteristic of CPPSDGSL80/50 as variants is their stroke length. CPPSDGSL80 has a stroke length of 80 mm and CPPSDGSL-50 has a stroke length of 50 mm. For processing the skills with a stroke length of 80 mm, CPPSDGSL-80 has a solenoid valve with two coils. It has a load bearing capacity of 185 g and two proximity sensors for observing the execution of the skills. For processing the skills with a stroke length of 50 mm, CPPSDGSL-50 employs a solenoid valve with a single coil. It has a load bearing capacity of 152 g and a single proximity sensor for observing the execution of the skills. The software subcomponent of the CPPSDGSL-80/50 has changes based on the differences in their hardware subcomponent.

The skills “MoveIn” and “MoveOut” of the CPPSDGSL-80/50 are processed by the same hardware components and they differ only in their functional behaviour. A “RequestMoveIn” makes a linear movement inwards and a “RequestMoveOut” makes a linear movement outwards. Hence, the implementation of these skills in AML are depicted as a common model as shown in Figure 8.4. The model employs the interface behaviour model of the skills based on VDMA SOArc and VDI 2860 standards as introduced in Section 7.1. The interface behaviour of the skills are implemented as an IEC 61499 model as introduced in [105]. As there exist no standard modelling means for IEC 61499 models inside AML, the modelling approach proposed in [117] is applied in this work.

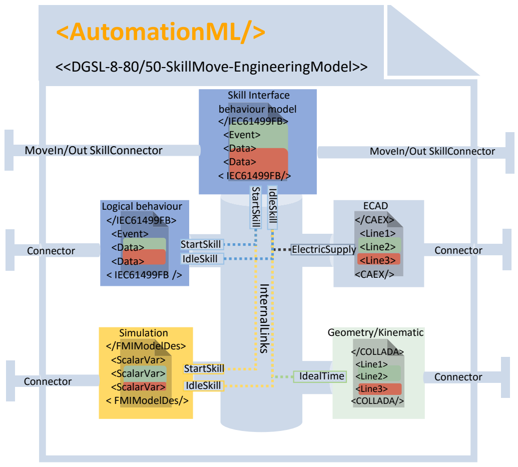


Figure 8.4: Engineering model of SkillMoveIn/Out of the CPPSDGSL-80/50.

In addition, the skill models have multiple domain specific models. The logical behaviour model of the component is implemented as an IEC 61499 model. A FMU [155] model is utilized for implementing the physical simulation model of the component. The kinematic model and the geometry model of the component are implemented using COLLADA [142]. The ECAD aspects are described within the CAEX base format of AML. Minimal *InternalLinks* are given to illustrate the interrelation among the different domain specific models. For example, the "IdealTime" variable of the kinematic model (depicting the ideal execution time of the skill) is connected to the "IdleSkill" interface of the skill interface behaviour model.

The variation in the characteristics of the double acting linear actuators CPPSDGSL-80 and CPPSDGSL-50 are reflected through their domain specific models, they use for implementing their skills. This means that, logic behaviour model, physical simulation model, the geometry model, the kinematic model and the ECAD model vary on CPPSDGSL-80 and CPPSDGSL-50. On the provision of version controlling mechanism, the variation in the domain specific models can be identified by the differences in the AML model. The differences in individual domain specific models are depicted as green and red boxes in the figure.

The generic self-diagnosis model of the skills of CPPSDGSL-80/50 reusing their engineering data is shown in Figure 8.5. The diagnosis model is implemented as an IEC 61499 model within the AML. The diagnosis model has input interfaces, which vary based on the domain specific models used in the model of skills. The "ElectricSupply" input varies based on the ECAD aspects from the engineering model. Apart from that the "IdealTime" is fed from the COLLADA kinematic model. The ideal behaviour of the skill is extracted from the FMU simulation model. The diagnosis model has interfaces from the consumer model to accept the "RequestSkill" and

“ResponseSkill”, which facilitate the diagnosis model to monitor the consumer behaviour of the skill. The consumer model also provides the “CompId” attribute which lets the diagnosis model to extract the location of the component in the plant. The interface behaviour model and logical behaviour model of the skill is used while defining the diagnosis models.

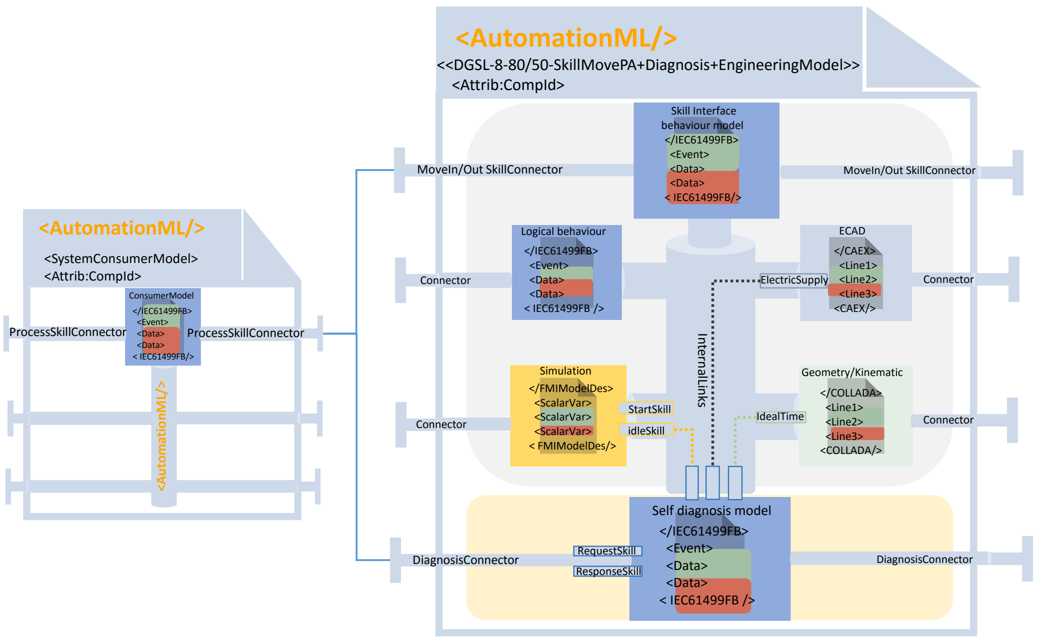


Figure 8.5: Diagnosis model of SkillMoveIn/Out reusing the engineering data of CPPSDGSL-80/50.

The diagnosis model includes different aspects of diagnosis such as software and hardware aspects introduced in Chapter 4. The different aspects of the diagnosis models of the CPPSDGSL-80/50 are described in the following sections.

Self-Diagnosing the Software Faults of CPPSDGSL-80/50

The interface behaviour model of the skills of CPPSDGSL-80/50 has a protocol and the skills are bound to the functional behaviour model of the components. Hence, CPPSDGSL-80/50 are plausible to Type 1 and Type 2 of the software faults defined within Section 4.3.1 of this thesis. Consequently, the software diagnosis model of the skills “MoveIn”and “MoveOut” can be implemented using Algorithm 1 introduced in Section 4.4.

The diagnosis model implemented in 4diac IDE as an IEC 61499 standard SubAppType is shown in Figure 8.6. The diagnosis model inputs the consumer model of the skills through its “App_RequestSkill” and “App_ResponseSkill” event interfaces. In addition, the “CompId” parameter maps the location of the component from the consumer model of the plant.

The FMU physical simulation model of the component implements the physical behaviour model of the component in a simulated environment. The kinematic model in COLLADA defines the ideal kinematic behaviour of the component and provides the “IdealTime” variable. The “Request Skill” from the consumer model is fed to the physical simulation model, on which the model produces “Ideal_ResponseSkill” in “IdealTime”. The “Ideal_ResponseSkill” and “IdealTime” input from these models are hence neutralized in AML and fed to the inputs of the diagnosis model.

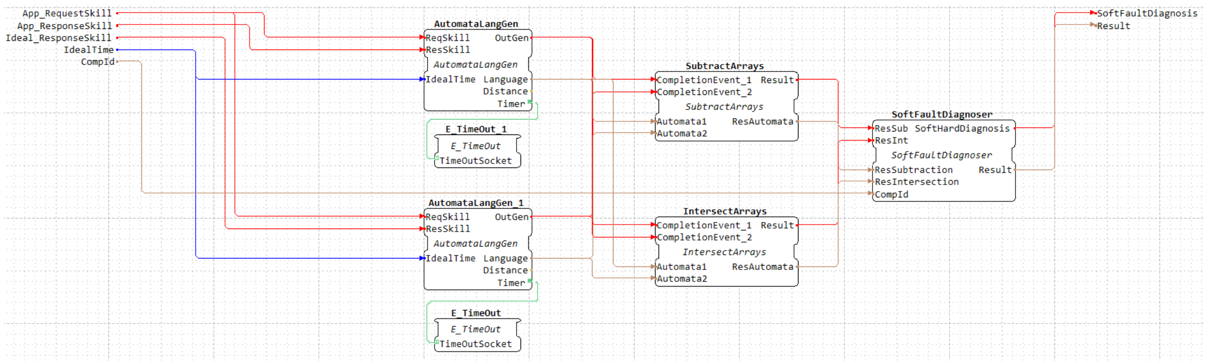


Figure 8.6: Software fault diagnosis model as a *SubAppType* in IEC 61499, with constituent *BasicFBTypes* AutomataLangGen, SubtractArrays, IntersectArrays and SoftwareFaultDiagnoser.

The simulation model and the kinematic model normally run in their native execution environments. The diagnosis models as introduced before, are implemented as IEC 61499 models. The software fault diagnosis model requires running the ideal physical behaviour model of the skill in parallel to the execution model of skill, such that the diagnosis result can be derived. The initial experiments revealed the real time constraints of the simulation model or kinematic model running in parallel to the IEC 61499 model. Hence, for the evaluation of the approach, the ideal physical behaviour of the component is implemented as an IEC 61499 logical simulation model within this thesis. Consequently, the physical behaviour model (IEC 61499 logical simulation) and the execution model of the skill can run in parallel within the 4diac runtime environment (forte).

The diagnosis model gets the ideal time of execution of the skill as an input “IdealTime” variable from the IEC 61499 logical simulation model. The IEC 61499 based logical simulation model also provides “Ideal_ResponseSkill” to the diagnosis model. The software fault is identified, when “App_ResponseSkill” event is not received after “AppRequest_Skill” is received and “IdealTime” has elapsed. The diagnosis algorithm for the software fault (Algorithm 1 as shown in Section 4.4) is implemented in Structured Text [108] within 4diac IDE. On identifying the fault, the diagnosis algorithm is executed within the diagnosis model. The diagnosis results are published through the output variable “Result” of the diagnosis model. The diagnosis result provides the causality of the fault along with the location of the component.

Self-Diagnosing the Hardware Faults of CPPSDGSL-80/50

As introduced in Chapter 4, the hardware faults depend on the type of hardware applied for the implementation of the skill. For defining the self-diagnosis of hardware faults, the plausible hardware faults have to be defined as an entry point. When the CPPSDGSL-80/50 receives

"RequestMoveIn/Out", this is physically processed by a pneumatic cylinder and observed by a proximity sensor.

The operation of the CPPSDGSL-80/50 has the following sequence:

1. The component receives "RequestMoveIn/Out", which signals the digital output of the PLC.
2. The digital output of the PLC triggers the voltage input of the solenoid valve/s of the component, which let the required pressure for the linear movement of the pneumatic cylinder through the outlet port of the pilot valve.
3. When the actuator reaches the 50/80mm end points (inwards or outwards), this is observed by a proximity sensor, which signals the "ResponseMoveIn/Out" output of the component.

Thus, the operation of CPPSDGSL-80/50 is dependent on the electric/voltage supply and pressure supply. Apart from that, there exist also constraints such as the load bearing capacity of the actuator, friction, drop/leakage in pressure supply.

Based on these findings, the physical faults are classified as shown in Table 8.1. The approach of hardware fault diagnosis based on injection of fault into the physical simulation model as shown in Section 4.4.3 was evaluated separately with a simulated electro-mechanical gripper [18]. This study revealed that, high effort is required for developing such a model. Relying on [18], for diagnosing the hard fault types, the limit checking approach and temporal analysis approach introduced in Section 4.4.3 are evaluated further. For the diagnosis model of the hardware faults of the CPPSDGSL-80/50, the proximity sensor is assumed to be working.

Table 8.1: Plausible list of hardware faults in the CPPSDGSL-80/50.

Fault Type	**Observability**
Electric supply failure	"ResponseMoveIn/Out" not received in ideal response time
Pressure supply failure	"ResponseMoveIn/Out" not received in ideal response time
Payload slightly higher than bearing capacity	Sequential delays in "ResponseMoveIn/Out" compared to the ideal response time
Payload largely higher	"ResponseMoveIn/Out" not received in ideal response time
Friction	Sequential delays in "ResponseMoveIn/Out" compared to the ideal response time
Leakage (Drop) in pressure supply	Sequential delays in "ResponseMoveIn/Out" compared to the ideal response time

Hardware Fault Diagnosis Based on Dedicated Sensors and Limit Checking

The hardware fault based on dedicated sensors uses the approach of implementing specific sensors for observing the causalities of faults within the system. Within the context of this thesis, a dedicated current sensor monitoring the electrical supply of the CPPSDGSL-80/50 was installed as an extra component.

The hardware fault diagnosis based on the dedicated current sensor and limit checking implemented as an IEC 61499 SubAppType is shown in Figure 8.7. Similar to the software diagnosis model, this model has input events “App_RequestSkill”, “App_SkillResponse” and parameters “IdealTime” and “CompId”. Additionally the model has one input variable “SetValue” for receiving the ideal electrical supply value from the ECAD model. The variable “PARAM” represents the input channel of the applied sensor. On not receiving “App_SkillResponse” signal within the “IdealTime” after “App_RequestSkill” is received, it runs the limit-checking algorithm for the electrical supply.

This approach produces accurate results in case of failure due to electrical supply. When the electrical supply value goes below the “SetValue” the algorithm identifies the cause as electrical supply failure. The diagnosis results are published through the “Result” interface and includes the localization. However, a sensor for diagnosis as mentioned in Section 4.4 is not cost efficient.

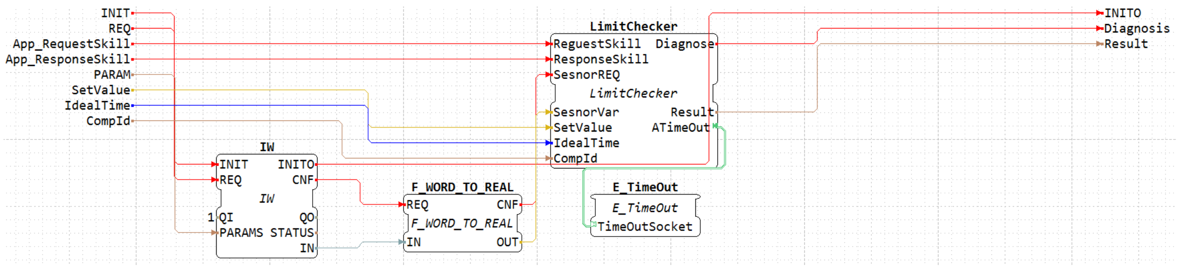


Figure 8.7: Hard fault diagnosis model using limit checking as a *SubAppType*, with constituent *BasicFBType* LimitChecker implemented in IEC 61499.

Hardware Fault Diagnosis by Temporal Analysis of Observable Entities

Section 4.4.3 introduced the approach of temporal analysis for hardware fault diagnosis, without using any additional sensors for diagnosis. The diagnosis algorithm based on temporal analysis implemented as a SubAppType in IEC 61499 is shown in Figure 8.8. The diagnosis model combines the approach of analysing the trend and the slope of the previous consecutive responses of the skill. The diagnosis model has input events “App_RequestSkill”, “App_ResponseSkil” and parameters “IdealTime” and “CompId”. A fault is identified when, “App_ResponseSkil” event is not received after “App_RequestSkill” is received and “IdealTime” has elapsed. “CompId” parameter is used to localize the fault.

On identification of the fault, the diagnosis algorithm runs and produces the result. The result reflects all of the hardware fault types as classified in Table 8.1 based on their observability. It is published through the “Result” interface and includes the localization. Thus, apart from the faults due to the dependencies such as electrical supply or pressure supply, the type of fault such as the delay in “Response Skill” due to friction can be diagnosed using the temporal analysis. Even though the diagnosis using temporal analysis does not produce results as good as that of the dedicated sensor based approach, the temporal analysis based approach is efficient in terms of cost and resources required.

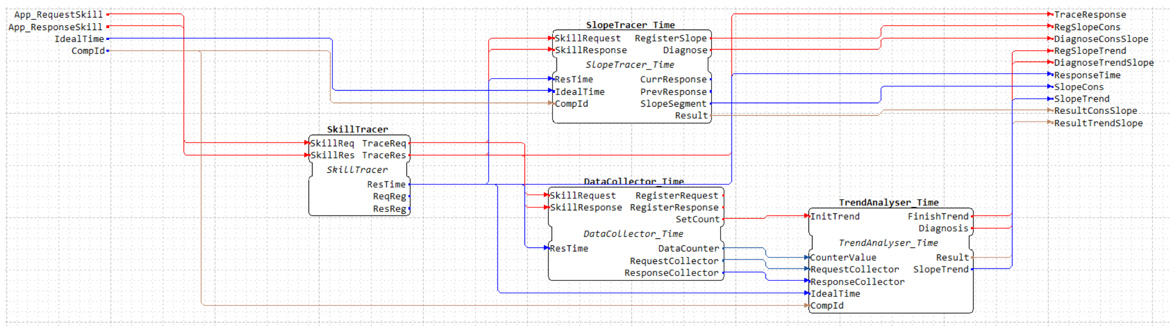


Figure 8.8: Hard fault diagnosis model based on temporal analysis implemented as a SubAppType in IEC 61499. SlopeTracer_Time *BasicFBType*, DataCollector_Time and TrendAnalyser_Time are the constituent *BasicFbTypes*.

8.2.2 Modelling the Self-Diagnosis of the CPPSVASB-15-1/8

The CPPSVASB-15-1/8 functions using the generated vacuum to grip a payload. The CPPS-VASB-15-1/8 is embedded with its own PLC from RevolutionPi [156]. The CPPSVASB-15-1/8 offers skills "Grip" and "Release" to its consumers. The interface behaviour model of the skills integrate the software subcomponents and hardware subcomponents of the CPPSVASB-15-1/8.

The skills of the CPPSVASB-15-1/8 are processed by a solenoid, which generates the vacuum and observed by a vacuum sensor. The CPPSVASB-15-1/8, as shown in Figure 8.3 integrate all those supporting components, which makes the independent functionality of a vacuum gripper possible. The software subcomponent is assumed to be similar to that of the generic model of a SISO automation component.

The generic implementation model of the skills "Grip" and "Release" of the CPPSVASB-15-1/8 in AML is similar to the implementation model of the skills of the CPPSDGSL-80/50 as shown in Figure 8.4. The model defines the logical and physical behaviour model of the skill it offers within AML, similar to the model shown for the CPPSDGSL-80/50. The skill interface behaviour model, based on standard VDMA SOArc and VDI 2856 act as the interoperating medium for all the discipline specific aspects of a skill model as shown in Figure 8.4. Hence, the generic diagnosis model of the CPPSVASB-15-1/8 in AML can be seen similar to that of the CPPSDGSL-80/50 shown in Figure 8.5.

Diagnosing the Software Faults of CPPSVASB-15-1/8

Since the interface behaviour model of every component is the same according to VDMA SOArc, the diagnosis model for software fault types (Type 1 & 2) as introduced in Section 4.4 can be seen similar to that of the CPPSDGSL-80/50. The model is implemented as a SubAppType in IEC 61499 similar to the CPPSDGSL-80/50 and the only difference, that appears is the value of "IdealTime" variable as the temporal behaviour of the skills "Grip/Release" differ from that of skills "MoveIn/Out".

Diagnosing the Hardware Faults of CPPSVASB-15-1/8

When the CPPSVASB-15-1/8 receives a “RequestGrip/Release”, this is processed by a suction cup operating with the help of generated vacuum. The sequence of operation of the CPPSVASB-15-1/8 is as follows:

1. The component receives a “RequestGrip/Release”, this signals the digital output of the PLC.
2. The digital output of the PLC triggers the voltage input required for the operation of the solenoid valve, which generates the vacuum required to grab the object.
3. The gripping process is observed by the vacuum sensor, which signals the “ResponseGrip/Release” of the skill.

Thus, the operation of the vacuum gripper has similar dependencies as that of the CPPSDGSL-80/50. However, the gripper does not have a constraint on friction, but only constraint on the pressure and the area of the payload. Hence, the hardware diagnosis models of the CPPSVASB-15-1/8, except the temporal analysis based model look similar to that of the CPPSDGSL-80/50. In the temporal analysis model, the constraints are defined only for payload area and the drop in pressure, in comparison to the CPPSDGSL-80/50. The results of the hardware fault diagnosis reflect only these constraints as shown in Table 8.2. The diagnosis model looks similar to that of CPPSDGSL-80/50 in all other aspects.

Table 8.2: Plausible list of faults in the CPPSVASB-15-1/8.

Fault Type	**Observability**
Electric supply failure	“ResponseGrip/Release” not received in ideal response time
Pressure supply failure/Drop	“ResponseGrip/Release” not received in ideal response time
Payload area smaller than the suction cup	“ResponseGrip/Release” not received in ideal response time
Leakage (Drop) in pressure supply	“ResponseGrip/Release” not received or Delay in “ResponseGrip/Release” compared to the ideal response time

8.2.3 Analysis of the Effort Required for Developing Self-Diagnosis Models

The application example of pick and place module clarifies that, self-diagnosis models of skills of the components can be prepared without much effort. Most of the proposed algorithms can be reused for different types and variants of the components and their skills.

The example of double acting linear actuators as variants shows the handling of variants by using the different domain specific engineering models as variable inputs for the diagnosing algorithm. The similarity of diagnosis model of the vacuum gripper CPPSVASB-15-1/8 with that of the CPPSDGSL-80/50 show that, in presence of standard model of a skill, most of the algorithm can be generalized for different components and their skills.

Apart from that, by using AML for implementation, the XML-based format of AML allows the changes in the domain specific models to be perceived as a difference in the XML data and thus enables automatic generation of the self-diagnosis algorithms in case of variants.

These results thus justify the answers to the research question 1 and 2 of this thesis. It is possible to create reusable models for self-diagnosis, if they implement their skill model in a standard format as proposed in this thesis. By reusing the engineering aspects of an automation component, it is possible to efficiently develop their self-diagnosis models.

8.3 Using SystemPlanner for the Planning of Pick and Place Module

An overview of application of the tool *SystemPlanner* has been already provided in Chapter 5. The *SystemPlanner* allows skill-based planning of automation systems in a component based architecture. This section elaborates the application of *SystemPlanner* yielding the pick and place module as the solution for the transformation of the product as explained previously. The planning activity carried out in *SystemPlanner* is a manual process based on the production requirements. The planning is expected to be carried out by an expert who holds the system and process knowledge required for the product transformation. *SystemPlanner* can be employed for planning of an automation system, each time when production demands a configuration/reconfiguration.

The metamodel, which functions as a backbone implements a library of process skills with *ProcessSkillConnectors* [117] required for the picking and placing process. This includes the following: “MoveIn50mm”, “MoveOut50mm”, “MoveIn80mm”, “MoveOut80mm”, “Grip” and “Release”. In addition, the metamodel contains a library of components with *ComponentSkillConnectors* providing the skills required by the process. The process skills “MoveIn/Out50mm” and “MoveIn/Out80mm” are provided by CPPSDGSL-50 and CPPSDGSL-80 from the component library. The skills “Grip” and “Release” required by the process are provided by CPPSVASB-15-1/8 in the component library. The *ProcessSkillConnectors* of the process skills can be connected to that of the components after matching the semantic and interface attributes.

The planning process combines the two workspaces of the *SystemPlanner*: the UML activity diagram based workspace for process planning and the 3D workspace for the 3D assembly of the system. The expert who employs the *SystemPlanner* for planning defines the constraints of the process and the system. Brandenbourger et. al [157] show the examples of such constraints. One of the examples of such constraints is that horizontal movement is not allowed while gripping. It is assumed that the physical design constraints of the plant necessitates placement of the storage unit behind the conveyor belt. An excerpt of the sequence of skills, applicable for the pick and place process based on this constraint is shown in Figure 8.9.

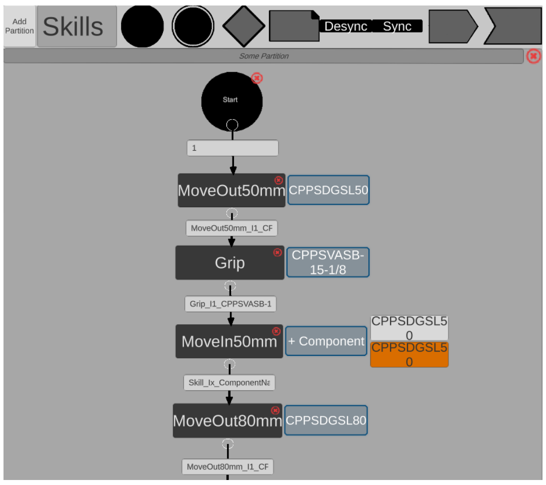
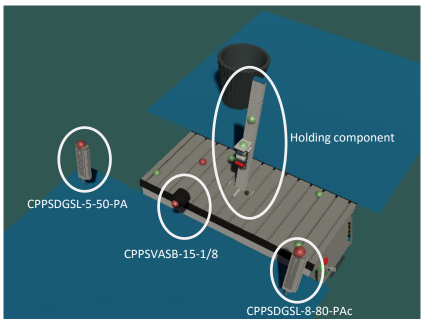


Figure 8.9: An excerpt from the skill-based planning sequence of the pick and place module in *SystemPlanner*. Every skill in the sequence has a corresponding component executing it.

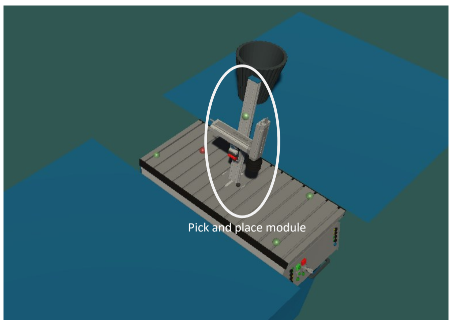
The sequence of the skill shown in Figure 8.9 is modelled with the UML activity diagram based process planning workspace of *SystemPlanner*. The skills mapped as activities inside the UML activity diagram are loaded from the metamodel of the *SystemPlanner*. Associated with each skill the corresponding component offering the skill from the metamodel can be seen. The "+ Component" button allows adding a component offering the skill required for the process. If there exist no component in the library of the *SystemPlanner* with the required skill, the component providing the skill can be imported to the *SystemPlanner* workbench from an external repository. The imported component model from the external repository should confirm to the standard recommended for modelling the automation components by the AML consortium. Otherwise they cannot be added to the metamodel of the *SystemPlanner*.

The pick and place process requires the skills from the library to be in a specific sequence as in Figure 8.9. The skills are provided by the components CPPSDGSL80, CPPSDGSL-50 and CPPSVASB-15-1/8 from the component library. The physical composition of the components required to complete the process is shown in Figure 8.10. This composition of the automation components, yielding the pick and place module is performed within the 3D workspace of the *SystemPlanner*. The Figure 8.10(a) depicts the automation components before assembly with mechanical connectors as snapping points. The Figure 8.10(b) shows the completed pick and place module yielding the sequence of skills as in the pick and place process.

In order to use the planning models in the later stage of the engineering of the pick and place module, it requires the output of the *SystemPlanner* to be exported as an AML model. The *SystemPlanner* allows the graphical planning models of the pick and place module to be exported as an AML *InstanceHierarchy*. The export generates an AMLLogicXML file representing the process of the pick and place module and also copies the self-diagnosis models of the employed components in a separate directory.



(a) Components of the module before assembly.



(b) The assembled module.

Figure 8.10: Assembly of the pick and place module in *SystemPlanner*.

8.4 Using Eclipse 4diac for the Self-Diagnosis Models of Pick and Place Module

Within the scope of this thesis, an AML importer plugin is developed for 4diac IDE. The AML importer plugin uses the AML output from the *SystemPlanner* and performs model transformation to generate control programs automatically in 4diac IDE. The generation of the self-diagnosis models in 4diac IDE depends on the sequence of activities required to develop and execute a control system application in 4diac IDE. Which is as follows:

1. Necessary function block types are created in the typelibrary of 4diac IDE.
2. An application is modelled in the application area of the IDE, using the function blocks from the typelibrary.
3. A hardware resource model with a compatible 4diac run time environment (forte) is created and the application is mapped onto different hardware resources.
4. The application is deployed to the hardware resources and executed.

8.4.1 Realizing Self-Diagnosis with the AutomationML Importer Plugin

In case of the pick and place module, the self-diagnosing models of the components modelled as a SubAppTypes are directly imported to the typelibrary of 4diac IDE. The fault tree based self-diagnosis model of the pick and place module is generated as a BasicFBType within the typelibrary. As the self-diagnosis models require the consumer model of the skill, this is generated as a SubAppType within the typelibrary. Subsequently, an application model is generated, based on the hierarchical relationship between the different components employed for the pick and place module as explained in the previous section.

The Figure 8.11 shows the organization of the self-diagnosis application of the pick and place module within 4diac IDE. The diagnosis models of skills of the applied components (which are not generated rather copied into the typelibrary from the AML model) are depicted in light grey boxes with brown outlines. The rest of the entities in the figure are generated based on the AML output of the *SystemPlanner*. As shown in the figure, the coordinating application (consumer) model of the pick and place module, generated as a SubAppType connects with self-diagnosis models of the employed components modelled as SubAppTypes. The self-diagnosis models of the automation components continuously monitor the execution of their skills and derive the self-diagnosis results. The self-diagnosis of the overall pick and place module generated as a BasicFBType, connects with the self-diagnosing SubApptype of individual components to derive the overall self-diagnosis based on a fault tree.

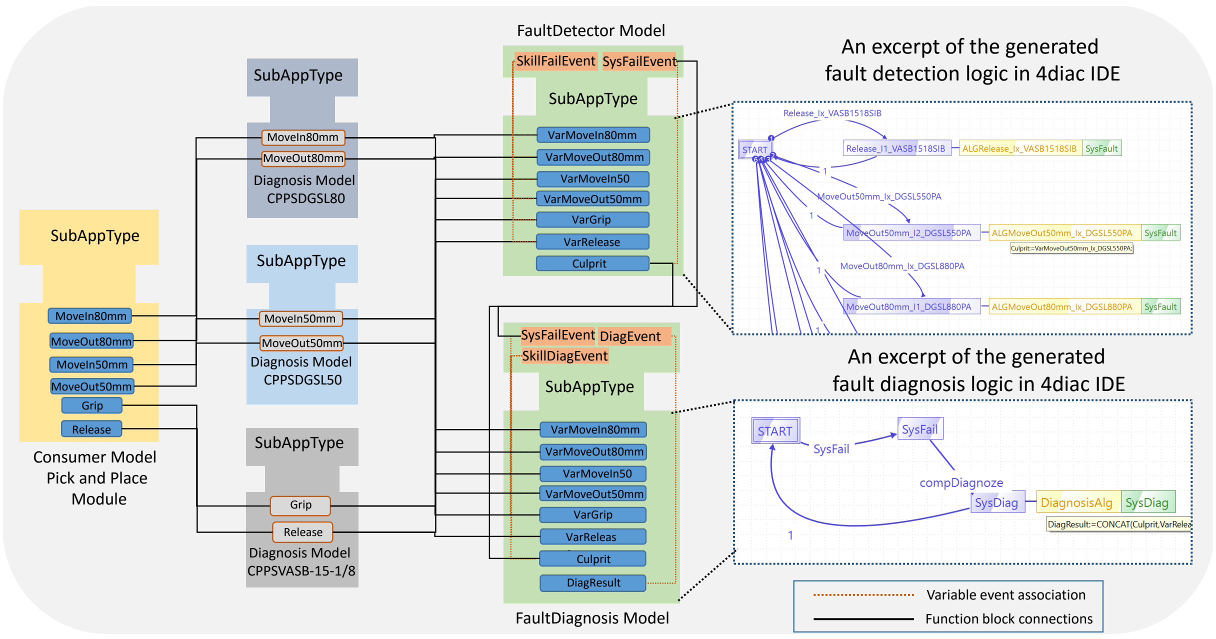


Figure 8.11: Key aspects of the generated self-diagnosis application in Eclipse 4diac IDE.

8.4.2 Analysis of the Effort Required for Realizing Self-Diagnosis

The current implementation of the AML importer does not generate the resource model or mapping model of the application. Automatic generation of the resource model will require a corresponding model in the AML output of the *SystemPlanner*. The current version of the *SystemPlanner* does not have provision for modelling the hardware configurations necessary for the resource model in 4diac IDE. Hence, the current version of the AML importer in 4diac IDE generates only the application model of the self-diagnosis of the pick and place module. However, with automatic generation of the application model the concept of reducing the effort for realization is justified. Since the function block types and the application model is generated automatically, it reduces the possibility of human error in a control application development using 4diac IDE.

Thus, the example of the pick and place module composed of automation components justifies the answers to research questions 2 and 4. The realization of self-diagnosis in automation systems can leverage the engineering and operational aspects of it. The AML importer is capable of generating the control model of the automation system along with the self-diagnosis model. Hence, the self-diagnosis models can be seen as a by-product of the engineering process. This thesis proposes that the tool *SystemPlanner* is used each time an automation system is (re)configured. Since the AML importer uses the output of the *SystemPlanner* as its input, the self-diagnosis models are reconfigured for each reconfiguration of the automation system.

8.5 Corrective Maintenance of the Self-Diagnosing Pick and Place Module

The automatically generated self-diagnosis feature of the pick and place module runs in the 4diac runtime environment (forte) parallel to the executed control program of the pick and place module. The self-diagnosis feature continuously monitors and derives the diagnosis in case any fault occurs in the pick and place module. To apply the self-diagnosis feature in the corrective maintenance of an automation system, the self-diagnosis feature has to be integrated within the corrective maintenance sequence of the automation system.

As detailed in Chapter 1, the corrective maintenance function is required when any system undergoes a failure and the corrective maintenance function involves activities of a maintenance personnel. The Section 7.3.4 of the previous chapter detailed the approach for integrating the self-diagnosis feature into the corrective maintenance function of an automation system with a visual human machine interface. This section evaluates the application of this approach for the corrective maintenance of the self-diagnosing pick and place module.

8.5.1 Taking Humans in the Loop with a Visual Interface in Node-RED

A prototypical user interface developed in Node-RED for integrating the self-diagnosis of the pick and place module in its corrective maintenance function is shown in Figure 8.12. Node-RED communicates with the diagnosis models of the individual skills and the fault tree of the pick and place module executed on the 4diac runtime environment (forte).

The user interface notifies its user, as soon as a fault occurs. Subsequently, it presents the results of the software and hardware fault diagnosis of the pick and place module in a text format. The interface is developed foreseeing an expert maintenance personnel as the user. Hence, the current implementation of the user interface provides also gauges and charts for the analysis of execution behaviour of individual skills.

The diagnosis results of the pick and place module are displayed within the fault tree of the pick and place module. The fault localization is depicted within the hierarchical tree structure of the module. On receiving the fault notification, a ticket is created automatically and a maintenance personnel is assigned to this ticket. The assigned personnel accepts the ticket, reviews

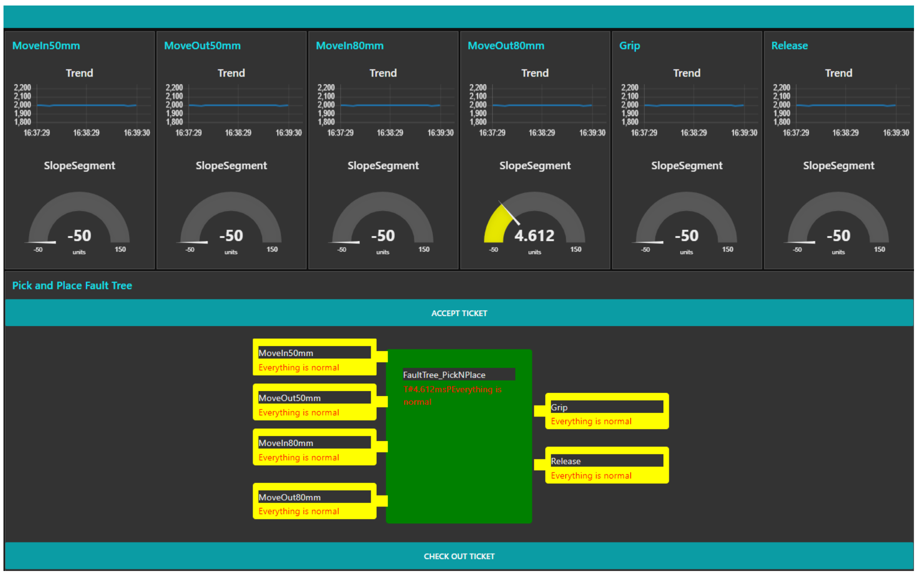


Figure 8.12: Screenshot of the prototypical corrective maintenance user interface of the pick and place module developed in Node-RED.

the self-diagnosis results and performs the corrective action. After performing the corrective action, checking out the ticket terminates the corrective maintenance. Thus, the solution takes the human as an element within the overall architecture of the system through the visual model of the corrective maintenance.

8.5.2 Performance Analysis of Self-Diagnosis for Corrective Maintenance

For evaluating the performance of the self-diagnosis feature of the pick and place module, some faults were injected into the pick and place module.

(1) Type 1 and 2 software faults

Software faults of Type 1 and 2 as shown in Section 4.3.1 were injected to all of the applied components by using the feature of monitoring in 4diac IDE [108]. By enabling monitoring on the application model of the pick and place module, the skill requests were triggered before their responses were received (Type 1 of software fault). In addition, in each component the requests of skills bound the behaviour model were triggered while the component is processing other skills; for example, the "Grip" was triggered while the component is processing "Release" (Type 2 of software fault). Injecting these software faults, produced the diagnosis result of: "Check the application software breaking the communication protocol or behaviour constraint of <SkillType>" message in the Node-RED visual interface.

(2) Hardware fault; disrupting electrical supply

This fault was diagnosed with two proposed approaches. First was with a dedicated current sensor for monitoring the electrical supply as a dependent factor for the physical execution of the skill in the actuator. By limit checking the value of the dedicated current sensor, whenever the electrical supply is disrupted the diagnosis result immediately reflects the same. The limit checking approach with the dedicated sensor is depicted in Figure 8.13. Accordingly, in case the monitored value of the current in the component changes, this is immediately detected using a dedicated sensor. The user interface presents the result of “Hardware fault: Broken electrical supply” to the human user.

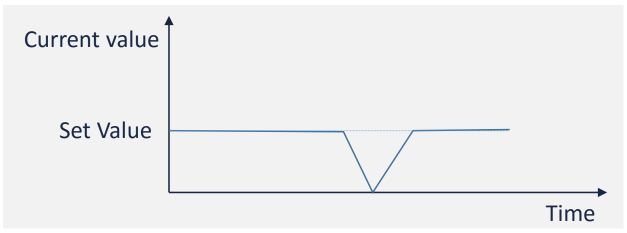
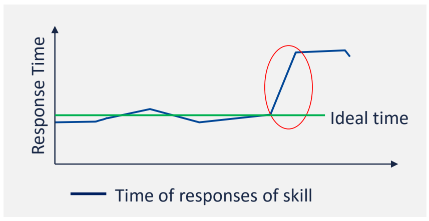


Figure 8.13: Limit checking the value of current for diagnosing failure in electrical supply.

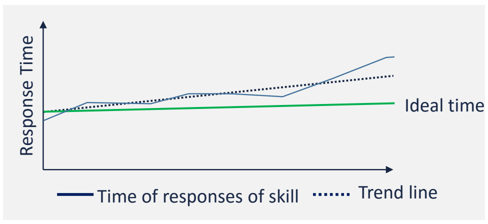
The second approach was using the temporal analysis. In this case, the result was produced by the slope of the time responses of the consecutive skills as the disrupted supply makes a sharp change in the consecutive response of a skill. This is identified by, limit checking the slope to the ideal value. This is depicted in Figure 8.14(a). The user interface prints the message: “Hardware fault please check for a broken electrical supply, pressure supply or broken part” in the user interface, as the same response is produced for a broken pressure supply or a broken component.

(3) Hardware fault; applying friction on the component

A frictional force was manually introduced on the linear actuators for evaluating the performance of the hardware diagnosis feature of the linear actuator against friction. The introduction of frictional force caused subsequent delay in the time of responses of the skills. The diagnosis of this issue was identified with the temporal analysis of the response time of the skills. A depiction of the trend of the response time of the skill is shown in Figure 8.14(b). The slope of the trend is analysed for n occurrences and a diagnosis leading to friction as the cause is produced on increasing slope value. The result prints the message “Hardware fault, please check friction or excess payload or drop in pressure” as the same behaviour is observed in increase of payload or drop in pressure in linear actuators.



(a) Slope of the consecutive responses.



(b) Trend of the responses.

Figure 8.14: Trace of event “Response Skill” for the hardware diagnosis based on temporal analysis.

Performance Analysis of Different Diagnosis Models for the Injected Faults

The diagnosis result produced for a broken electrical supply clearly shows the advantage of the sensor based approach over the temporal analysis. The sensor based approach concluded the result to be the actual cause. However, the temporal analysis based approach lists three probable causes. Hence, if the causalities of the faults are observable with sensors, this produces more accurate results than using the temporal analysis based approach. However, the cost of implementing dedicated sensors makes the cost of initial commissioning high, which is not desired by many companies.

Hence, comparing the three approaches, the result of this study shows the combination of sensor based and temporal analysis as the best applicable solution for self-diagnosis in industrial automation systems. The cost optimal solution considering the effort and cost of development is the temporal analysis based diagnosis. The results thus justify the answers to the research questions 4 and 5.

Performance Analysis of Self-Diagnosis for the Corrective Maintenance of Pick and Place Module

This thesis proposes a human-machine collaborative environment for the corrective maintenance of FoF. The humans are given the provision to make decisions and collaborate with other disciplines with a visual human-machine interface. The visual interface integrates the human by implementing the sequence of activities in the state-of-the-art industrial corrective maintenance. The results thus strengthen the answers to the research questions 4 and 5.

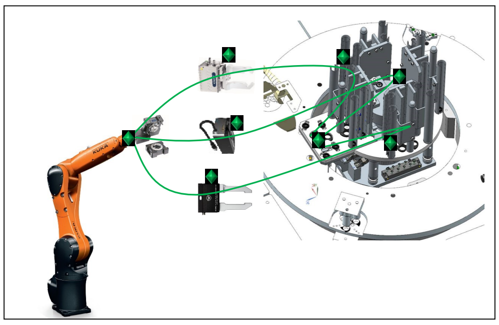
If self-diagnosis is enabled, the diagnosis results are produced immediately after the occurrence of fault. Hence, the sequence of activities involving a human in the state-of-the-art industrial corrective maintenance [24] until the stage diagnosis are no longer needed. This shows that, the MTTR reduces in self-diagnosing automation systems. Overall, it is clear that in the presence of a self-diagnosing automation system, the probability of occurrence of human error and the effort for corrective maintenance is reduced. Hence, the results of this thesis substantiate the research objectives of this thesis 1, 2 and 3.

It is important to note that, the overall results satisfy all the requirements elicited in Section 3.4 except those concerned with the automated management of maintenance personnel. They are: 1) the scheduling of corrective maintenance; 2) recommendation of required corrective action based on the type of faults in automation systems. These are seen as future work.

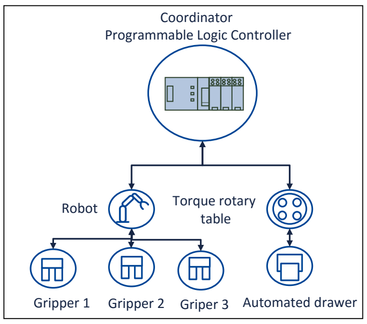
8.6 Scalability Evaluation of the Approach with an Industrial Assembly Station

To evaluate the scalability of the proposed solution to an industrial environment, an industrial assembly demonstrator set up by the VDMA Robotics + Automation group [126] is used. This demonstrator primarily aims to showcase the running example of a component oriented, reconfigurable, interoperable and skill-based architecture of the FoF. The demonstrator integrates 15 different component manufacturers, offering the skill model of their components implemented as OPC UA information models for this purpose. The demonstrator is composed of seven distributed stations, and presents an use-case of assembly of fidget spinners. The demonstrator has already been presented in several trade shows throughout Germany and is continuously improved by applying research results [126].

This thesis utilizes only a single station (Station 1) of this demonstrator. The architecture of Station 1 is shown in Figure 8.15. The Station 1 consists of a robot, 3 types of grippers, one torque rotary table and an automated drawer. All the components have a CPPS architecture and are coordinated by a PLC, in a hierarchical architecture. The functionality of Station 1 is to select the wings, and position the ball bearings of the fidget spinner between its wings.



(a) Reconfigurable paths of the robot (green lines) with exchangeable grippers for each path.



(b) Reconfigurable Physical hierarchy of the station.

Figure 8.15: Reconfigurable physical architecture of the station.

The demonstrator offers fidget spinners with three different wing colours: yellow, blue and brown, named as: Type 1, 2 and 3 respectively. The customers have the provision to choose the type they wish, and Station 1 assembles the product accordingly. The variations in the customer choice are used to showcase the Station 1's capability to exchange the components in a plug and work manner [105]. Since the different wings are stored in different positions of the rotary table, the position of the rotary table changes with each customer selection. In addition, the three types of grippers from different manufacturers get exchanged automatically for picking the wings from different positions of the rotary table. This is depicted in Figure 8.15(a) and 8.15(b).

The control program of the Station 1 gets reconfigured automatically by using the OPC UA skill model implemented by the gripper manufacturers. Thus, Station 1 holds three different control architectures. This is depicted in Figure 8.16. For Type 1 of the product the station uses Gripper 1, for Type 2 of the product the station uses Gripper 2 and for Type 3 of the product, the station uses Gripper 3.

This thesis addresses the following challenges concerning the self-diagnosis based corrective

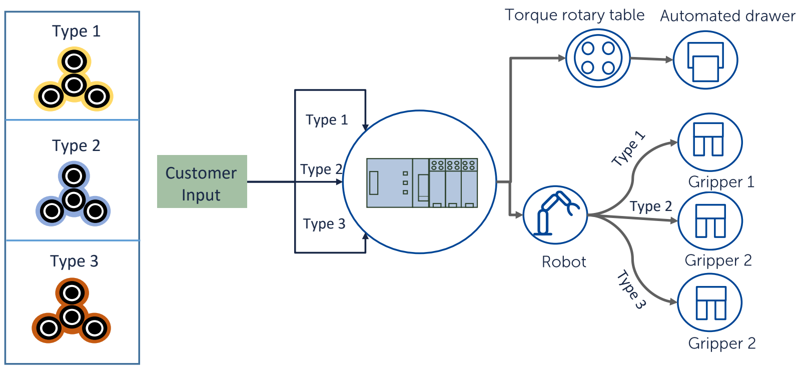


Figure 8.16: The change in the architecture of the station based on the customers input. The customers choose the type of the fidget spinner they require from the options.

maintenance of this demonstrator:

1. Modelling the self-diagnosis of the components of the station.
2. Generating the self-diagnosis model of the station with reconfigurability feature.

The evaluation of the corrective maintenance requires occurrence of a fault in the station. As a running example showcasing the engineering aspects of FoF, injecting faults onto the station is not recommended. Hence, the evaluation of the corrective maintenance of this demonstrator is kept out of the scope of this thesis. The following sections describe how the challenges described above are addressed and hence, evaluate the scalability of the proposals in this thesis to an industrial environment.

8.6.1 Modelling the Self-Diagnosis of Components of the Station

Station 1 has a total of 6 components; a robot, 3 types of grippers, one torque rotary table and an automated drawer. Considering the complex, hybrid characteristics and system of systems architecture as elaborated in Section 2.1.3, the modelling of self-diagnosis of the robot is kept out of the scope of this thesis. This section briefs the modelling of self-diagnosis of the rest of the components of the Station 1.

All the components of Station 1 process their skills using servo based electrical actuators and observe the skills with integrated positioning systems. Thus, the components wholly depend on electro-mechanical principle for their functioning. They do not have dependency on pneumatic supply, as in the components of the pick and place module introduced in Section 8.2. The components offer a plug and produce architecture [105] with a sealed hardware and minimal interfaces. Hence, for their hardware fault diagnosis the sensor based approach is not applicable. Therefore, this thesis considers the temporal analysis based approach.

Modelling the Self-Diagnosis of 3 Types of Grippers

The self-diagnosis of all the three types of grippers can be modelled with the same methodology, as they use the same principle for gripping. The grippers offer skills “Grip” and “Release” as their software interfaces and integrate the physical and logical behaviour of the gripper. The generic implementation of the model of the skills in AML can be seen similar to that of the skills "MoveIn/Out" of the CPPSDGSL-50/80 as shown in Figure 8.4.

The grippers provide their skills "Grip" and "Release" with their interface behaviour implemented according to VDMA SOArc. Both the skills are processed by the same hardware resource. Hence, both the Type 1 and Type 2 of software faults introduced in Section 4.3.1 are applicable to the grippers. These can be diagnosed using Algorithm 1 introduced in Section 4.4.

Three types of hardware faults were identified, which are diagnosable using the temporal analysis based approach. They are electrical supply failure, fault due to excess payload weight and error due to plausible friction. The temporal characteristics of the gripper can be obtained from the kinematic model and the simulation model of the component. The variation point of the diagnosis algorithm is similar to that of the "Grip/Release" of CPPSVASB-15-1/8 introduced in Section 8.2: the "IdealTime" variable from the kinematic model.

Modelling the Self-Diagnosis of Torque Rotary Table

The torque rotary table provides the skill "Rotate" with an option for parameter specifying the rate of change of an angle. The angle values are mapped onto positions 1, 2, 3 respectively. The positions are observed with the integrated position sensor. The implementation of the model of "Rotate" in AML can be seen similar to that of the " MoveIn/Out" of the CPPSDGSL-50/80.

The torque rotary table provides only a single skill to the external consumers. Hence, only the Type 1 of software fault is plausible to the torque rotary table. The software fault Type 1, can be diagnosed using Algorithm 1 introduced in Section 4.4.

The electrical supply failure, payload weight greater than bearing capacity and error due to friction were identified as hardware faults diagnosable with temporal analysis. The temporal analysis based diagnosis is applied by analysing the temporal behaviour of the torque rotary table in each position. The algorithm for the torque rotary table differs with the other components. It requires different analysis for each position of the torque rotary table, as each position has different temporal characteristics.

Modelling the Self-Diagnosis of Automated Drawer

The automated drawer offers skills "Extend" and "Retract" to its consumers. Similar to the other components, these skills are processed by a servo motor and observed by an integrated position sensor. The software faults of the drawer can be diagnosed using Algorithm 1 introduced in Section 4.4. The hardware faults diagnosable with temporal analysis were found to be the same as that of the grippers. Hence, the diagnosis algorithm can be of the same type as that of the grippers, with change in the "IdealTime".

8.6.2 Generating the Self-Diagnosis Model of the Station

The Station 1 has a reconfigurable architecture based on the customer input. In order to showcase reconfigurability and component exchange capability of the demonstrator, the customer is given the provision to choose the colour of the fidget spinner they wish. Based on the customer input, the gripper gets exchanged automatically leading to a new physical hierarchy of the station. The skill-based workflow of the overall station remains the same, but the execution of “Grip” and “Release” are performed by different types of grippers based on the customer input.

The demonstrator does not have a planning tool, as the reconfiguration is performed only for a defined set of components. Nevertheless, the change of architecture of the station based on the customer input has to be reflected in the deployment of control programs. The customer input also affects the generation of the fault tree based self-diagnosis model of the station, as the physical hierarchy and the applied components change.

Within the scope of this thesis, the customer inputs are used as the variation points of the architecture of the system. Hence, this thesis proposes that, based on the customer input, an AML model can be generated using the same concept used in the tool *SystemPlanner*. Consequently, this AML model can be used for generating the self-diagnosis model. The AML model of the station, which reconfigures based on the customer inputs is shown in Figure 8.17.

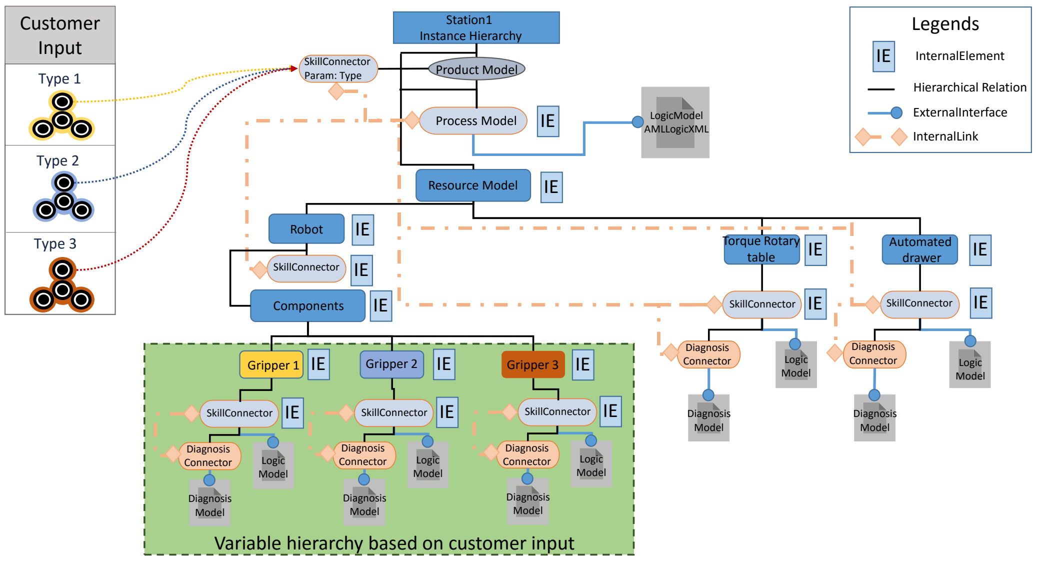


Figure 8.17: AutomationML model of the station, which reconfigures based on the customer input. The variable part of the station based on the customer input is highlighted in the green box.

The AML model is implemented according to the PPR based architecture [69] as described in Section 7.2. The customer inputs are mapped to the model by using a special parameter on skills “Type” referring to the type of a fidget spinner, a customer requires. Based on the customer input, the parameter of the *SkillConnector* in the product model changes. The *InternalLinks* between the product model, process model and the resource model are generated based on the customer inputs. Consequently, the changes are reflected in the process model and the hierarchy of the station. The AML model can be used to generate the diagnosis model in the 4diac IDE based on the transformation rules as shown in 7.11.

8.6.3 Analysis of the Scalability of the Approach

The self-diagnosis models of the components of Station 1 clarify that most of the self-diagnosis models proposed in this thesis is also applicable for the industrial components. Nevertheless, the granularity of the models are limited. For example, the servo motor internal errors, the errors on the circuit and communication related errors could not be identified and diagnosed based on the proposed models. This makes the applicability of self-diagnosis models proposed in thesis limited, as the complexity of the component increases. Hence, this points to the requirement of developing more diagnosis models addressing the granularity requirements by reusing engineering aspects as proposed in this thesis.

The results of this application example show that, the generation of the diagnosis models based on the AML model is irrespective of the size of the automation system. The self-diagnosis model of the station reconfigures with each reconfiguration of the station. The application of self-diagnosis feature in the corrective maintenance of the station has to be evaluated further, based on the occurrence of faults in the station. Nevertheless, the scalability of the key aspect of this thesis “the resource efficient realization of self-diagnosis model” is justified with this application example.

8.7 Review of the Results and Discussion

This thesis aimed at improving the corrective maintenance within the context of FoF. The basic analysis of the literature on FoF [5, 3, 6] showed that complexity is a key challenge and complexity will negatively affect the human efficiency in the FoF. Further analysis of the state of the art and literature in corrective maintenance [24, 36, 37] revealed that, currently the corrective maintenance is human intensive. The human error and inefficiency contribute highly to the increase in the cost of corrective maintenance. Later a hypothesis was made by reviewing the literature on self-diagnosis of industrial systems [90, 30, 87] that, “Implementing self-diagnosis will improve the corrective maintenance of industrial systems in the context of FoF”. Subsequently methodologies for self-diagnosis based corrective maintenance for the FoF were proposed.

For the overall evaluation of the approach, the proposed self-diagnosis based corrective maintenance was implemented in a pick and place module. The corrective maintenance of the self-diagnosing pick and place module was simulated by injecting certain faults manually on to the pick and place module. The results clarify that, by implementing self-diagnosis on the skills of automation components, the complexity of corrective maintenance and probability of human error reduces. A human-machine collaborative corrective maintenance with a visual human-machine interface, reduces the human effort for maintenance and reduces the MTTR. Thus, it can be concluded that the methodologies proposed in this thesis improve the corrective maintenance within the context of FoF.

A detailed analysis of the self-diagnosis models revealed the high effort and cost is required for the development of self-diagnosis models [90, 36, 89, 24]. Hence, for applying self-diagnosis in industrial automation, it required development methodologies that yield cost and resource efficient solutions. Consequently, this thesis proposed the application of components with standardized skills in the automation systems of the future, which have self-diagnosis enabled. For enabling self-diagnosis on the skills of automation components, a methodology reusing the engineering data of the automation components is proposed. The evaluation of the methodology on different components and their variants shows that, standardized and reusable self-diagnosis models applicable for different types and variants of components can be developed. The previous approaches of developing self-diagnosis models [89, 90, 30] employ, system specific self-diagnosing models and application specific development approaches. Hence, the proposed methodology shows substantial improvement in comparison to the previous approaches [89, 90, 30].

For the realization self-diagnosis models in component based automation systems, a three-stakeholder, skill-based engineering process is proposed. The three-stakeholder engineering process has justified its capability, in reducing the human error and preserving the consistency in complex engineering processes [114]. Different studies show the characteristics of future automation systems to be flexible and reconfigurable in nature, such that they can dynamically respond to the varying customer requirements [5, 3, 6]. In order to reduce the realization effort of the self-diagnosis models of reconfigurable automation systems, a generative approach is proposed for the self-diagnosis models of the automation system. As the generative process is based on planning models of automation systems, it can be inferred that the proposed solution meets the flexible and reconfigurable characteristics of the FoF.

The reconfigurability of the self-diagnosis models corresponding to the automation systems' reconfiguration is justified with a second application example, an industrial assembly demonstrator. The second application example also proves the scalability of the proposed solution to a modular, service oriented and reconfigurable industrial environment. Thus, as a whole with its service based modular and reconfigurable architecture, the proposed solution satisfies the fundamental characteristics of FoF [45, 8, 105, 3, 6].

Several literature on FoF [45, 50] assert that the future automation systems are intelligent and cognitive in nature. Hence, they define the role of humans as the strategic decision makers within FoF. The proposed solution in this study, takes the human in the loop for the future automation systems corrective maintenance, where the automation systems are self-diagnosing in nature. For the future automation systems' corrective maintenance, the role of human (maintenance personnel) is defined as a strategic decision maker, who verifies the results of self-diagnosis of the system and performs corrective action based on that. In addition, it is also proposed that the maintenance personnel interact with other disciplinary teams such as the production team, inventory team, etc., to improve production based on the data collected from maintenance. Thus, the system foresees a human-machine collaborative environment which improves the corrective maintenance function and thus production in the FoF.

Chapter 9

Conclusions and Outlook

9.1 Summary

This thesis was initiated by identifying the necessity of reforming corrective maintenance whilst the reformation of the state-of-the-art industries to so called the FoF. Considering high human effort and human errors as the key issues of state-of-the-art corrective maintenance, this thesis hypothesizes that "enabling self-diagnosis and visual assistive features in the automation systems will improve the corrective maintenance". Finding high effort and cost for realizing self-diagnosis, this thesis further focuses on the efficient realization of self-diagnosis in automation systems.

This thesis proposes re-usage of engineering data to efficiently realize self-diagnosis in automation systems. In addition, a visual model encapsulating the corrective maintenance function, which integrates the self-diagnosis feature of an automation system is introduced. This visual model is proposed as a means to improve the efficiency of a human, performing the corrective maintenance of an automation system. The proposed concepts are implemented as a combination of state-of-the-art industrial standards and their extensions.

IEC 62714 standard AML facilitates the reuse of engineering data for realizing self-diagnosis. An AML based prototypical automation system planning tool named *SystemPlanner* produces self-diagnosis models integrated in its output model. From the output of *SystemPlanner*, the executable self-diagnosis models are generated in IEC 61499 standard tool Eclipse 4diac. Within the scope of this thesis, an AML importer plugin for Eclipse 4diac is developed for this purpose. The visual model that assists the human in performing the corrective maintenance of a self-diagnosing automation system is implemented as a web-based interface using Node-Red. The usage of standards facilitates seamless application of the proposed solution within the industrial manufacturing domain.

The proposed solution was evaluated with two application examples. The first application example (a lab scale pick and place module) justifies the enhancement in realizing self-diagnosis by reusing engineering data. It also confirms the improvement in corrective maintenance function, by applying self-diagnosis and visual assistive features. The second application example (an industrial assembly station) demonstrates the scalability of the solution to a complex and reconfigurable industrial environment. The results from the two application examples, thus justify the hypothesis and objectives 1, 2 and 3 of this thesis.

Additionally, an in-depth analysis of the pick and place module clarifies the strength and weaknesses of different self-diagnosis models introduced within the context of this thesis. Among the constructed models, the sensor based approach produces the most accurate results. However, the use of dedicated sensors for diagnosis leads to a high initial commissioning cost, which is not desired by many companies. Although the temporal analysis based approach is cost effective, it requires further enhancements for accurate results. Thus, a combination of sensor based and temporal analysis based approach is identified as the best applicable solution. The second application example of an assembly station shows the limitation of the diagnosis models considering an industrial environment. Nonetheless, both the demonstrators shows reusability of the models on variants of components from different manufacturers and hence the improvement in self-diagnosis realization.

It is important to note that, some of the implementation aspects related to AML proposed in this thesis are reviewed by members of the AML consortium. The rest of the aspects are under review. Consequently, it is envisioned that the AML related models and implementation approaches will be adopted by the industries in the future. This thesis devises the foundation for implementing diagnosis libraries within IEC 61499 standard. In addition, the fundamental aspects necessary for supporting AML models within IEC 61499 standard tools are also proposed.

9.2 Contributions

This thesis makes remarkable research contributions based on five research questions. This section describes the research contributions of this thesis.

Perceiving the system specific nature of current self-diagnosis models, **Research Question 1 addresses the possibility to create reusable models for self-diagnosis in production systems. Additionally it examines the prerequisites for the same.** The answer to the first question leverages the concept of skill of an automation component. Skills represent standardized functionalities of automation components and act as their standardized software interfaces. This thesis devised a methodology for modelling the self-diagnosis of standardized skills of automation components. Hence, the self-diagnosis models can be reused for different types and variants of automation components. A model of the skill, integrating its logical and physical behaviour and their interactions is identified as the prerequisite for the same.

Research Question 2 investigates the methodology for realizing the self-diagnosis models in a cost efficient manner. In addition, it examines the possibility of leveraging the engineering and operational aspects of an automation system for the same. For answering the second question, an analysis of the state-of-the-art plant engineering and operation was performed. This analysis revealed generation of digitized and interoperable domain specific engineering data from the plant engineering process. Accordingly, a novel methodology for deriving the key aspects of the diagnosis model, reusing the domain specific engineering data is provided. Consequently, the diagnosis models are able to handle types and variants of automation components, and are cost efficient. Further, a methodology for seamless deployment of self-diagnosing automation systems, leveraging the operational information exchange standards in the industrial automation domain is devised.

Considering the reconfigurable and flexible characteristics of the FoF, **Research Question 3 set out to add flexible and reconfigurable characteristics to the self-diagnosis feature of the production systems.** To address this question, the state-of-the-art plant engineering and its phases were analysed individually. This analysis clarified that, the reconfiguration of a plant affects all the phases of its engineering and is initiated in the planning phase of an automation system. Based on this analysis, a novel framework for generating the self-diagnosis models of automation systems, based on the planning model of the automation system is introduced. The framework yields the reconfigurable self-diagnosis models as a by-product of the plant engineering process and avoids manual development effort for self-diagnosis models.

Research Question 4 set out to examine the methodology for effectively integrating visual assistive features for corrective maintenance with reusable self-diagnosis models. For answering this question, the corrective maintenance function was analysed in detail, which revealed the sequence of activities in it. The first activity is the fault detection, the second activity is the localization and the third activity is the diagnosis. Then comes corrective action and checkout activities. Accordingly, a visual assistive tool integrating the detection, the localization and the diagnosis of the fault is introduced. In addition, the assistive tool includes the provision for the maintenance personnel to communicate with the production system/team.

Research Question 5 seeks to manage the maintenance personnel allocation, leveraging the self-diagnosis and visual assistive features of the automated production systems. Analysing the corrective maintenance function in detail and also the literature, a corrective maintenance solution, where the maintenance personnel act as strategic decision makers is devised. With self-diagnosis integrated in the corrective maintenance, the solution reduces the effort of maintenance personnel to carry out corrective maintenance. The solution also facilitates the maintenance personnel to collect information from corrective maintenance for improving the production.

9.3 Outlook

The solutions proposed in this work, raise further research challenges leading to the improvement of the FoF. Some of the important challenges to be addressed in the future are listed below:

- This thesis presented open text based diagnosis models with high level of granularity. Since more detailed diagnosis models require protecting the intellectual properties of the companies, more detailed diagnosis models are not addressed. The following challenge has to be addressed in future: How to develop diagnosis models with lowest granularity of complex components protecting the intellectual properties of the companies?
- This thesis provides the foundation for facilitating interoperability and information exchange between maintenance and other disciplines within a manufacturing environment. Consequently, it raises the following challenge, which is still unsolved: How to improve the management of human and other resources for corrective maintenance, leveraging the interoperability and information exchange possibilities within the context of FoF.
- Similarly, is it possible to improve the life cycle of industrial production resources within the context of FoF, leveraging the information exchange from corrective maintenance?
- The proposed solution does not support the legacy systems. Hence, how to realize self-diagnosis in large legacy systems in a cost efficient manner? Is it possible to reuse the engineering data for the realization of self-diagnosis in legacy systems?
- Using the data collected from maintenance for improving the production is a recent area of research. Thus, the following question has to be addressed in the future: What kind of data from corrective maintenance are relevant for improving the production and how to use the data effectively for improving the production?
- The visual tool presented in this thesis, is developed manually based on the application example. The concept of reusing engineering data might be also applicable for the visual development tools. Hence, the following challenges: How to develop a visual model for the self-diagnosis of automation components? How to generate visual assistive tool automatically for the component based automation system reusing the engineering data?

9.4 Concluding Remarks

This thesis investigated means and methodologies for cost effective improvement of corrective maintenance function in the context of FoF. The results of this thesis proves that, self-diagnosis and visual assistive features facilitate a human-machine collaborative environment for the corrective maintenance of automation systems. Consequently, the human performance improves and hence corrective maintenance. The efficiency in cost is achieved by realizing self-diagnosis by reusing engineering data.

This thesis raises the following key challenge foreseeing the materialization of the FoF in the near future: 1) How to improve the production by improving corrective maintenance within the context of FoF? Thus, by enhancing the solution a substantial enhancement in industrial manufacturing is foreseen. Application of existing standards facilitate, creation of reusable and cost efficient self-diagnosis models in this thesis. Hence, for extension of the solution or integration of the legacy or non-modular automation systems in the proposed solution, the applied standards in this thesis are recommended.

Acronyms

AML Automation Mark-up Language. 16, 80–93, 96, 99–101, 103, 106, 108–112, 118–120, 123, 124, 133

CAEX Computer Aided Engineering Exchange. 82, 83, 93, 101

CPPS Cyber Physical Production Systems. 2, 4, 5, 11–15, 17, 34, 36, 37, 40, 46–48, 50, 53, 58, 59, 62–64, 89, 92, 97–104, 106–109, 116, 118, 132, 133, 135

FoF Factories of the Future. 2–7, 9–20, 23–25, 29–31, 37, 38, 61–63, 69, 73, 75, 76, 79, 91, 97, 115–117, 120–123, 125–127

I4.0 Industry 4.0. 2, 10, 12, 19, 131

ICT Information and Communication Technologies. 2, 24

MTTR Mean Time To Repair. 22, 25, 28, 30, 69, 77, 115, 121

PLC Programmable Logic Controller. 46, 47, 53, 64, 82, 100, 104, 106, 107, 116

SISO Single Input Single Output. 47, 50–53, 106, 132

SOArc Service Oriented Architectures and Realtime Control. 71, 85, 99, 100, 106, 118

VDI German Association of Engineers. 71, 85, 100, 106

VDMA German Association of Mechanical Engineers. 71, 85, 99, 100, 106, 115, 118

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