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Pannon Egyetem

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Gépi tanulás alapú ipar 4.0 megoldások fejlesztése szerszám menedzsment támogatása érdekében

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DOCTORAL (PhD)THESIS

Machine learning-based industry 4.0 solutions for tool management

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A természeti életet vizsgáló tudomány nem keres Istent, csak a természet titkait. S mégis ahogy ezeket fejti, folyton az Istent találja: lépésről lépésre közeledik hozzá. A tudomány bányászai ezek: sötétben indultak, apró lámpásokkal, s íme lassankint a világosság bányájában találják magukat. Minden csákányütésre új fény ragyog elő.

Gárdonyi Géza

The science of natural life does not seek God, only the mysteries of nature. And yet as it unravels them, it keeps finding God: step by step, it comes closer to Him. They are the miners of science: they started out in the dark, with tiny lamps, and now they find themselves in a mine of light. With each blow of the pickaxe, a new light shines forth.

Gárdonyi Géza

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Kivonat

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Philosophiæ Doctor

Gépi tanulás alapú ipar 4.0 megoldások fejlesztése szerszám menedzsment támogatása érdekében

írta: Darányi András Pál

A kutatás célkitűzése olyan gépi tanuláson alapuló Ipar 4.0 megoldások fejlesztése, melyekkel a rugalmas gyártórendszerek szerszámkezelési feladatai hatékonyan megvalósíthatók. A szerszámmenedzsment problémákat nagy fokú összetettség és sztochasztikus folyamatok jellemzik, amely korlátozza a hagyományos, manuális folyamatokon és emberi döntéshozatalon alapuló megközelítések eredményességét. Olyan adatvezérelt megoldásokra van szükség, amelyek figyelembe veszik a nagy számú kölcsönhatást és a bizonytalanságot. A disszertáció három fő szerszámmenedzsmenttel kapcsolatos problémát céloz meg. Nem kötött pályás gyártórendszerekben, a szerszámok nyomonkövetése nehéz feladat, sokszor túl nagy a beltéri pozícionáló rendszer pontatlansága ahhoz, hogy szerszám felhasználásra vonatkozó információt tudjunk kinyerni belőle. Egy olyan módszert fejlesztettem, amelyben a beltéri pozíció adatokra illesztett valószínűségi modell képes egyszerre feltérképezni a gyár releváns helyszíneit, és megmutatni az egyes eszközök kihasználtságát az egyes helyekre vonatkozóan. A gyengén megtervezett szerszám allokáció gyakori átállásokhoz, szerszámcserékhez, így alulhasznált gyártókapacitásokhoz vezethet. Egy termékcsoportosítási eljárást dolgoztam ki, amely az egyes termékek szerszámigénybeli hasonlóságán alapul, csökkentve az átállások számát. Az optimalizálási folyamat heurisztikus szabályokon alapul, így biztosítva a kedvező számításigényt. Rugalmas gyártórendszerek esetén az egyes szerszámok felhasználása folyton változik, amelyet figyelembe kell venni a karbantartás tervezésekor. Erre egy olyan módszertant javaslok, ahol az optimalizálás alapját képező kockázatértékelő modell figyelembe veszi, hogy a folyton változó gyártási igényekből fakadóan folyamatosan változik a degradációs karakterisztika, és a hibakövetkezmények súlyossága.

UNIVERSITY OF PANNONIA

Abstract

Faculty of Engineering
Department of System Engineering

Doctor of Philosophy

Machine learning-based industry 4.0 solutions for tool management

by András Pál DARÁNYI

The aim of this research is to develop machine learning algorithm-based Industry 4.0 solutions for efficient tool management tasks in flexible manufacturing systems. Tool management problems are characterized by a high degree of complexity and stochastic processes, which limit the effectiveness of traditional approaches based on manual processes and human decision-making. Data-driven solutions that take into account the large number of interactions and uncertainties are needed. In my research, I target three main tool management problems. In non-fixed path manufacturing systems, tool tracking is a difficult task. Often, the system is too imprecise to extract usage information. In response, I have developed a method that can simultaneously map relevant locations in the factory using a probabilistic model fitted to indoor position data, and show the utilization of each tool at each location. Poorly planned tool allocation can lead to frequent changeovers and thus underutilized manufacturing capacity. In my work, I developed a product grouping procedure based on the similarity in tooling requirements of each product, reducing the number of changeovers. The optimization process is based on heuristic rules, thus ensuring a favorable computational effort. In flexible manufacturing systems, the tool usage of each tool is constantly changing and needs to be taken into account when planning maintenance. To this end, a methodology is proposed where the risk evaluation model on which the optimization is based takes into account that both the degradation characteristics and the severity of the failure modes are constantly changing due to the ever-changing production needs.

PANNONISCHE UNIVERSITÄT

Auszug

Fakultät für Ingenieurwissenschaften
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Doktor der Philosophie

Auf maschinellem Lernen basierende Industrie 4.0-Lösungen für die Werkzeugverwaltung

von András Pál Darányi

Das Ziel dieser Forschung ist die Entwicklung von auf maschinellen Lernalgorithmen basierenden Industrie 4.0-Lösungen für effiziente Werkzeugverwaltungsaufgaben in flexiblen Fertigungssystemen. Werkzeugverwaltungsprobleme sind durch ein hohes Maß an Komplexität und stochastische Prozesse gekennzeichnet, die die Wirksamkeit herkömmlicher, auf manuellen Prozessen und menschlichen Entscheidungen basierender Ansätze einschränken. Es werden datengesteuerte Lösungen benötigt, die die große Anzahl von Interaktionen und Ungewissheiten berücksichtigen. In meiner Forschung befasse ich mich mit drei Hauptproblemen der Werkzeugverwaltung. In Fertigungssystemen ohne feste Wege ist die Werkzeugverfolgung eine schwierige Aufgabe. Oft ist das System zu ungenau, um Nutzungsinformationen zu extrahieren. Deshalb habe ich eine Methode entwickelt, die mit Hilfe eines probabilistischen Modells, das an die Positionsdaten in der Fabrik angepasst ist, gleichzeitig die relevanten Standorte in der Fabrik abbilden und die Nutzung jedes Werkzeugs an jedem Standort anzeigen kann. Eine schlecht geplante Werkzeugzuweisung kann zu häufigen Umrüstungen und damit zu einer unzureichenden Auslastung der Fertigungskapazität führen. In meiner Arbeit habe ich ein Verfahren zur Produktgruppierung entwickelt, das auf der Ähnlichkeit der Werkzeuganforderungen der einzelnen Produkte basiert und die Anzahl der Umrüstungen reduziert. Der Optimierungsprozess basiert auf heuristischen Regeln, was einen günstigen Rechenaufwand gewährleistet. In flexiblen Fertigungssystemen ändert sich die Werkzeugnutzung der einzelnen Werkzeuge ständig und muss bei der Planung der Instandhaltung berücksichtigt werden. Zu diesem Zweck wird eine Methode vorgeschlagen, bei der das der Optimierung zugrunde liegende Risikobewertungsmodell berücksichtigt, dass sich sowohl die Degradationscharakteristika als auch die Schwere der Ausfallarten aufgrund der sich ständig ändernden Produktionsanforderungen ständig ändern.

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Dedicated to my Family and Friends. Without them, I would not have been able to accomplish this journey.

Contents

Chapter 1

Introduction and motivation of the thesis

1.1 Introduction of the research topics - problem statement

This section provides an overview of the topics and motivations that led to the research. First, subsection 1.1.1 presents the field of tool management and its responsibilities, then subsection 1.1.2 introduces the concept of Industry 4.0 or smart manufacturing. Then 1.1.3 describes the challenges that tool management faces. Section 1.1.4 highlights the advantages of implementing digitalization and Industry 4.0 in tool management.

1.1.1 Introduction of tool management and its responsibilities

Modern and flexible manufacturing systems (FMSs) utilize multifunctional machines with the help of various replaceable tools. As a result, the number of tools in a medium-sized factory can exceed the order of a hundred [1, 2]. Tooling costs can account for as much as $20-30\%$ of total manufacturing costs. [3, 4, 5]. Tooling cost can be reduced by the careful selection of the number of tools [6], by the optimization of the manufacturing process [7, 8], and by the application of tool management systems. Due to the importance and complexity of these problems, tool management is an essential and long-studied area of production management [9].

A tool management strategy defines how the right tool should be placed in the right place at the right time to reduce machine stops [10]. Machine stops can be due to tool changeovers when the required tool for manufacturing the product is not loaded in the magazine. A reasonable tool allocation plan can be the solution to this problem. A tool allocation problem includes the following attributes: tool magazine capacity, which restricts the number of tasks processed in a single tool setup; tool life, which is comparable with operation times; and tool size, which can be considered as the number of slots a tool occupies on tool magazine [11]. CNC machines may have limited tool magazine capacities, and tool loading can be time-consuming. The lack of stock infeed and tool changeover time reduces the availability of the machine and results in inefficient equipment utilization [12]. Thereby, the tool allocation problem is crucial in FMSs [13].

In FMSs, tool usage monitoring is critical because it directly impacts productivity, operational efficiency, and cost management [14]. Tools are one of the most expensive consumables in a manufacturing system. Efficient monitoring ensures optimal use, preventing unnecessary replacements and controlling costs [15]. FMS is characterized by the need to adapt quickly to different product types. Tool monitoring may help fine-tune the system to handle various jobs efficiently, ensuring a smooth transition between tasks and minimizing setup time [16]. Real-time localization by indoor positioning systems (IPS) can greatly enhance the monitoring process [17]. Location data enables real-time tracking of tools within the manufacturing facility. This is especially important in flexible systems where tools may be used on different machines or workstations. Knowing the exact location of tools in real-time eliminates delays caused by searching for tools or transferring them between stations [18]. Significant productivity losses can be avoided by monitoring tool movements on the shop floor [19]. An understanding of the material and information flow through real-time location tracking allows for the optimization of the overall manufacturing process flow and the implementation of an appropriate layout design [18].

Another important duty is to keep tools in good condition so that they can perform their function. Therefore, in addition to their location, their condition should be tracked. Tool health monitoring provides data that can be used for predictive maintenance [20]. This means that tools are maintained based on actual conditions rather than fixed schedules, making maintenance more efficient and reducing unnecessary downtime. Condition monitoring can include direct measurements of wear or other parameters that correlate with wear [21]. Tools deteriorate over time due to wear and tear caused by regular operation. Consequently, condition-based maintenance can also be implemented through usage-based modeling of remaining useful life (RUL) [22]. It is especially relevant in an environment where the production demands are constantly changing and tooling loads vary as a result. By monitoring the utilization of tools, manufacturers can schedule maintenance or replacement before tool failure occurs. This helps in reducing downtime and ensuring continuous production flow.

1.1.2 Introduction of the Industry 4.0 concept

Flexibility is a critical dimension of competitive and efficient business operation [23] since it enables a quick response and adaptation to changes. The concept of Industry 4.0 has brought a dynamic development trend in the field of FMSs, which now forms the basis of intelligent and digital manufacturing [24]. The term Industry 4.0 was a strategic initiative of the German government for the digital transformation of the manufacturing sector [25]. Today, the concept represents a set of tools to increase productivity, flexibility, and efficiency of manufacturing processes and reduce costs and downtime. It includes the application of new technologies such as digital twin (DT), cyber-physical systems, reconfigurable systems, Industrial Internet of Things (IIoT), data-driven decision-making, and cloud computing [26]. A cyber-physical system is the integration of computation, communication, and physical processes. It requires advanced sensing through the application of the IIoT, which involves a network of connected sensors and actuators, interoperable communication protocols that collects and analyze data, and enables better decision-making [27]. This is supported by cloud computing, edge computing, and embedded software. A higher level of integration (both horizontally and vertically) is achieved by connecting different software systems such as enterprise resource systems (ERP), manufacturing execution systems (MES), computerized maintenance management systems (CMMS), and other enterprise systems [28]. DT is the virtual representation of the system that enables simulation, analysis, and control of the physical objects and processes [29]. The wide range of data collected allows sophisticated analysis and application of machine learning techniques in many areas such as quality monitoring, fault diagnosis, process mining, and optimization [30]. The above-mentioned tools enable more comprehensive monitoring, deeper understanding, and stronger control of systems, increasing the flexibility and adaptability of manufacturing processes to changing circumstances [31]. It is particularly important in FMSs due to the complexity caused by the large number of tools and their interdependencies.

1.1.3 Challenges of the traditional tool management

In earlier, traditional manufacturing environments, tool management relies on manual processes and minimal digital integration. Perera *et al.* [32] highlighted that the companies that do not have sufficient data about their tooling are unaware of tooling problems, so there is a significant loss if the necessary information is not available.

Manual data collecting and tool tracking cannot provide the level of information needed and are prone to error [33]. Before the millennium, when tool positional information was not yet available, it was typically the case that workers have to search the tools for over 20% of their working hours [34] and production is stopped for nearly 15% of the time due to the unavailability of tools [3]. When the tools circulating in the factory cannot be found, the workers increase the size of the local inventory to enhance availability at their workstations. In such cases, the tool concerned does not return to its storage location but stays at the machine and remains poorly utilized, which is responsible for 15% of the tool inventory [34]. Furthermore, changeover times and downtimes can also significantly increase [35]. Therefore, in some companies, the amount of time spent finding the right tool can constitute 30% of the total preparation time of the tool [34].

Initially, tools were often assigned to tasks based on fixed schedules or manual decisions, leading to suboptimal use of tool capacity and a high number of changeovers. A proper tooling plan should ensure that tools are assigned to machines to meet not only machining requirements but also production needs [10]. Traditional systems may allocate tools without considering how to optimize tool usage for multiple product runs. Manual decisions cannot take all factors into account due to the high complexity of the tooling inventory. If the tool needed for a particular job is not available in a tool magazine due to suboptimal planning, it requires a changeover process that can result in significant downtime, reducing the productivity of the system [36].

Failures due to poor tool condition also result in significant downtime and loss. Consequently, maintenance is a strategic function that adds value to the organization by ensuring operational reliability, efficiency, and safety [37]. However, it has not always been seen that way. Initially, maintenance was considered a necessary evil, a cost center. Maintenance was done only when unavoidable, such as when a failure occurred that hindered production. This reactive approach results in lower service costs at the expense of increased repair costs and time, and unexpected downtime resulting in lost revenue [38]. Traditional tool management uses a preventive approach in addition to a reactive approach, which aims to sustain the functionality of tools through regular inspections, replacements, or repairs. This approach reduces unplanned downtime but can cause losses by replacing tools that may still be operational. One problem is that each asset operates under different conditions and requires a different preventive maintenance plan [39]. In a flexible manufacturing system with hectic tool use, uniform, calendar-based scheduling would result in significant waste.

Because of all these challenges, the Industry 4.0 framework should be integrated into the tool management.

1.1.4 Industry 4.0 / digital transformation in tool management

A shift towards digitalized tool management is gaining importance since better transparency and data availability allows higher-level analysis and strategy development [34]. Effective tool management requires computer support [40] and information integration [41]. Tool management requires important information on the tool location and condition and utilization of tools as well as the production schedule, necessitating an integrated database and tool tracking system [34]. Integrated tool management software addresses the technical and business interdependencies of tools in decision-making [42]. Existing production systems may face challenges when implementing smart manufacturing solutions on legacy equipment, but brownfield Industry 4.0 solutions provide a cost-effective retrofit option that covers all layers of the IIoT [43].

Proper tool management requires a reliable identification system that provides full traceability and a data collection system that can capture in real time all information relevant to the tool lifecycle, such as operating conditions, wear, and technical parameters. Lack of this information can lead to inefficient use and, worse, accidents while having it can optimize planning and control [44]. The key to process automation is complete traceability, which means not only tracking the physical location of assets but also monitoring their health and status throughout their lifecycle [45]. In a flexible manufacturing system, the layout of the shop floor may be constantly changing and tools do not move along a fixed path. Therefore, the key to traceability is identification in addition to localization. Information can be associated with location data through geofencing, event-, or motion-based triggers. Feature engineering and data processing techniques are required to ensure the reliability and reasonable accuracy of this information. Tool usage is correlated with the usage of other objects, such as machines, people, etc., so utilization monitoring is not limited to individual tools, providing potential for broader optimization [46]. A good traceability system allows the study of processes and their bottlenecks. Tracking the position of individual tools and monitoring their machining history provides valuable information that can be used to optimize maintenance [47].

Maintaining desired tool availability requires higher-level approaches such as predictive and condition-based maintenance. Both aim to assess the condition of the tool and determine the remaining useful life and optimal level of service without under- or over-maintenance [48]. These are data-driven solutions that require advanced sensing, sophisticated algorithms such as signal processing, anomaly detection, and prediction for diagnostics and prognostics [49], and the application of an intelligent management system that incorporates e-manufacturing, IIoT, and DT technologies [50], which necessitates significant investment. A prerequisite for a Prognostics and Health Management system is an appropriate data acquisition system that provides data in sufficient quantity and quality and considers the differences between different types of tools [51]. If historical data is available, machine learning and deep learning algorithms can be trained to predict tool life or identify failures [52]. Predictive models are used to maximize tool life through different optimization techniques such as dynamic programming [53] or metaheuristic optimization [54].

Computational and optimization methods are also strongly needed to achieve optimal solutions in the context of tool allocation [55]. For the optimization of operation and changeovers, several methods and models have been developed, e.g., dynamic [56], integer [57], multicommodity flow [58] mathematical models or hybrid genetic algorithms [59]. Furthermore, quantum computation-based optimization has been used for machine allocation and job shop scheduling which offers short computation time in even problems containing a large number of jobs and machines [60]. Clustering methods are applicable in tool allocation problems since clustering aims to group similar instances/objects (products) based on a measure that can identify if two objects are similar or dissimilar [61]. Through distance measures and similarity measures, the relation between these products can be estimated [61]. The group technology approach exploits the similarity among the attributes of the given objects (products). Thereby, the same machine can be assigned to similar products, e.g., in geometry, manufacturing process, and functions [62].

Although implementation costs are high, the return on investment for smart factories is higher than for traditional factories [63]. Today's CNC manufacturers often offer advanced tool management solutions themselves to optimize production efficiency and ensure seamless tool availability. These systems integrate DTs, automation, and centralized storage to enhance planning, logistics, and real-time tracking. They offer modular and scalable tool magazines that allow for efficient space utilization and flexible expansion. They also provide automated tool loading and transport solutions to streamline operations, reducing manual intervention and downtime. Overall, these innovations improve productivity, standardization, and operational flexibility in modern manufacturing.

1.2 Proposed framework for supporting tool management by machine learning-based Industry 4.0 solutions

My research aimed to support tool management in several aspects. One duty of tool management is to ensure a reasonably high availability of tools by maintaining their functionality to keep production running smoothly. An appropriate maintenance plan can facilitate this outcome. Furthermore, when a tool is available and capable of performing its intended function, it should be employed to its fullest potential. The optimal use of a tool is to utilize it to its maximum capacity. It is therefore essential to implement a comprehensive allocation plan to guarantee the requisite tools are assigned to the locations where they are needed most frequently. The duties mentioned above necessitate the continuous monitoring of tool utilization by employing complex estimation models. My work focuses on these three fundamental aspects of tool management (Figure 1.1): the allocation of tools, the monitoring of tool utilization, and the maintenance of tools. I have developed three methodologies in these three areas that offer a solution for adapting tool management to challenges due to the highly changing and customized production demands and complexity.

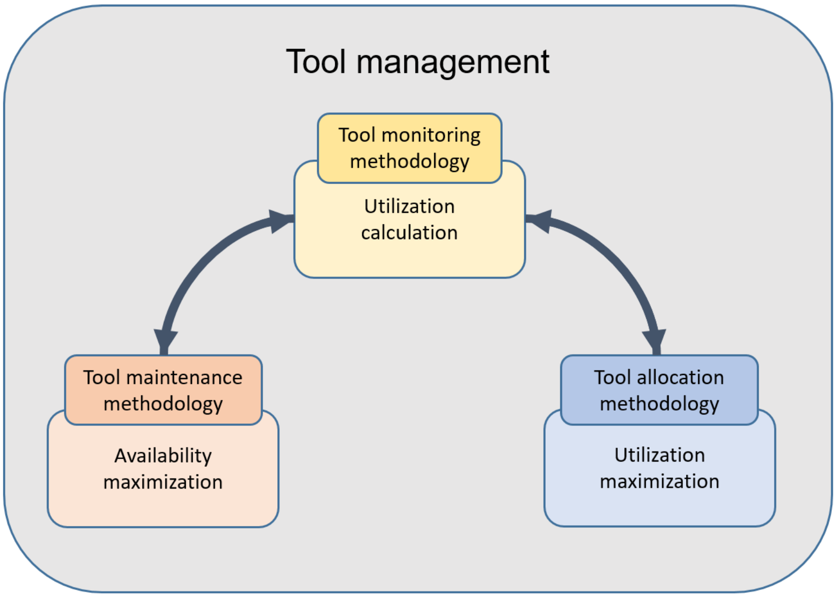

FIGURE 1.1: The proposed framework supporting tool management

1.2.1 Tool allocation support

The inefficient and manual allocation of tools results in the suboptimal utilization of tools and machines, as well as frequent changeovers. The creation of an effective allocation plan that prevents the loss of capacity necessitates the application of optimization techniques, which, in turn, entail a considerable computational burden. These issues are addressed through a methodology [64] that employs a clustering algorithm to group the products based on their tool demand. The proposed methodology also seeks to achieve a more balanced distribution of tools among the various groups. This is achieved through the implementation of a hierarchical clustering process, whereby the minimization of the two objectives through the application of heuristic rules forms the basis of the clustering process. The two objective functions ensure that the allocation plan will result in well-exploited capacities, while the heuristic rules guarantee the low computational requirements of the method.

1.2.2 Tool monitoring support

The implementation of continuous improvement strategies is a critical factor in maintaining a company's competitive advantage. Consequently, the allocation plan should be subject to continuous revision in a dynamic environment. This is contingent upon the existence of a tool monitoring system that provides reliable information on tool utilization. Location data can form the basis for calculating asset utilization. By calculating the utilization of tools and machines, the hidden inefficiencies in the manufacturing process can be explored and the under-utilized spots can be highlighted. These insights support lean-based improvements to the production process and shop floor layout. For this reason, I developed a methodology [65] that uses probabilistic fuzzy models based on tool IPS data to simultaneously identify the relevant locations on the shop floor and estimate asset utilization at those locations. The method enables the mapping of process flow and usage patterns in a manufacturing environment.

1.2.3 Tool maintenance support

Knowledge about the utilization of the tools and machines can also support scheduling maintenance activities, which can provide significant economic benefits as tool condition affects production performance, product quality deterioration, and energy consumption. The utilization history of the tool can be used to estimate its health, and this information is essential for creating a predictive, risk-based maintenance plan. A static tool maintenance plan may lead to significant waste in a flexible manufacturing system on the one hand, due to unexpected downtimes, on the other hand, due to excessive maintenance. In a constantly changing manufacturing environment, both the tool usage and therefore the degradation process and the consequences of the failures vary, resulting in dynamically changing risk profiles. Tool maintenance planning should be done in a dynamic way to match the risk evolution determined by the variable production demands. To overcome this problem, I introduced a risk assessment model that considers the usage history, maintenance history, and production plan to predict risks. A genetic algorithm is used to find the assignment of different tool maintenance tasks at the most opportune times to minimize the overall financial risk to the system.

1.2.4 Dissertation roadmap

The following chapters of this dissertation are structured around the three research works mentioned in the previous subsections. Chapter 2 presents the study of the proposed multi-objective hierarchical clustering method for tool allocation. Chapter 3 describes the proposed supervised fuzzy clustering method for location-based utilization calculation. Chapter 4 introduces the proposed dynamic risk-based optimization method for tool maintenance. Each research chapter includes an introduction section, a methodology section where the problem and the proposed method are mathematically formulated, an application section where the applicability of the proposed method is demonstrated, and a conclusion section. Due to the large number of notations, unique nomenclature is introduced in each chapter. Research findings and theses are summarized in a final conclusion chapter (Chapter 5).

Chapter 2

Tool allocation by multi-objective hierarchical clustering

Research in optimizing tool allocation within a flexible manufacturing environment approaches this problem from various perspectives but with a common aim to maximize the system's efficiency by minimizing the frequency of tool changeover. Optimization-based tool allocation in an FMS environment is typically computationally demanding [66] and sensitive to parameter uncertainty, which problems make it difficult to use these algorithms in real-world situations where the problem is constantly changing and evolving.

Heuristic approaches can provide feasible approximate and robust solutions for real-life tool allocation problems [67]. Meta-heuristic search strategies are computationally less demanding algorithms, which makes them applicable in uncertain and time-varying FMS environments [68]. A hierarchical approach to machine batching, loading and tool allocation problems have been applied in cellular manufacturing with a single and multi-machine environment to optimize the production of batches [69]. Clustering methods for production and scheduling in FMS are favorable for identifying products with similar tool demands and assigning these products to machines by limiting tool usage conflicts [70].

In the proposed method the tool allocation problem is formulated based on a similar clustering-based interpretation. Clustering-based solutions can be originated from the classical group technology approach of Production Flow Analysis (PFA) widely used to obtain better production layout planning [71]. In the context of manufacturing systems, group technology refers to the clustering of products and machines based on tooling requirements and production characteristics, forming manufacturing cells where similar products are produced using shared resources [72]. This approach reduces setup times and enhances operational efficiency by optimizing the grouping of tasks and tools. Most of the PFA methods [73] can be considered as goal-oriented clustering algorithms as these methods are based on the similarities calculated from the machine-product incidence matrices [74].

The novelty of the work is the following:

- A goal-oriented multi-objective agglomerative hierarchical clustering-based PFA algorithm is proposed that can directly solve the tool allocation problem based on the production schedule.
- The tool changeovers and machine downtime are decreased based on two objectives of proposed hierarchical clustering 1) minimizing the size of tool groups and 2) minimizing the additional tool requirement when two groups are merged.
- The tool assignment problem has also been formulated as a bin-packing optimization task, and the results of the related linear programming were used as a benchmark reference.
- The performance of the bin packing optimization method and the proposed heuristic multi-objective clustering method is compared through an application study at a Hungarian medium-sized assembly company with customized and small series production. The comparison is based on their total tool usage, number of machines used, and execution time. The analysis of the results demonstrates that the proposed method provides a feasible solution for large real-life problems with low computation time.

2.1 The multi-objective hierarchical clustering method for tool allocation

This section formulates the tool allocation problem first as a bin packing optimization problem [75], then discusses the methodological details of the proposed multi-objective hierarchical clustering approach for grouping products based on their tool demand similarity and the asymmetry of the additional tool requirement for joint production.

Table 2.1 summarizes the notation used in the tool allocation methodology.

Notation	Explanation
P	Set of products, and $\|P\|$ its cardinality
T	Set of tools, and $\|T\|$ its cardinality
M	Set of machines, and $\|M\|$ its cardinality
C	Set of groups
$i = 1, \ldots, \|T\|$	Index of tools
$j = 1, \ldots, \|M\|$	Index of machines
$k = 1, \ldots, \|P\|$	Index of products
$m = 1, \ldots, N_c$	Index of product groups
$a_{i,k}$	The i-th tool is used for the production of the product k
$x_{i,j}$	The i-th tool is used at machine j
y_j	Usage of the j-th machine
$z_{j,k}$	The k-th product production by the j-th machine
w_j	Tool magazine capacity of machine j
A_k	Bit-string that represents the required tools for producing the k^{th} product
$p(C_m, C_n)$	The number of tools required for the joint manufacturing of the products in the C_m and C_n groups
$d(C_m, C_n)$	the number of additional tools required for manufacturing of the products in the C_n group next to the C_m group
λ	Weighting parameter
z_1, z_2	Objective functions

TABLE 2.1: Notation of the tool allocation method

2.1.1 General formulation of the tool allocation problem

It is assumed that each machine has a tool magazine with a maximum capacity within a flexible manufacturing environment. A significant issue arises when the product is highly customized, and due to the various tool demands of the diverse products, the number of changeovers between products can increase significantly. The inefficient allocation of tools within and between machines can increase downtime and decrease equipment efficiency due to under-utilization. Therefore, manufacturers must rethink and optimize their production schedule to maximize efficiency and minimize waste of time and expenses. A grouping of products is proposed that minimizes the required number of tool changes during joint production, *i.e.*, the tools required for producing products in the group should be as identical as possible. Tool changeover is needed in the tool magazine if the number of tools in the product group exceeds the tool magazine capacity. Otherwise, tool changeover happens within the magazine.

The tool allocation problem can be formalized as presented in the next paragraph which is illustrated by Figure 2.1.

A set of products (P), a set of tools (T), and a set of machines (M) are available in a specific manufacturing environment. Each element of the product set requires a subset of tools for its production (for example, *Tools 3, 4,* and *5* are needed for the manufacturing of *Product 2*, as shown in Figure 2.1). There are overlaps between the subsets of required tools, which form the basis for the product grouping. According to the example of in Figure 2.1, both *Products 1* and *2* requires *Tools 3* and *5*. The product groups will be assigned to different machines with specific tool magazine capacities. Dashed lines in Figure 2.1 indicate the possible assignments of the groups to machines, while the continuous lines indicate the best assignments, which minimizes downtimes and the number of changeovers. In this example, assigning *Group 1* to *Machine 1* is the best option. This group includes *Products 1* and *2*, which require five tools in summary: *Tool 1*, *Tool 2*, *Tool 3*, *Tool 4*, and *Tool 5*.

It should be noted that the model is static and the optimization is only interpreted for a certain period of time. For this reason, in the following formulations the indices are linked to objects such as tools, machines and products, but not to time, which better reflects the practical structure of this static problem.

2.1.2 Formulation of the tool allocation problem as a bin-packing optimization task

First, we assess tool allocation as a bin-packing optimization problem. The bin packing optimization aims to assign items with given weights into bins with limited capacity so that the sum of the weights does not exceed the capacity and the number of bins used is minimum [75].

In this case the machines represent the bins:

$$y_j \in \{0, 1\} \quad \forall j \in M \,, \tag{2.1}$$

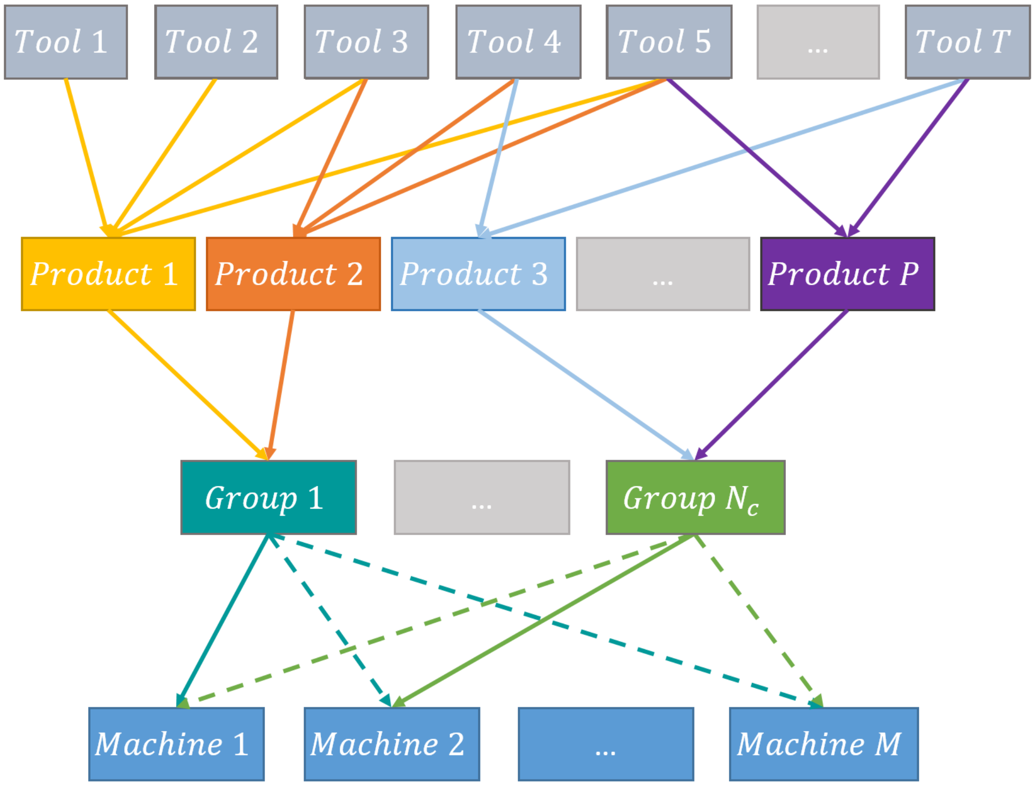

FIGURE 2.1: Schematic representation of the tool allocation problem.

where $y_j = 1$ indicates that the j-th machine is used, and M represents the set of available machines. So according to the example of Figure 2.1, $y_1 = 1$ because *Machine 1* is used since tools are allocated to it.

The first set of decision variables represents which tools are used in which machines. T is the set of available tools in the plant which can be used in machines (M). Therefore, $x_{i,j} = 1$ will mean that the tool i is used in machine j:

$$x_{i,j} \in \{0, 1\} \quad \forall i \in T, j \in M\,, \tag{2.2}$$

Regarding the example shown in Figure 2.1, $x_{1,1} = 1$, as *Tool 1* is allocated to the first machine, but $x_{3,2} = 0$ as *Tool 3* is not allocated to the second machine.

Accordingly, $|M||T|$ is the number of possible variations of tools used in machines. The availability of tools is not restricted, and there are multiple tools of each type. Therefore the same type of tool can be allocated to different machines (such as *Tools 4* and *5* could be allocated to both *Machines 1* and *2*).

The machines have tool capacities, represented by w_j, so the following inequalities should be fulfilled:

$$\sum_{i \in T} x_{i,j} \leq w_j y_j, \quad \forall j \in M \tag{2.3}$$

Therefore we have $|M|$ constraints regarding the formula above. The machine capacity of how many tools can be allocated equals the bin capacity. The tools are used to produce P set of products. Products are represented as the items needed to pack into the bins, and the assigned products define which tools are packed into the bins. There are $|P|$ variables regarding the formula below. Parameter $a_{i,k}$ represents when the i-th tool is used for the k-th product, which is formulated as:

$$a_{i,k} \in \{0, 1\}, \quad \forall i \in T, \forall k \in P \tag{2.4}$$

In the example of Figure 2.1, the tool demand of *Product 1* can be represented as a bitstring: $A_1 = \{1, 1, 1, 0, 1, \ldots, 0\}$.

We introduce a decision variable $z_{k,j}$ to represent that the j-th machine produces the k-th product.

$$z_{k,j} \in \{0, 1\} \quad \forall k \in P, \forall j \in M, \tag{2.5}$$

Products 1 and *2* are produced on *Machine 1*, but *Product 3* is not. They can be represented as follows: $z_{1,1} = 1, z_{2,1} = 1, z_{3,1} = 0$. The products define which tools have to be assigned to the machines by the following $|P||M|$ inequality constraints:

$$\sum_{i \in T} a_{i,k} x_{i,j} \geq \sum_{i \in T} a_{i,k} z_{k,j} \quad \forall k \in P, \forall j \in M \tag{2.6}$$

Last, we ensure that each product has to be produced at one machine and should not be assigned any product for a machine that is not used:

$$\sum_{j \in M} z_{k,j} = 1, \quad \forall k \in P \tag{2.7}$$

$$z_{k,j} \leq y_j, \quad \forall k \in P, \forall j \in M \tag{2.8}$$

Therefore, Equation 2.7 defines $|P|$, while Equation 2.8 introduce $|P||M|$ constraints.

Two objectives 2.9 are considered during the assignment: 1) minimize the number of used machines; 2) minimize the number of tools assigned to the machine.

The two objective functions address the two main reasons for tool changes. On the one hand, frequent tool changes are caused when there is a few overlap in the tooling requirements of a product assigned to a particular machine. This is what the first objective function tries to address, because if the tools are allocated between fewer machines overall, the complexity of the production system is reduced and there will be fewer times when a tool needs to be relocated between machines. Fewer active machines means that tools are concentrated in fewer places, so there will be more overlap in the tooling requirements of products in those places. On the other hand, if a machine cannot accommodate all the tools needed for the assigned products due to a lack of capacity, this will also lead to tool swapping. This is addressed by the second objective, which is to minimize the number of tools assigned to machines. This ensures that the tools are distributed in more compactly and within the capacity limits of the machine. In other words, it contributes indirectly to reducing changeovers by aiming to efficiently group tool use.

$$\min \lambda \sum_{j \in M} y_j + (1-\lambda) \sum_{\substack{i \in T \\ j \in M}} x_{i,j} \tag{2.9}$$

The weighting parameter $\lambda \in [0,1]$ allocates the importance between objectives. When $\lambda = 1$ the algorithms the algorithm focuses only on the minimization the machines, while $\lambda = 0$ the number of tools is minimized. As a result of the optimization, the minimal number of machines will be used to produce the required set of products, and all the products and tools will be assigned to the machines by the $z_{k,j}$ and $x_{i,j}$ binary variables.

The number of variables can be defined based on the variables indicated in Equations 2.1, 2.2, and 2.5. Therefore, the number of variables is written accordingly: $|M| + |M||T| + |M||P|$.

While the number of constraints can be defined based on the constraints indicated in Equations 2.3, 2.6, 2.7, and 2.8. The number of constraints can also be expressed accordingly as $|M| + |P||M| + |P| + |P||M|$.

2.1.3 The proposed clustering algorithm for tool allocation

Tool allocation can also be considered a clustering problem, where a product can be represented as the bit-string of the tools required for manufacturing. We consider the P set of products produced in the plant. A_k denotes the bit-string that represents the required tools for producing the k^{th} product.

The bits represent different tools and are denoted by $a_{i,k}$, where subscript i denotes the i^{th} tool. Consequently, the length of the strings is equal to the number of all potentially applicable tools in the plant ($|T|$). If the k^{th} product requires the i^{th} tool for its production, then $a_{i,k} = 1$, otherwise it takes value of 0.

$|A_k|$ stands for the number of required tools for the k^{th} product:

$$|A_k| = \sum_{i \in T} a_{i,k} \tag{2.10}$$

The quantity of required tools for the joint production of the k^{th} and l^{th} product is denoted by $|A_k \cup A_l|$. Our purpose is to group all products into N_C groups. The m^{th} group is the union of the sets of the tools required for the contained products ($\cup_{k \in C_m} A_k$), which C_m denotes. It denotes the number of tools required for the joint production of the products included in the C_m group. An example with two products, A_1 and A_2 forming C_1 group is shown in Table 2.2.

Table 2.2: An example bit string representing the group of two imaginary products. For the production of this imaginary group, all the tools required by one of the group members are needed.

	T_1	T_2	T_3	T_4	T_5	T_6	T_7
A_1	1	1	1	0	1	0	0
A_2	1	1	0	0	1	1	0
C_1	1	1	1	0	1	1	0

The condition that the number of tools required for the joint production of products in a given group must not exceed the magazine capacity forms a constraint: ($| \cup_{k \in C_m} A_k| \leq w_j \quad \forall m$). Furthermore, the groups must cover all products $| \cup_{m=1}^{N_C} C_m| = |P|$.

Agglomerative hierarchical clustering is proposed to find a heuristic solution for our problem. Our goal is twofold: In the clustering process, we want the number of members of the resulting group to be as small as possible. Furthermore, it is advisable to group those products or product groups that are similar in terms of the required tools. Therefore, we need two different properties to consider both objectives.

According to the first objective the size of the merged groups should be minimized during the iteration process:

$$p(C_m, C_n) = |C_m \cup C_n| = p(C_n, C_m) \tag{2.11}$$

These properties are stored in the P input matrix in each k iteration step, which is a symmetric square matrix, and the length of its rows/columns is equal to the number of groups in the current iteration step.

$$\mathbf{P} = \begin{array}{c|cccc} & C_1 & C_2 & \cdots & C_{N_C} \\ \hline C_1 & p(C_1, C_1) & p(C_1, C_2) & \cdots & p(C_1, C_{N_C}) \\ C_2 & p(C_2, C_1) & p(C_2, C_2) & \cdots & p(C_2, C_{N_C}) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ C_{N_C} & p(C_{N_C}, C_1) & p(C_{N_C}, C_2) & \cdots & p(C_{N_C}, C_{N_C}) \end{array}$$

TABLE 2.3: The **P** matrix, which stores the input properties of the first objective function.

The elements of this matrix represent the size of all possible groupings. The diagonal gives the absolute values of the union of the groups with themselves, that is, the size of the group itself. In a practical context, the matrix shows how many tools will be needed to merge different pair of groups, *i.e.*, indicates the number of tools in the magazines of the groups in the case of possible groupings. The capacity of the tool magazines restricts us.

Therefore, all elements should be excluded, which results in a bigger group size than the capacity.

Let is $p(C_m, C_n) > w_j \Rightarrow$ the merging of C_m and C_n is permitted in the t^{th} iteration step.

The proposed clustering-based optimization method assumes that the total number of products and their associated tooling requirements can be distributed among the available machines without exceeding their individual capacities. If this condition is violated, the method is not guaranteed to provide a solution. If the cumulative tooling requirements of all products exceed the combined capacity of the available machines, no feasible allocation can be achieved.

The difference between the capacity and the maximum of the diagonal $\Big(w_j - max(p(C_m, C_n))\Big)$ gives the maximum number of tools to be added by grouping to this group in the next iteration. Therefore, it is preferred that the maximum of the diagonal is not increased in the next iteration step. We try to minimize the values of the diagonal elements during the iteration process to create as small groups as possible. Hence, it is worth selecting the smallest group to merge. Consequently, the first merging rule is:

$$z_1 = \arg\min_{C_m} \Big(p(C_m, C_m) \Big) \quad m = 1...N_C \tag{2.12}$$

According to the second objective, we strive to merge groups as similar as possible to minimize the additional tool usage.

Therefore, it is necessary to define a dissimilarity measure that reflects how different the tooling needed for the production groups is. Accordingly, the distance of the C_m group from C_n is defined based on how many additional tools are necessary for the joint production. It can be expressed as the absolute value of the difference between their union and C_m or C_n:

$$\begin{aligned} d(C_m, C_n) &= |C_m \cup C_n \setminus C_m| \\ d(C_n, C_m) &= |C_m \cup C_n \setminus C_n| \end{aligned} \tag{2.13}$$

This dissimilarity metric has asymmetric properties because the set differences from their union are not equal $d(C_m, C_n) \neq d(C_n, C_m)$.

We aim to merge groups with a minimal number of additional tool demands by the use of the second merging rule, that is: .

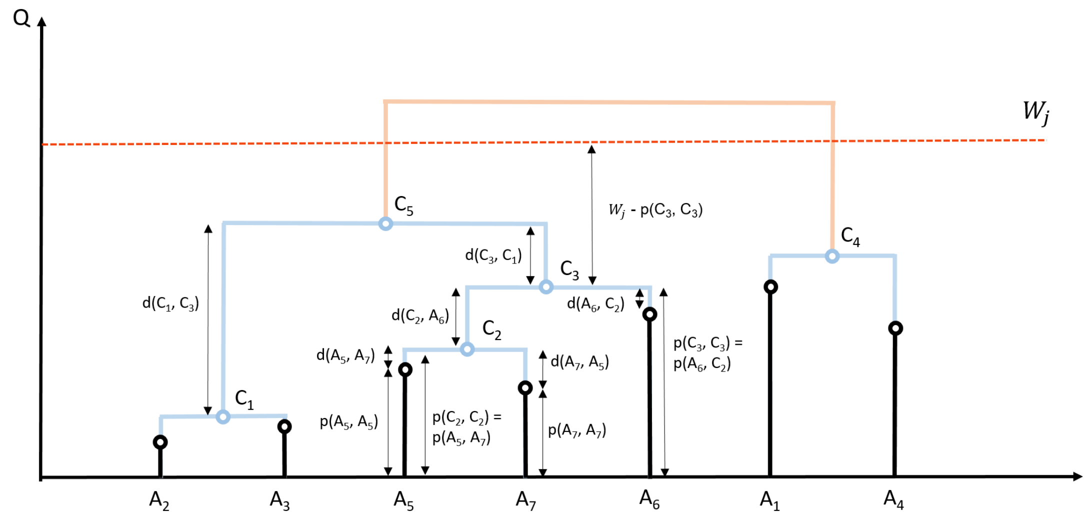

FIGURE 2.2: Illustrative dendrogram. The x-axis represents the products, while the y-axis shows the number of tools required for manufacturing. The red dashed line refers to the magazine capacity (w_j), the orange line that connects groups is out of the magazine capacity, while the blue ones can fit and not exceed w_j. The black lines represent the tool demand of product A_k.

$$z_2 = \arg\min_{C_n} \Big(d(z_1, C_n) \Big) \quad m, n = 1 ... N_C \quad m \neq n \tag{2.14}$$

Figure 2.2 summarizes the objectives and the clustering via a dendrogram. Both objectives are denoted on the figure to show the distances and the unions. The x-axis represents the products, while the y-axis shows the number of tools required for manufacturing. In this figure, the red dashed line refers to the magazine capacity (w_j), and the orange line that connects groups is out of the magazine capacity, which means that tool changeover is required to produce. While the blue ones can fit and not exceed w_j, and the black lines represent the tool demand of product A_i. The dissimilarity between the groups to be merged is well noticeable.

The clustering process is realized by the iteration of a heuristic multi-objective decision cycle where in each iteration two groups are merged that are selected based on the Pareto front defined by the two objectives (Figure 2.3). By definition, Pareto front includes those solutions for which no other solution can improve one objective without worsening at least one other objective [76].

In the first stage of the cycles, we select the product or product group that requires the minimal tool demand ($z_1 = \arg\min_{C_m}(p(C_m, C_m))$), while in the second

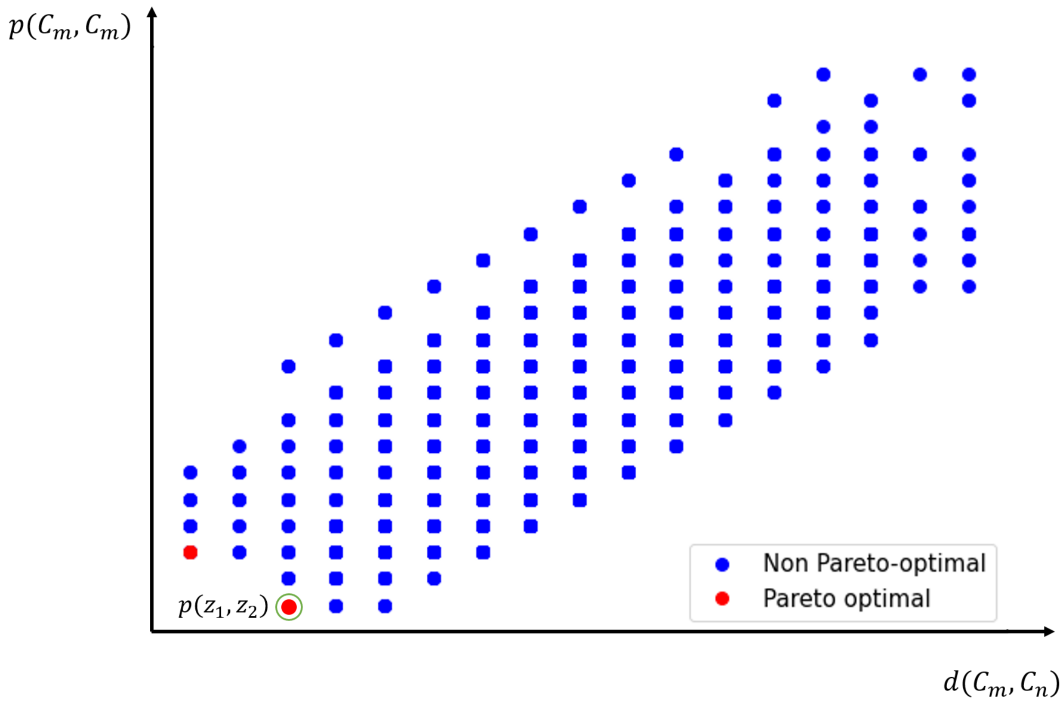

FIGURE 2.3: Schematic representation of the Pareto front of the group selection problem. The point to be selected is circled in green.

stage, we select the group that is most similar to the group that we selected previously (z_2=$\arg\min_{C_n}(d(z_1, C_n))$). According to this order, the one with the lower $p(C_m, C_m)$ property is chosen from the two Pareto optimal points. After merging the selected C_{z_1} and C_{z_2} groups the $p(C_m, C_m)$ and $d(C_m, C_n)$ values are recalculated, the groups that are selected in the presented multi-objective decision are merged. The iteration continues until the merged groups have a smaller tool demand than the capacity of the tool magazines.

The following section introduces the application study where the developed multi-objective hierarchical clustering algorithm is compared with the bin packing method.

2.2 Application study - Comparing bin packing and multi-objective hierarchical clustering methods

The application study of the proposed methodology occurred through a Hungarian assembly company with highly customized and small series production. According to the company's original operation, the manufacturing of products occurred in order of arrival, which usually leads to downtime due to several necessary tool changeovers performed by an operator. The aim is to maximize the utilization of CNC machines and reduce the number of tool changeovers to allow better planning for operator workload. We demonstrate the proposed method through two case studies:

- Firstly, a subset of a larger allocation problem is defined. It includes 16 products/items ($|P| = 16$) and 90 tools ($|T| = 90$).The maximum magazine capacity is $w_j = 25$.
- Secondly, a larger scale problem is solved of allocating 134 different products ($|P| = 134$) with a total tool demand of 90 ($|T| = 90$). The maximum magazine capacity is $w_j = 30$.

Figure 2.4 provides an illustrative representation of the common tool usage of products in the lower scale example in a cluster-map format. The cluster-map visualizes the tool-product binary matrix. Each row corresponds to a tool, and each column corresponds to a product. The heat map cells indicate whether a tool is required for a product (1: light cell, 0: dark cell). The rows and columns are hierarchically clustered based on Jaccard distances [77] to reveal patterns of similarity among tools and products. The rows (tools) and columns (products) are rearranged to match the hierarchical clustering structure. The clustering groups tools with similar usage profiles and products with overlapping tool requirements, providing insights into their relationships.

We seek to allocate these products to a minimal number of machines (bins) with the same maximal capacity constraint of w_j and allocate as few tools to the machines as possible. We assume there are multiple tools of different types, and each machine has access to each tool without any constraint. The small-scale example study is solved as a bin packing optimization problem using the Solving

Constraint Integer Programs algorithm [78] and the proposed multi-objective agglomerative hierarchical clustering algorithm to demonstrate the differences and similarities between the two methods. The λ parameter was set to 0.5 to balance the importance of the two objectives. The multi-objective agglomerative hierarchical clustering algorithm only solved the larger scale study due to the high computation time requirement of the bin packing algorithm. The algorithms were implemented in Python environment and ran on a PC with Intel(R) Core(TM) $i7-10770$ CPU @ $3.60GHz$ $3.60GHz$ CPU and $32GB$ of RAM specifications.

The primary objectives of the comparison are 1) the total number of tools used, 2) the number of machines used, and 3) the execution time. For the lower scale

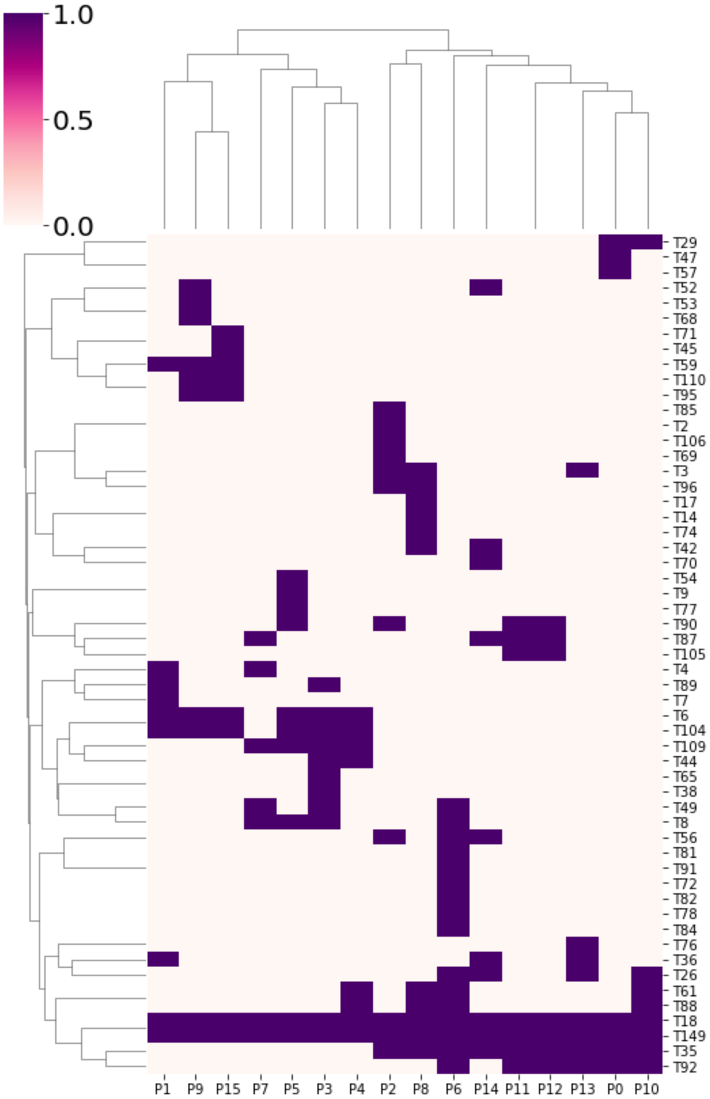

FIGURE 2.4: Cluster-map of similarities between products and tools. The dark clusters indicate similarities in the use of tools for the products and the similarities of tools in terms of the products they are used to manufacture.

example, the comparison between the methods based on these three objectives is shown in Figures 2.5 and 2.6.

1) *The total number of tools used*

   The first subplot in Figure 2.5 indicates how many tools the algorithm used totally to produce the number of products. It highlights that there are only minor differences in tool usage. The most significant difference was eight additional tools used by multi-objective agglomerative hierarchical clustering in the case of 16 products.

2) *The number of machines used*

   The second subplot in Figure 2.5 shows the number of machines used for producing the indicated number of products. It shows that the maximum difference in machine usage is one. In Figure 2.6, the dendrogram of the proposed multi-objective hierarchical clustering-based solution is shown. The x-axis refers to the products, and the y-axis shows the cluster size (number of tools in the cluster). The different groups' colors represent the machines, so products with the same color are assigned to the same machine. On the x-axis with blue color, the bin packing-based allocation of products is shown.

3) *The execution time*

   The most noticeable difference between the two solutions is the execution time. The visual representation of the execution time differences is shown in the third subplot in Figure 2.5. The bin packing optimization algorithm is time-consuming, and an explosive growth can be seen by increasing the number of products to be optimally assigned to machines. It is not surprising because the increasing complexity results in exponentially growing in computation time [79]. It is easy to see how computational demands in the case of a plant producing hundreds of items can escalate dramatically, making full optimization procedures impractical. However, the computational time regarding multi-objective agglomerative hierarchical clustering grows linearly with complexity, so the increases are not noticeable at this scale. Bin packing executed the optimization for 16 products in 9.58 minutes, while the proposed approach solved the same problem in 2.27 seconds.

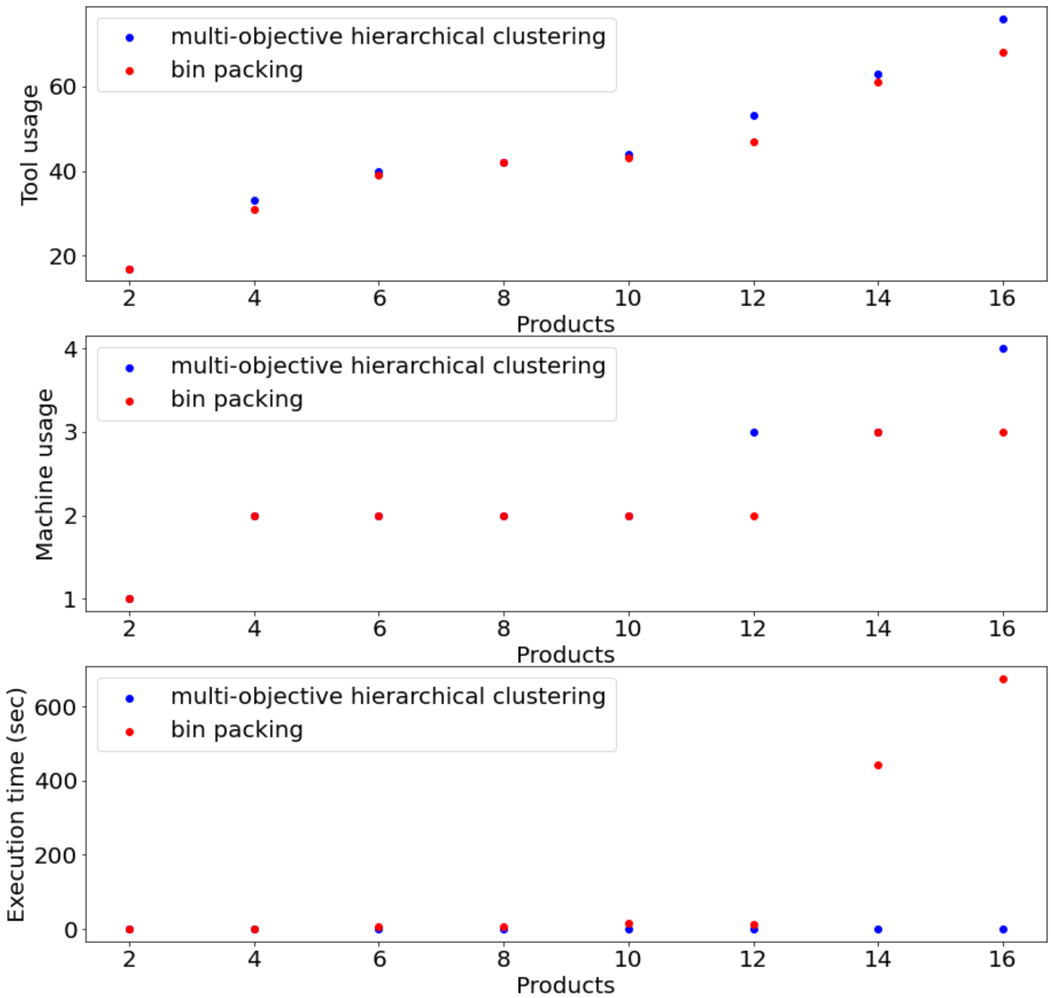

FIGURE 2.5: Comparison of bin packing and multi-objective agglomerative hierarchical clustering-based algorithms efficiency in 1) the total number of tools used, 2) the number of machines used, and 3) the execution time.

The smaller-scale study allowed us to compare the bin packing and the hierarchical clustering method. In order to show the applicability and robustness of the proposed method, we defined a larger-scale study. The proposed heuristic approach is applied by solving a more extended problem with 134 different products ($|P| = 134$) with a total tool demand of 90 ($|T| = 90$). The tools can be classified into various categories based on their types. Most are different types of milling cutters and rotary attachments, with the remainder being various bits and others. We have distinguished 11 categories, as shown in Figure 2.7.

The maximum magazine capacity is 30 ($w_j = 30$). Even in the case of 134 different products, the computation time was only 12.91 seconds, which is much lower than

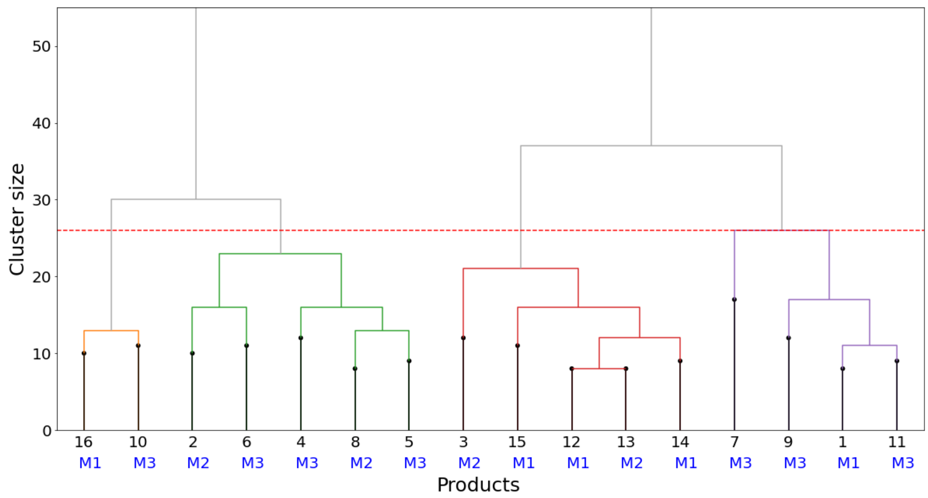

FIGURE 2.6: Multi-objective hierarchical clustering-based grouping of products. Colors indicate different groups (machines) based on the hierarchical-clustering method. Below are the product numbers. M1, M2, and M3 labels at the bottom indicate which machine the product is assigned based on the bin packing method for the sake of comparison.

bin packing for only 16 products. The algorithm created 16 product groups that tool demands are not exceeding 30. Figure 2.8 illustrates it. We must note that this is a heuristic, feasible approach, but the visualization also helps us determine which product groups could be allocated to the same machines in case of the limited number of machines and what would be the additional tool usage requirement for their joint production.

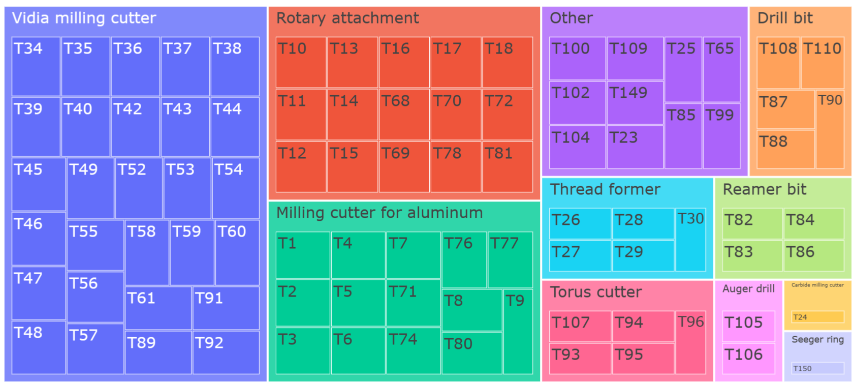

FIGURE 2.7: Treemap of tools by types - Vidia milling cutters, rotary attachments, milling cutters for aluminum, thread formers, torus cutters, drill bit, reamer bits, auger drills, Seeger ring, carbide milling cutter, and others.

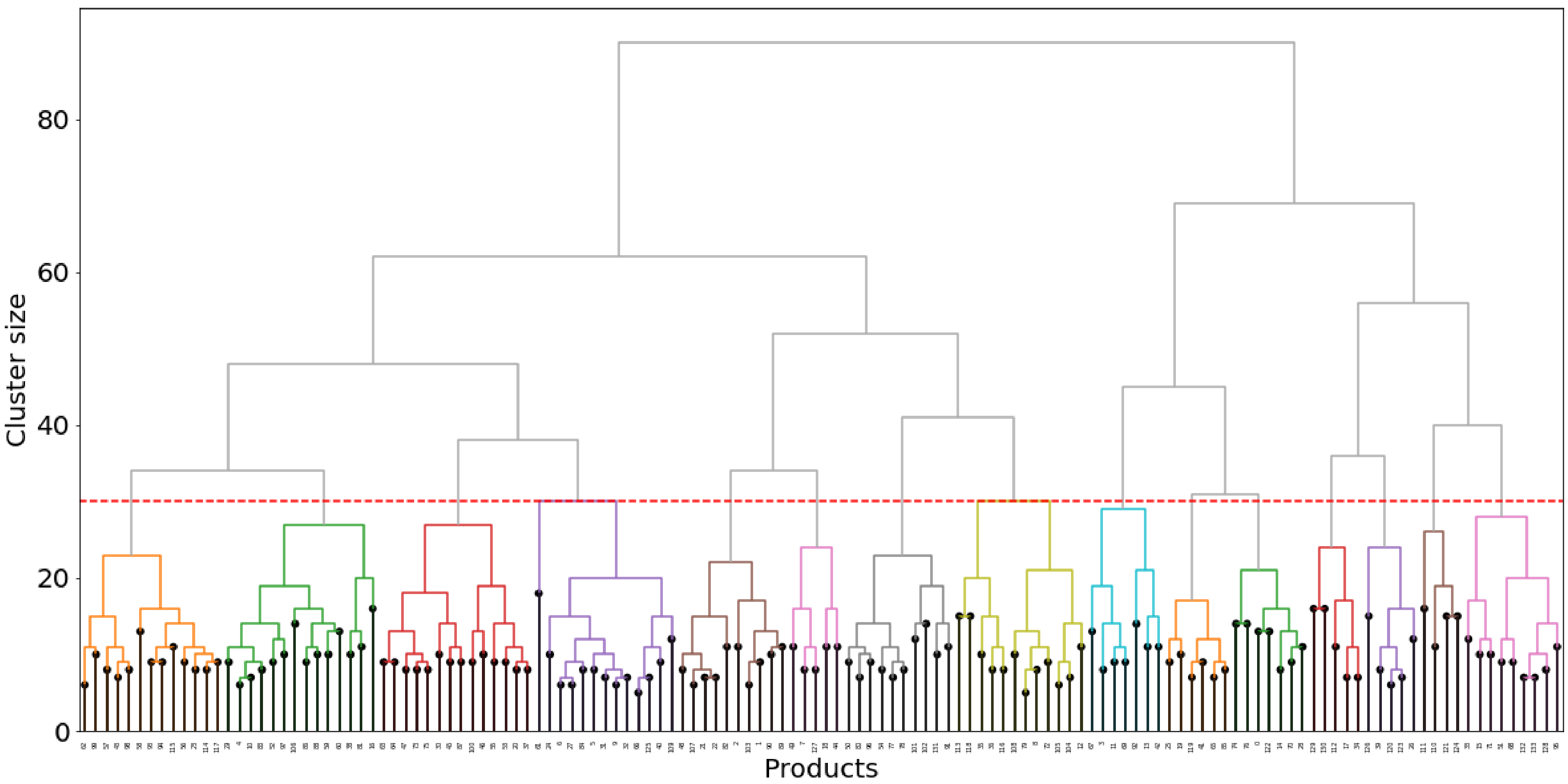

FIGURE 2.8: Multi-objective hierarchical clustering-based grouping of 134 products.

Based on the example analysis, we can conclude that; however bin packing is a well-known and valuable optimization solution, due to its high computation time demand, it is not suitable to optimize larger datasets. The multi-objective agglomerative hierarchical clustering method promotes a feasible heuristic approach with similar results (the number of machines used and the total number of tools involved) and low computation time. Furthermore, the proposed method can be applied for extensive input data with a short execution time. The proposed method can support these features since a large amount of data has to be handled quickly in a manufacturing environment.

2.3 Concluding remarks on the proposed tool allocation methodology and future directions

Custom and small series production require a flexible manufacturing system (FMS) environment to manage the dynamic change in changeovers. $25-30\%$ of the operating cost origin from tool-related activities. Therefore, efficient tool management strategies are necessary.

A method is proposed for tool allocation in FMS environment that is applicable in data-intensive manufacturing with low computation time. First, the tool assignment problem is formulated as a bin packing optimization problem, and a multi-objective hierarchical clustering algorithm was proposed as a feasible solution. The proposed method uses a clustering approach to access the tool allocation problem, where products are grouped with similar tool demands. The aim is to minimize the number of changeovers during the joint production of the products under a magazine capacity constraint. Thereby decreasing machine downtime and related expenses and increasing machine availability and overall equipment efficiency. The similarity of the product groups is defined by the tool demand of the product groups. For the optimization, the following objectives were considered 1) minimizing the size of the resulting groups (number of tools for joint production) and 2) minimizing the additional tool requirement between the groups to be merged (dissimilarity). The dissimilarity metrics between the two groups to be merged are asymmetric since the number of additional tool requirements for joint manufacturing differs.

An industrial case study is carried out at a Hungarian assembly company with a highly customized and small series product portfolio. This study has been solved using bin packing and multi-objective hierarchical clustering methods. Their results were compared from three perspectives: the total number of tools used, the number of machines used, and the execution time. The comparison highlighted only minor differences between the optimal and heuristic approach regarding the tool and machine utilization, however, the execution time is significantly lower in the proposed method.

It can be concluded that multi-objective hierarchical clustering is efficient, provides a feasible tool allocation solution, and can be applied to extensive data sets. The proposed method further allows a general application in an FMS environment.

The proposed method has some limitations, serving as possible future development potentials. The recent study has not considered the technological constraints of machines and tools, e.g., the number of resources was not limited, and it was assumed that the tools are compatible with all of the machines. Our future research will focus on how resource and compatibility constraints can be integrated into the tool allocation optimization and how the algorithm can be modified to solve the related scheduling problems where robustness and tool lifetime are also considered.

Chapter 3

Tool utilization monitoring by goal-oriented supervised fuzzy clustering of position data

IPSs can generate valuable tracking data about the position of tools [19]. In the case of flexible production systems, the application of an IPS is crucial for production monitoring [17]. Real-time tracking data can be converted into information that helps to control cycle times [80], explore the value streams [81] and integrate DTs [82].

The data-based identification of the production zones and the calculation of tool utilization are not straightforward tasks. The first problem is related to data uncertainty. The inaccuracy of IPSs can be at least in the order of several tens of centimetres [83]. In workshops and production halls, the layout can constantly change so that tracked tools can be obscured by high shelves, machines, and metal surfaces. Consequently, some non-line-of-sight (NLOS) places often have no direct view from the IPS anchor points. As a result, position data are scattered depending on the accuracy of the IPS at specific locations. This measurement noise introduces uncertainty inherent to these systems, so IPS applications often require advanced data-processing solutions, like Kalman filters [45] or clustering algorithms [84]. Fuzzy logic can also handle measurement imprecision of localization [85]. Since imprecision is connected mainly to measurement errors, the probabilistic approach to the problem is also beneficial [86].

In this research, a method is presented that integrates the benefits of fuzzy logic and probabilistic approach with the help of probabilistic Gaussian mixture models that can be interpreted as fuzzy rules [87]. The key idea is that the Gaussian mixture model can approximate the spatial distribution of the tools, so the model can be used to segment the shop floor into zones. When information about the activity of tools is also available, we can use this during the clustering resulting in conditional cluster probabilities that can be interpreted as tool utilizations. The novelty is a new clustering algorithm that is suitable to convert noisy tracking data into business value by segmentation of the shop floor and calculation of the tool utilization at the identified locations.

3.1 The supervised fuzzy clustering-based tool monitoring method

The identification of relevant operations or operating zones from noisy position data can be interpreted as finding the distinct distributions generating a mixture of data distributions. The positioning system allows activities of tools that can be used during this identification process to be determined.

Table 3.1 summarizes the notation used in the tool monitoring methodology.

3.1.1 Problem formulation

By turning this problem into a data-related task, a supervised fuzzy clustering (SFC)-based method is proposed for the detection of distinct clusters of manufacturing position data. The methodology is summarised in the following points:

1. Feature transformation: determination of tool activity
2. SFC-based modelling of tool positions
3. Zone categorization and utilization calculation
4. Validation of the number of clusters

Notation	Explanation
$l = 1, \ldots, L$	Index of tools
$i = 1, \ldots, C$	index of clusters
$n = 1, \ldots N_l$	Index of timestamps
t	Time
$\mathbf{x_n^l}$	The position record of tool l at time t_n^l
$\mathbf{X^l}$	All position measurements of tool l
x_1	Horizontal coordinate
x_2	Vertical coordinate
y	Activity state
r	Activity state label
R	Number of activity states
$\mathbf{Z}$	Measurement data matrix
$\mathbf{z}$	Measurement vector
Δt_n	Time difference between the t_n and t_{n-1} timestamp
Δx_n	Spatial distance between the position records at time t_n and t_{n-1}
v_n	Speed of a tool at time t_n
c	Cluster (Gaussian distribution component that could represent machine or storage area)
C	Number of clusters
d	Number of dimensions
$\mathbf{v}$	Mean position
$\mathbf{F}$	Position covariance matrix
$p()$	Probability distribution function
$\mathbf{U}$	Fuzzy partition matrix
μ	Fuzzy membership degree
η	Cluster centroid
$J(\mathbf{Z}, \mathbf{U}, \eta)$	Objective function
U_i	Utilization of machine c_i
U^l	Utilization of tool l
U_i^l	Utilization of tool l on machine c_i
SC	Partition index (cluster validity measure)
S	Fuzzy cardinality (cluster validity measure)

Table 3.1: Notation of the supervised fuzzy clustering-based tool monitoring methodology

The problem is formalized as follows. It is assumed that with the help of an internal positioning system, at time t, the position estimation of tool l ($l = 1, \dots, L$) is recorded. The timestamp of the n^{th} record on tool l is denoted by t_n^l. The position of tool l at time t_n^l is stored in the vector $\mathbf{x}_n^l$. In our example, the position vector consists of the raw horizontal ($x_{1,n}$) and vertical ($x_{2,n}$) coordinates of the located position $\mathbf{x}_n^l = \left[x_{1,n}^l, x_{2,n}^l\right]$. The set of the N_l observations of the l^{th} tool is stored in a matrix of the observation data $\mathbf{X}^l = \left[\mathbf{x}_1^l \dots, \mathbf{x}_{N_l}^l\right]$. The matrix containing the observation data of all tools is denoted as $\mathbf{X} = \left[[\mathbf{X}^1]^T, \dots, [\mathbf{X}^L]^T\right]^T$.

However, as the recorded position information is obtained based on the wireless communication of the receiver unit and a small tag fixed on the monitored tool, the recorded position data are somewhat inaccurate, the inaccuracy of which is a function of its actual position (mainly due to radio frequency interference). This inaccuracy, paired with the stochastic working habits of the human workforce (moving the tools, placing them at arbitrary places based on the convenience of the workers, taking breaks, *etc.*), makes the monitoring of tool usage an extremely complex task. Due to these problems the usage of a tool cannot be measured simply according to its position or movement, as neither of these pieces of information clearly determines the working conditions. However, besides the recorded position, the activity state of the monitored tool can be derived from the sampling time and the speed at which the tool moves as will be discussed in the following section. The activity state of tool l during the n^{th} observation is marked as $y_n^l \in \{r_1, \dots, r_R\}$ and describes whether the tool is stationary, being moved or actively in use at the time.

Due to the inaccurate nature of the information, instead of the simple analysis of the raw position data to monitor tool usage, an advanced clustering algorithm is proposed to obtain accurate information on tool activities. Our task is to partition the data in matrix $\mathbf{Z}^l = [\mathbf{z}_1^l, \dots, \mathbf{z}_n^l, \dots, \mathbf{z}_N^l]$ into C clusters. The data matrix $\mathbf{Z}^l$ consists of $\mathbf{z}_n^l = \left[\mathbf{x}_n^{l\,T}, y_n^l\right]$ row vectors, which include the input $\mathbf{x}_n^l$ and output data (activity class labels) y_n^l of the n^{th} observation on the l^{th} tool.

By applying the proposed SFC approach, the time-weighted activity rate of a specific zone in the production directly represents the utilization of the applied tool in the related zone. As a result, the active and inactive zones are identified simultaneously according to the activity rate of the tool in the related zone, moreover, a more accurate evaluation of tool usage is made. For the sake of simplicity, the feature transformation and clustering algorithms are given in the case of one tool ($\mathbf{X} = \mathbf{X}^l$),therefore, the l superscript is omitted in the following subsections.

3.1.2 Feature transformation - The determination of tool activity

Even though an IPS primarily records the position of the monitored tag, further information can be derived from the recorded data.

The Δt sampling time, namely the time difference between two consecutive position measurements on the same tag, is a function of the activity of the tag due to energy-saving considerations: each tag is equipped with a gyroscope sensor, which indicates whether the tool is actively moved or not. If the tag is moved (or subject to vibrations), its sampling frequency is much higher, $2-10$ *sec*, while if the tag is inactive, its sampling frequency is reduced to ~ 30 *sec*. The time difference between two consecutive measurements is simply formulated as $\Delta t_n = t_n - t_{n-1}$. Similarly, the Euclidean distance between two consecutive position points can be calculated as well: $\Delta x_n = D(\mathbf{x}_n, \mathbf{x}_{n-1})$. As we obtained the time and distance between two consecutive data points on the same tool, naturally the speed of the tag can be subsequentally calculated as follows: $v_n = \frac{\Delta x_n}{\Delta t_n}$.

Based on the available and derived variables, R number of different states are assigned to the monitored tool. In the present work, utilising the time difference between the recorded positions before (Δt_{n-1}) and after (Δt_n) the data point on the same tag, the arriving (v_{n-1}) and leaving (v_n) speed of the tag at the recorded position as well as the corresponding user-defined thresholds (Δt_{thr} and v_{thr} for the sampling time and the speed of the tag, respectively), three states ($R = 3$) are defined, symbolizing the activity of the monitored tool:

- The tool is stationary and is not being actively used ($y_n = r_1 | \Delta t_{n-1} > \Delta t_{thr}$, $\Delta t_n > \Delta t_{thr}$)
- The tool is stationary, but is actively being used ($y_n = r_2 | \Delta t_{n-1} < \Delta t_{thr}$, $\Delta t_n < \Delta t_{thr}$, $v_{n-1} \leq v_{thr}$, $v_n \leq v_{thr}$)
- The tool is moving (or position data of the tag is noisy, showing quick jumps over long distances) ($y_n = r_3 | v_{n-1} > \Delta v_{thr}$, $v_n > \Delta v_{thr}$)

From the aforementioned list of activity states, only the ones where the tool is stationary or being used are of primary interest, therefore, in our analysis, the first two states, r_1 and r_2, are considered. It is important to note that a fourth state could be defined when all tools in a tool magazine are moving. This research deals with machines that do not have an automatic magazine, so we will ignore this type of state.

3.1.3 Supervised fuzzy clustering for tool monitoring

The methodology is based on the idea that the spatial distribution of position data originating from different sources (with optimally different statistical characteristics) represents the probability of finding a given tool at a given position in a given state represented by a specific class label. Our goal is to determine the distribution of the data. For this purpose, a clustering algorithm is applied. The number of clusters is denoted by C, which describes the spatial distribution of the data considering the R number of states.

The probability distribution of finding that particular tool at a given position in a given state ($p(\mathbf{x}_n, y_n)$) is approximated by elementary Gaussian distributions. Furthermore, the joint distribution of these local distributions can be broken down further into conditional probabilities:

$$\begin{aligned} p(\mathbf{x}_n, y_n) = \sum_{i=1}^{C} p(\mathbf{x}_n, y_n, c_i) = \sum_{i=1}^{C} p(\mathbf{x}_n, y_n | c_i) p(c_i) = \\ = \sum_{i=1}^{C} p(y_n | \mathbf{x}_n, c_i) p(\mathbf{x}_n | c_i) p(c_i) = \sum_{i=1}^{C} p(y_n | c_i) p(\mathbf{x}_n | c_i) p(c_i) \end{aligned} \tag{3.1}$$

where c_i $(i = 1...C)$ denotes the i^{th} distribution component or cluster and $p(c_i)$ stands for the prior probability of distribution component c_i, representing the probability that an arbitrary data point is generated by the distribution c_i, which is calculated as the ratio of the data points in this cluster to the whole data set. Since the probability of finding a data point with a specific class label depends on the local distribution that generated it rather than its exact position: $p(y_n|\mathbf{x}_n, c_i) = p(y_n|c_i)$.

The $p(\mathbf{x}_n|c_i)$ conditional probability models the density of data point $\mathbf{x}_n$ belonging to distribution component c_i. It can be expressed as:

$$p(\mathbf{x}_n|c_i) = \left(\frac{1}{|2\pi\mathbf{F}_i|^{d/2}}\left(-\frac{1}{2}(\mathbf{x}_n - \mathbf{v}_i)^T(\mathbf{F}_i)^{-1}(\mathbf{x}_n - \mathbf{v}_i)\right)\right) \tag{3.2}$$

where d denotes the number of dimensions, $\mathbf{v}_i$ (Equation 3.4) stands for the cluster center, which is a d element vector, and $\mathbf{F}_i$ (Equation 3.5) represents the covariance matrix of the distribution, which is a matrix with dimensions $d \times d$.

The parameters of the joint distribution model of Equation 3.1 can be obtained by the Expectation-Maximization (EM) algorithm [88]. First, the model is initialized by assigning random values to the parameters. In the *Expectation* step, assuming the values these parameter are correct, the $p(c_i|\mathbf{x}_n, y_n)$ posterior probability is computed, which can be expressed by Bayes rule:

$$p(c_i|\mathbf{x}_n, y_n) = \frac{p(\mathbf{x}_n, y_n|c_i)p(c_i)}{p(\mathbf{x}_n, y_n)} = \frac{p(\mathbf{x}_n, y_n|c_i)p(c_i)}{\sum_{i=1}^{C} p(\mathbf{x}_n, y_n|c_i)p(c_i)} \tag{3.3}$$

In the *Maximization* step, the current distribution model is assumed to be correct and the parameters that maximize its likelihood are calculated as follows:

$$\mathbf{v}_i = \frac{\sum_{n=1}^{N} p(c_i|\mathbf{x}_n, y_n)\mathbf{x}_n}{\sum_{n=1}^{N} p(c_i|\mathbf{x}_n, y_n)} \tag{3.4}$$

$$\mathbf{F}_i = \frac{\sum_{n=1}^{N} p(c_i|\mathbf{x}_n, y_n)(\mathbf{x}_n - \mathbf{v}_i)(\mathbf{x}_n - \mathbf{v}_i)^T}{\sum_{n=1}^{N} p(c_i|\mathbf{x}_n, y_n)} \tag{3.5}$$

$$p(c_i) = \frac{1}{N}\sum_{n=1}^{N} p(c_i|\mathbf{x}_n, y_n) \tag{3.6}$$

$$p(y_n|c_i) = \frac{\sum_{n|y_n=r_l} p(c_i|\mathbf{x}_n, y_n)}{\sum_{n=1}^{N} p(c_i|\mathbf{x}_n, y_n)} \tag{3.7}$$

The expectation and maximization steps iterate until the parameters converge to a certain value.

This alternating optimization can be interpreted as an SFC task [87].

The fuzzy partition represented by $\mathbf{U} = [\mu_{i,n}]_{C\times N}$ matrix, where the degree of membership ($\mu_{i,n}$) represents, how the $\mathbf{z}_n$ measurement is in c_i cluster. The degree of membership can be expressed as the posterior probability $p\left(c_i|\mathbf{x}_n\right)$ of the cluster given the data point. The clustering algorithm minimizes the sum of weighted $D_{i,n}^2$ squared distances between the data points and the i^{th} cluster centroid represented by η_i.

$$J(\mathbf{Z}, \mathbf{U}, \eta) = \sum_{i=1}^{C}\sum_{n=1}^{N}(\mu_{i,n})^m D_{i,n}^2(\mathbf{z}_n, c_i) \tag{3.8}$$

where m denotes the fuzzy weighting exponent determining the fuzziness of the resulting clusters: $m = 1$ means a hard partition of the data points and the cluster centroid is the mean of the cluster members. As m increases, the partition becomes fuzzy and the cluster means are equal to the grand mean of $\mathbf{Z}$. Conventionally, $m = 2$. The cost function is subject to the restrictions on the $\mu_{i,n}$ membership values:

$$\begin{aligned} \mu_{i,n} &\in [0,1] \quad \forall i,n; \\ \sum_{i=1}^{C} \mu_{i,n} &= 1 \quad \forall n; \\ 0 < \sum_{n=1}^{N} \mu_{i,n} &< N \quad \forall i \end{aligned} \tag{3.9}$$

The membership values can be interpreted as probabilities : $\mu_{i,n} \cong p(c_i|\mathbf{x}_n, y_n)$. The positional data is not equally sampled in time, so the $\mu_{i,n}$ membership degrees should be weighted by Δt_n time to represent temporal probability.

The distance is based on the joint probability of finding a data point in a given position with a given class label (Equation 3.1):

$$\begin{aligned} \frac{1}{D^2_{i,n}(\mathbf{z}_n, c_i)} &= p(y_n|c_i)p(\mathbf{x}_n|c_i)p(c_i) = \\ = \frac{p(c_i)}{|2\pi\mathbf{F}_i|^{d/2}} &\left(-\frac{1}{2}(\mathbf{x}_n - \mathbf{v}_i)^T(\mathbf{F}_i)^{-1}(\mathbf{x}_n - \mathbf{v}_i)\right) p(y_n|c_i) \end{aligned} \tag{3.10}$$

The alternating optimization algorithm includes the following steps:

Initialization: Given a dataset $\mathbf{Z}$, determine the C number of clusters, the termination tolerance $\epsilon > 0$ and the weighting exponent m (which is equal to 2 in our case). Initialize the $\mathbf{U} = [\mu_{i,n}]_{C\times N}$.

Repeat for $k = 1, 2\ldots$ (k is the iteration counter)

Step 1 Parameter estimation

- Calculate the mean vectors, covariance matrices and prior probability of the Gaussian components.

$$v_i^{(k)} = \frac{\sum_{n=1}^{N}(\mu_{i,n}^{(k-1)})^m \mathbf{x}_n \Delta t_n}{\sum_{n=1}^{N}(\mu_{i,n}^{(k-1)})^m \Delta t_n} \tag{3.11}$$

$$\mathbf{F}_i^{(k)} = \frac{\sum_{n=1}^{N}(\mu_{i,n}^{(k-1)})^m (\mathbf{x}_n - \mathbf{v}_i)(\mathbf{x}_n - \mathbf{v}_i)^T \Delta t_n}{\sum_{n=1}^{N}(\mu_{i,n}^{(k-1)})^m \Delta t_n} \tag{3.12}$$

$$p(c_i)^{(k)} = \frac{\sum_{n=1}^{N}(\mu_{i,n}^{(k-1)})^m \Delta t_n}{\sum_{n=1}^{N} \Delta t_n} \tag{3.13}$$

- Calculate the consequent probability parameters.

$$p(y_n = r_l|c_i)^{(k)} = \frac{\sum_{n|y_n=r_l}(\mu_{i,n}^{(k-1)})^m \Delta t_n}{\sum_{n=1}^{N}(\mu_{i,n}^{(k-1)})^m \Delta t_n} \tag{3.14}$$

Step 2 Compute the distances according to Equation 3.10.
Step 3 Update the partitioned matrix

$$\mu_{i,n}^{(k)} = \frac{1}{\sum_{j=1}^{C}(D_{i,n}(\mathbf{z}_n, c_i)/(D_{j,n}(\mathbf{z}_n, c_j))^2/(m-1)} \tag{3.15}$$

Until $||\mathbf{U}^{(k)} - \mathbf{U}^{(k-1)}|| < \epsilon$

3.1.4 Zone categorization and calculation of tool utilization

The $p(y_n = r_2|c_i)$ conditional probability carries important information. Based on the probability of finding a data point in an active state in a given environment represented by c_i cluster, this environment can be categorized according to its function. For example, if a specific place represents a machine, this probability will be higher. In contrast, the probability of a storage-type cluster finding data points with active class label (while $p(y_n = r_1|c_i)$ takes a higher value) will be low. For the purpose of categorization, a decision threshold value α should be determined. If the conditional probability of finding an active data point in the given cluster is higher than this value, this cluster can be considered to be a machine. If not, it should be regarded as a storage area. If $p(y_n = r_2|c_i) > \alpha \Longrightarrow c_i$ is considered to be machine.

In the case of clustering the position data of all the tools together, this probability will represent the utilization of the tools available in the vicinity of that machine which can be interpreted as the utilization of that machine:

$$U_i = p(y_n = r_2|c_i) \tag{3.16}$$

It should be noted that cases can occur when inactive and active tools are in the machine simultaneously (due to operators having left a tool there following the previous operation), which decreases the value of this probability. It can be said that when there is an active tool in the vicinity of the machine over a given period, then only that tool is counted. This method allows the utilization of a machine to be calculated but this is not our goal. We aim to calculate the utilization of specific tools in specific regions. The utilization of a single tool can be calculated as the ratio of its working hours to the whole period ($T = \sum_{n=1}^{N_l} \Delta t_n^l$). The working hours are known as the summation of the time differences related to data points with active class label:

$$U^l = \frac{\sum_{n=1}^{N_l} I({y_n}^l = r_2){\Delta t_n}^l}{T} \tag{3.17}$$

The utilization value of tool l can be determined for machine c_i in two ways. On the one hand, it can be calculated as the ratio of the summation of time-weighted posterior probabilities of c_i to the whole time period, but on the other hand, if we build the model from the data of one single tool, $p(y_n = r_2|c_i)$ can be interpreted as the utilization of tool l on machine c_i:

$$U_i^l = \frac{\sum_{n=1}^{N_l} p(c_i|\mathbf{x}_n^l, y_n^l)\Delta t_n^l}{T} \cong p(y_n = r_2|c_i) \tag{3.18}$$

By totaling this for all clusters, the utilization of that particular tool can be determined:

$$U^l \cong \sum_{i=1}^{C} U_i^l \tag{3.19}$$

3.1.5 Definition of the number of clusters

The application of the algorithm requires the careful selection of the number of clusters. The optimal number of clusters can be evaluated by running the algorithm multiple times with different numbers of clusters and the monitoring cluster validity measures, like partition index (SC) and the separation index (S) [89].

In order to explain these validity measures, additional cluster measures should be in place. The fuzzy variation of cluster c_i is expressed as:

$$\sigma_i = \sum_{n=1}^{N_l} ((\mu_{i,n})^m ||\mathbf{x}_n - \mathbf{v}_i||)^2 \tag{3.20}$$

And the fuzzy cardinality of cluster c_i is expressed as:

$$n_i = \sum_{n=1}^{N_l} \mu_{i,n} \tag{3.21}$$

Then, the compactness of cluster c_i can be calculated as the ratio of the variation to the cardinality of this fuzzy cluster:

$$\pi = \frac{\sigma_i}{n_i} = \frac{\sum_{n=1}^{N_l} (\mu_{i,n})^m ||\mathbf{x}_n - \mathbf{v}_i||)^2}{\sum_{n=1}^{N_l} \mu_{i,n}} \tag{3.22}$$

Separation of c_i is defined as the sum of the distances of its center from the other centers:

$$s_i = \sum_{j=1}^{C} ||\mathbf{v}_j - \mathbf{v}_i|| \tag{3.23}$$

The partition index is the ratio of the sum of the compactness of the clusters to their separation. It is expressed by:

$$SC = \sum_{i=1}^{C} \frac{\pi_i}{s_i} = \sum_{i=1}^{C} \frac{\sum_{n=1}^{N_l} (\mu_{i,n})^m ||\mathbf{x}_n - \mathbf{v}_i||}{\sum_{n=1}^{N_l} \mu_{i,n} \sum_{j=1}^{C} ||\mathbf{v}_j - \mathbf{v}_i||} \tag{3.24}$$

While the partition index uses fuzzy cardinality and distances from all other clusters in the denominator to calculate the degree of separation of clusters, the separation index uses the minimum distance:

$$S = \frac{\sum_{i=1}^{C}\sum_{n=1}^{N_l}(\mu_{i,n})^2||\mathbf{x}_n - \mathbf{v}_i||}{N \min_{i,j}||\mathbf{v}_j - \mathbf{v}_i||} \tag{3.25}$$

3.2 Application of the goal-oriented supervised fuzzy clustering method

The development of the methodology was motivated by an industrial case study where the crimping tools of cable manufacturing machines were tracked by an IPS.

3.2.1 Description of the tool-management problem

The factory that defined the research and development task produces wire harnesses for the car industry. The harnesses are composed of single wires which are attached to different terminals. The machines crimp the terminals onto the end of wires using tools (Figure 3.1). Different tools are designed for different terminals. Since its establishment, the plant has manufactured a wide range of products, including 1820 different types of terminals. 2698 crimping tools have been involved in the production of these products, however, the number of tools used simultaneously over a specific period is less than one thousand. Only one or two tools can work in a machine at a time. The machines do not have tool magazines, so tools that are not being used are stored in storage areas (such as cabinets or tables).

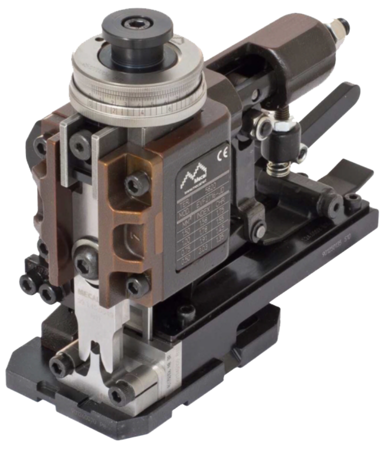

FIGURE 3.1: A crimping tool used in cable production.

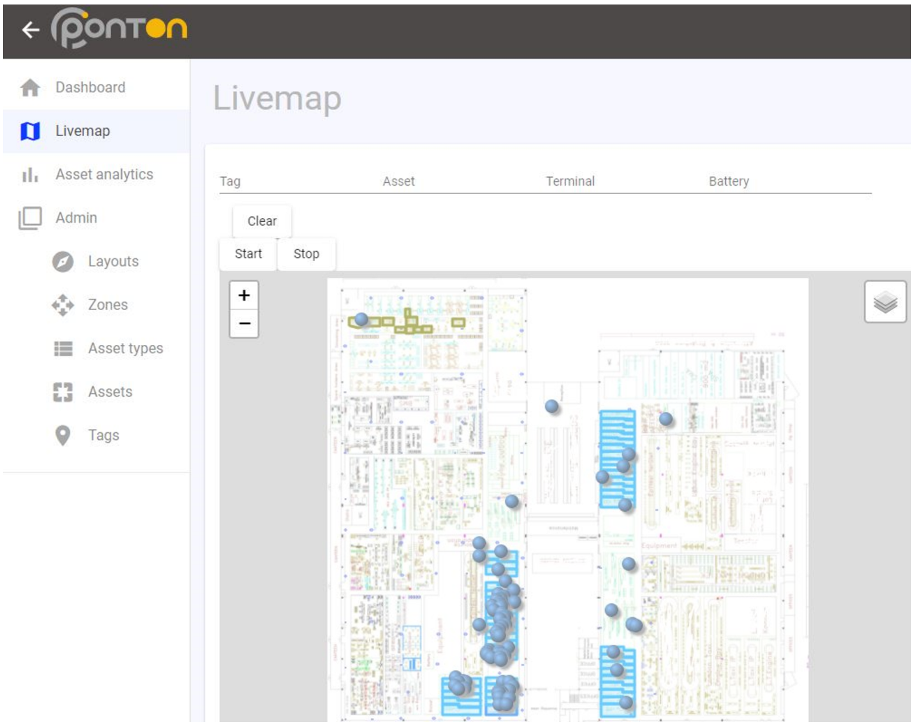

FIGURE 3.2: The live map of the positioning system.

We analysed one of the two production halls of the plant containing 23 machines and their associated storage areas. The tools may be located in these storage areas or at the machines, or being carried between them. Due to the high quantity of tools, their positions are tracked by an UWB-based IPS developed by Sunstone-RTLS Ltd.

Tool management requires information related to position data:

- Where was each tool located and for how long was it?
- Do these locations represent a machine or a storage area?
- To what extent were the individual tools are used in the specific locations?

3.2.2 Data generation and trasformation

The positioning system generates data that contains the horizontal and vertical coordinates ($\mathbf{x}_n = [x_{1,n}, x_{2,n}]$), a timestamp ($t_n$) ,and the IDs of the monitored tools. The system also provides continuous visual information on the positions of tools according to an IPS real-time map (Figure 3.2).

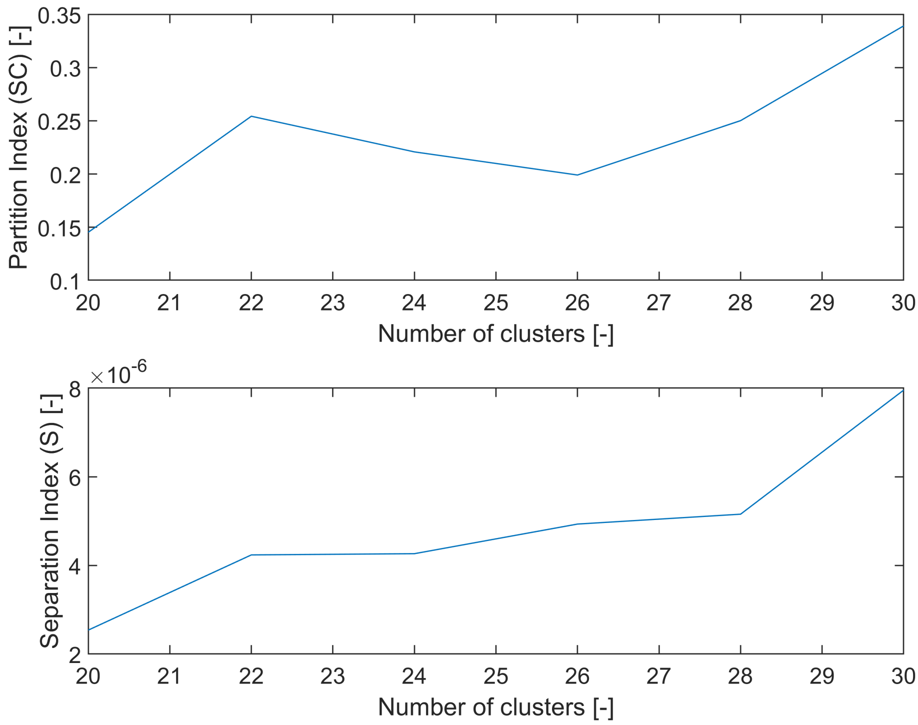

FIGURE 3.3: Determination of the number of clusters. The upper plot shows the partition index values as a function of the number of clusters and the curve has a local maximum at 22. The lower plot shows the separation index as a function of number of clusters, where the curve starts to flatten out at 22. Based on these plots, 22 seems to be the optimal number of clusters.

For our investigation, the recorded data of 14 tools between 4 : 50 a.m. on 01/03/2019 and 4 : 50 a.m. on 05/03/2019 were available. Only the data concerning the area of the smaller production hall were investigated, which included a data set of 195, 404 data points. To extract the required information from the position data, the described SFC algorithm was applied.

Supervised clustering needs training data. The training data is obtained by labeling each position according to its activity status. The activity statuses were defined as described in Section 3.1.2. We set Δt_{thr} to 20 seconds and v_{thr} to 0.1 m/s. First, data points representing moving tool (e.g., between machines or storage areas) were removed. This represented $\sim$ 58.5% of the data or 114, 221 data points. Second, inactive states were defined. This represented $\sim$ 8.4% of the original dataset, or 16, 502 data points. Thirdly, the active status was defined. 64, 681 data points, i.e., $\sim$ 33.1% of the total dataset, were labeled as active.

3.2.3 Position data-based calculation of tool utilization

The optimal number of clusters were determined according to the methodology presented in Section 3.1.5. Based on the cluster validity measures depicted in Figure 3.3, the optimal number of clusters was set to 22. The value of the weighting exponent m and termination tolerance ϵ were set at 2 and 10^{-3}, respectively. Figure 3.4 illustrates the results of clustering the data. The position data of different tools are represented by lines in different styles and colors. The resultant cluster centers are represented by black stars, while the zones with the equal probabilities of occurrence are represented by the contour plots. As can be seen, it is possible that the different clusters can be very close to each other and their recorded position data can easily overlap due to inaccuracies in their measurement.

The activity levels of the clusters were obtained as the probability of finding active data point in that cluster (Equation 3.16). 10 clusters found where the probability of activity is greater than 1%. These clusters may represent machines. To interpret Figure 3.4, it is worth incorporating available engineering knowledge about layout and processes. From the point of view of the positioning system, the hall can be divided into zones along the horizontal axis of the system, and the zones can

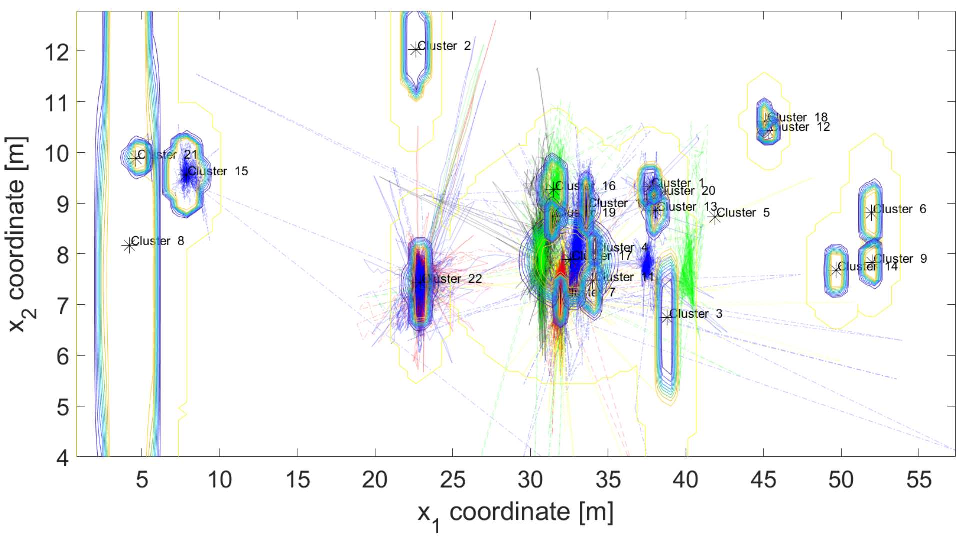

Figure 3.4: The results of the SFC of tool position data: the cluster centers are indicated by black stars, while the zones with equal probability of tools being located there are represented by the contour plots. The position data of different tools are denoted by lines in different colors and styles. Some clusters are so close to each other that they overlap, which may be caused by these clusters representing different locations on the same desktop storage.

be divided into machine and storage areas along the vertical axis. This vertical boundary which divides the zones into machines and storages is approximately at $x_2 = 8$. It is likely that the storage areas will be 'above' and the machinery 'below' this line. Therefore, it is expected that the machine type clusters found will also be located in the lower half of the diagram. It is worth comparing this information with the spatial and activity attributes of the clusters found. The expected x_2 value of possible storage clusters (where the activity is below 1%) are all located above this boundary. Of the possible machine clusters (where the activity is larger than 1%), clusters 4, 5 and 8 did not meet the expectations because they have expected x_2 values greater than 8. The probability of activity of these clusters is less than 15%, which is significantly lower than the activity of the other possible machine clusters (among which cluster 3 has the lowest with 19.6%). Hence, the selection of 0.15 as the value of the α threshold seems reasonable: cluster in which this probability was higher than the chosen value of α were considered to be machine while all the others were considered to be storage areas. 7 locations were identified as machines in this way. In these cases, these probabilities directly calculate the utilization values at those locations, which are presented in Figure 3.5.

The utilization of a single tool on a single machine can be calculated as the ratio of its working hours at that machine to the whole period. The utilization values of different tools in different clusters are shown on a heatmap (Figure 3.6). With the help of the proposed system, the paths of the tools can be tracked, so the networks of the stations can be generated and visualized as a spaghetti diagram illustrated in Figure 3.7.

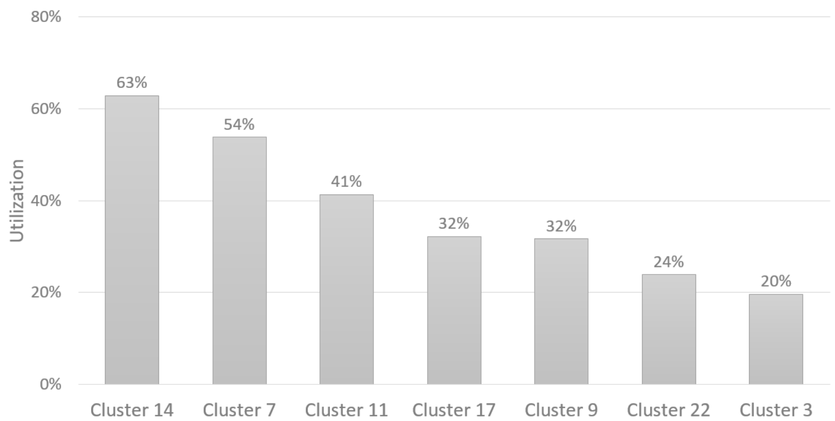

FIGURE 3.5: The utilization values of the machines in percentage. The columns illustrate the temporal probability of finding active data points in a cluster represents machine.

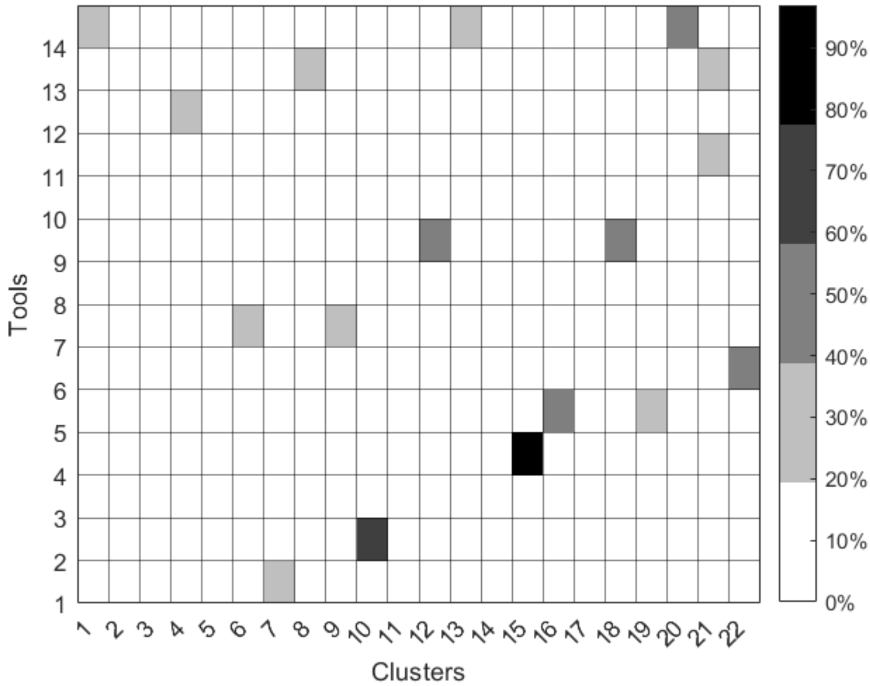

FIGURE 3.6: The heat map of the utilization values of tools on the different machines. The darker the color, the higher the utilization of the tool.

3.3 Concluding remarks on the proposed supervised fuzzy clustering-based utilization monitoring methodology and future directions

Advanced tool management requires accurate position-relevant information about the state of the tools. For Lean Six Sigma improvement projects, the KPIs of tools can be derived and the tool-related processes identified. Although IPS can

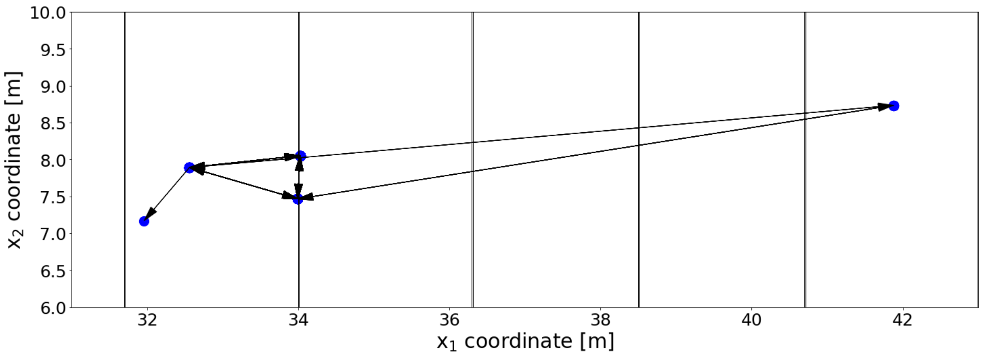

FIGURE 3.7: The path of tool with ID 12. The blue circles represent the different cluster centers where the tool has been.

facilitate position tracking, the accuracy of position data is not always sufficient for direct application. Therefore, the processing and cleaning of the position data are necessary.

The proposed time-weighted supervised fuzzy clustering can simultaneously explore the relevant tool locations, categorize their functions, and calculate the utilization of the tools and the machines.

The obtained information can be used in Digital Lean developments. Therefore, the positioning system can contribute towards tool management much more than shortening the time spent searching for tools and changeovers between them by facilitating the identification of underused tools, thereby reducing the extent to which they are hoarded. Furthermore, bottlenecks can be detected as evidence of overused tools, and the early detection of their overuse helps avoid or shorten unexpected stoppages due to tool failures by balancing the utilization or acquisition of spare tools at an appropriate time.

Chapter 4

Risk-based tool maintenance under dynamic manufacturing conditions

Opportunistic maintenance [90] is an approach that aims to reduce maintenance costs and downtime by grouping maintenance tasks and performing them when an "unscheduled opportunity" arises, such as a production stoppage due to other reasons beyond maintenance.

Maintenance planning should consider not only the frequency of failures but also their consequences, which can be achieved through risk-based maintenance. Risk is defined as the combination of the probability of failure and the severity of the consequences [91]. Risk-based maintenance strategy focuses on reducing the overall risk to the system that originates from unexpected failure consequences [92]. This approach is made up of three main pillars [93]. The first is risk estimation, which involves identifying failure scenarios, calculating the probability of these events based on their frequency of occurrence, and quantifying their potential consequences. The second is the risk evaluation where the calculated risks are compared to an acceptance criteria. The third is decision-making, which prioritizes maintenance actions according to the risks of the system components. The most commonly used techniques are fault tree [94] and failure modes and effects analysis [95]. Because these methods are designed for complex systems with multiple interacting components to identify the causes of failures and their cascading effects throughout the system, they may not be the most practical choice for maintaining individual, simpler tools. Another problem with traditional methods is that they consider the probability of failure to be static. Several techniques are used to deal with the changing probability of failure, such as Bayesian Networks [96, 97], Markov models [98], and reliability models [99]. Reliability analysis is widely used for tools in a flexible manufacturing environment such as CNC machine tools [100], cutting tools [101], crimping tools [102], and molding tools [103]. In reliability modeling, tool degradation or lifetime is assumed to be a stochastic variable that follows a probabilistic distribution [104]. Weibull is the most popular distribution type for modeling the time dependence of failures because of its customizability [105]. Proportional Hazard (PH) models [106] and Accelerated Failure Time (AFT) models [107] allow the effects of different operational conditions on degradation characteristics to be considered. Such conditions may include cutting speed and feed rate in the case of a cutting tool [108]. Model parameters can be identified by maximum likelihood estimation [109].

The probability of failure is affected not only by tool degradation due to use but also by the maintenance performed [110]. Maintenance models such as Virtual Age and Improvement Factor describe the success of maintenance and therefore its impact on the level of degradation (and hence on the probability of failure) [111].

The other component of the risk measure, in addition to the probability of failure, is consequence or criticality. It is also assumed to be constant in traditional methods, which is not consistent with real-world scenarios. Factors that influence criticality have been considered in several papers, such as the traffic in the case of bridge maintenance [112] or power demand in the case of electricity network maintenance [113]. In both examples, the demand for assets determines the current criticality, which is analogous to tools in a FMS. The products to be produced according to the current production plan have different values and tooling requirements, thus determining the consequence of the failure of a specific tool in a given period, which should be considered in the risk estimation.

If an appropriate risk model is available, optimization methods can be used to determine the best maintenance timing and activity types [114]. Other outcomes of maintenance optimization models can be the optimal grouping of components for opportunistic maintenance [115], the selection of an optimal maintenance strategy [116], the determination of thresholds for triggering maintenance actions [117], or the assignment of resources to maintenance tasks [118]. Common solution-finding approaches are mixed-integer programming [119], dynamic programming [120], or metaheuristic search [121]. The Genetic Algorithm (GA) [122] is one of the most popular metaheuristic algorithms that has been proven in a wide variety of risk-based maintenance applications. Optimal redundancy level and preventive maintenance duration were determined for cutting tools by considering the costs of reactive and preventive actions, downtime, and failure probabilities [123]. A scheduling method of system components was developed that minimizes the risk of under-maintenance, defined by the expected probability of failure and its losses, as well as the risk of over-maintenance by considering maintenance costs [124]. The minimum cost between preventive action and replacement was found, during which the impact of different decisions on failure probability was modeled by dynamic reliability model and improvement factor [125]. Selection of maintenance alternatives was realized by minimizing life cycle costs and maintaining reliability in the case of highway bridges [126].

This research proposes a method for selecting maintenance works for manufacturing tools and assigning them to opportunity windows, where the risk evaluation model includes the expectations of the probability of failure and the resulting losses as well as the maintenance costs. The failure probability and criticality of tools are considered dynamically due to the changing manufacturing environment. Reliability models are used to model the evolution of the probability of failure due to tool usage, and the consequences are calculated based on system information, matching losses and costs with the current production plan. A genetic algorithm is applied to find the best selection of tools for maintenance in each production cycle that minimizes the overall risk. Figure 4.1 visually summarizes the proposed method.

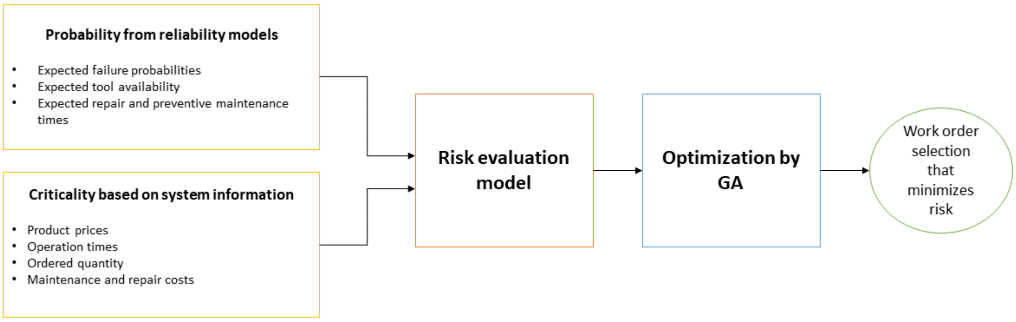

FIGURE 4.1: Scheme of the proposed methodology. The risk function is used in genetic optimization, and the risk is evaluated based on the probabilities calculated from dynamic reliability models and the criticality represented by costs.

The key contributions of this research can be summarized as follows:

- Introduction of a risk-based maintenance selection method for tools, that accounts for the variability of production conditions
- The changing conditions of use are considered through the Accelerated Failure Time reliability model
- Effective operating time formula is provided to help consider the impact of maintenance activities during maintenance planning
- A risk evaluation function is developed that dynamically incorporates the losses from under- and over-maintenance
- The effectiveness of the proposed method is demonstrated by a numerical example

4.1 Methodology of the proposed dynamic risk-based maintenance

Production tools degrade with use, increasing the likelihood of failure and production defects, which results in higher downtime and jeopardizes on-time delivery. Products may share tooling requirements, and the criticality of a specific tool depends on the current production plan. The value and quantity of the orders requiring that particular tool influence the severity of the consequences of its failure. A flexible manufacturing system is a dynamic and rapidly changing environment where the production schedule is constantly evolving. As a result, the utilization and criticality of tools vary from one production cycle to another. The schedule also determines tool usage, which in turn influences how failure probabilities develop over time. Fluctuations in product demand lead to changes in the time-varying importance of tools, while the uneven wear caused by intensive tool usage necessitates maintenance planning that is both predictive and risk-aware. By leveraging failure probability distributions, maintenance tasks can be scheduled and prioritized based on projected tool utilization. The proposed methodology incorporates all of these considerations by formulating effective tool operating times, integrating reliability models, and defining a risk-based objective function derived from the current production plan.

Table 4.1 summarises the notation used in the method.

Table 4.1: Notation of the dynamic risk-based optimization model

Notation	Explanation
Sets and Indices	
P	Set of products, and $\|P\|$ its cardinality
T	Set of tools, and $\|T\|$ its cardinality
K	Number of production orders
$i = 1, \dots, \|T\|$	Index of tools
$j = 1, \dots, \|P\|$	Index of products
$k = 1, \dots, K$	Index of production cycles
$g = 1, \dots, N_{gen}$	Index of generations (GA)
$h = 1, \dots, N_{pop}$	Index of individuals (GA)
Production Parameters	

Continued on the next page

Table continued

Notation	**Explanation**
p_{ji}	Time to perform operation with tool i on product j
N_j^k	Quantity of product j in cycle k
pr_j	Price of product j
r_j	Unit revenue of product j
Reliability and Failure Model Parameters	
λ	Hazard function (failure rate)
Λ	Cumulative hazard function
R	Reliability function
F	Failure function
β	Shape parameter of Weibull distribution
η	Scale parameter of Weibull distribution
μ	Location parameter of lognormal distribution
σ	Scale parameter of lognormal distribution
Φ	CDF of the standard normal distribution
$\mathbf{z}$	Covariate vector for failure probability evolution
γ	Coefficient vector for covariate effects
Schedule-Dependent Quantities	
Δ_i^k	Expected operating time of tool i in cycle k
Δ^k	Total operating time across all tools in cycle k
τ_i^k	Cumulative operating time of tool i up to cycle k
A_i^k	Predicted availability of tool i in cycle k
ϕ_i^k	Failure probability of tool i in cycle k (given survival so far)
Expected maintenance time values	
$IMR_{rm}T_i^k$	Mean repair time for tool i in cycle k
$IMR_{pm}T_i^k$	Mean PM time for tool i in cycle k
Input Cost Parameters	
c_i^r	Repair cost for tool i
c_i^p	Preventive maintenance cost for tool i
Decision Variables	
x_i^k	Binary: 1 if tool i is selected for PM in cycle k, 0 otherwise
Auxiliary Variables	

Continued on the next page

Table continued

Notation	**Explanation**
y_i^k	1 if tool i has had maintenance by cycle k
ζ_i^k	Most recent maintenance cycle for tool i up to k
Objective and Optimization Parameters	
$\mathcal{R}$	Risk function
q	Penalty function
$\mathcal{F}$	Fitness function
N_{pop}	Genetic algorithm population size
N_{gen}	Number of generations
p_{mut}	Mutation rate in genetic algorithm

4.1.1 Description of manufacturing environment and the associated tool maintenance scheduling problem

This subsection introduces a FMS and an associated tool maintenance scheduling model. A set of products P is produced using a set of tools T in a particular manufacturing environment.

The model of this system is described as follows:

- The tool set T is heterogeneous in terms of functionality. Each product requires a subset of tools for its production because for manufacturing the j^{th} product, specific operations requiring processing time p_{ji} must be carried out by using the i^{th} tool.
- The type and number of operations required to manufacture different products differ.
- The tooling requirements for different products are only partially different, i.e. the tools needed to perform different operations are in some cases the same.
- The topology of the operations is sequential, i.e. in the case of the production of a specific product, the operations to be performed follow one after the other.

- A tool can only work on one product at a time, and a machine can only produce one product at a time. As a result, tools that are not needed for the current operations in progress represent a loss of production capacity.
- There is a production plan with K production orders. Each k^{th} production order is for the production of a specific product j with the quantity N_j^k.
- The K production orders divide the planning horizon into K cycles. These cycles are homogeneous in terms of criticality assessment.
- The length of each k cycle is different, depending on the duration of the required operations p_{ji} and the number of products demanded N_j^k.
- Each j^{th} product has a specific price pr_j.

The condition of manufacturing tools deteriorates with use, increasing the likelihood of tool failure as a function of elapsed operating time. Keeping them in good condition is therefore a necessity. On the other hand, preventive or predictive maintenance is expensive. Both over- and under-maintenance pose risks to the system. The tools should be scheduled in such a way that the overall risk of the system is minimized. To formulate the maintenance work selection problem, some assumptions must be made:

- Although many types of failures can occur in realistic scenarios due to different causes, this model assumes only one failure mode, after which the tool is unable to perform its function.
- There are two types of maintenance activities: planned maintenance, which is performed when the tool is still capable of performing its function, and repair after failure.
- Planned maintenance in this model can indicate either a major overhaul (in the case of repairable tools) or replacement (in the case of non-repairable tools), which is considered perfect maintenance because it returns the tool to like-new condition.
- Repair is considered minimal maintenance. It restores a system to the same failure probability as before the failure
- The costs associated with reactive and planned maintenance activities are distinct denoted by $c_i^{(r)}$ and $c_i^{(p)}$, respectively.

- Production stoppage is not allowed, only unexpected failure can lead to stoppage
- During the k^{th} production, only those tools that are not needed for this production can be selected for planned maintenance. Therefore, planned maintenance does not interfere with production.
- The model does not address planned maintenance in the case of those tools that are required for every production.
- The model does not account for the time between the detection of the failure and the start of the repair. Immediate repair after failure is assumed.
- There is a maximum risk R_{max} that is still acceptable. The risk R^k involved in a given production must not exceed this.

While there are no such pure conditions in a real situation - the assumptions collectively do not completely depart from the real problems. These assumptions reflect a trade-off between modeling fidelity and tractability, and many are supported by the literature on maintenance optimization in FMSs. For example, heterogeneity of tooling and operation sequencing per product are widely used in FMS job-shop models [127, 128]. The degradation mechanism assumes a single failure mode with increasing failure probability over time—an accepted simplification in reliability modeling [129]. Preventive and corrective maintenance are modeled as perfect and minimal, respectively, in line with traditional analytical frameworks, while the distinction between perfect planned maintenance and minimal repair also has precedent in analytical maintenance cost models [130]. A distinguishing feature of our approach is the restriction that planned maintenance can only occur during production cycles in which the tool is not required. This aligns with the idea of opportunity-based maintenance [131], which aims to minimize production disruption by performing maintenance during idle periods. Tools that are critical to all production orders are thus excluded from scheduled PM in this model—reflecting real-world systems where such tools must remain continuously available. Additionally, we assume that repairs occur immediately after failure, which, while idealized, is common in modeling approaches, especially in Markovian frammeworks where systems transition directly from a failure state to a repair state without explicitly modeling detection delays or repair queueing [132]. These assumptions collectively provide a realistic yet solvable framework that supports the integration of production-aware risk assessment into the maintenance planning process.

The proposed maintenance work selection method aims to select the tools to be maintained during each production job, minimizing the overall risk to the system over the entire planning horizon. The probability component of the various risks is derived from probabilistic reliability models of the tools, and the severity component of the risks is calculated by considering available system information and production orders.

4.1.2 Model of effective operating times of tools incorporating varying production schedules and maintenance activities

Assume a planning horizon that involves a K long sequence of production orders. The expected operation time of the i^{th} tool in the k^{th} production cycle can be expressed as the product of the tool operation time required for the product to be manufactured p_{ji} and the quantity of the product to be manufactured N_j^k, according to k^{th} production order:

$$\Delta_i^k = \sum_{j \in P} p_{ji} N_j^k, \quad \forall i \in T, \forall k \in \{1, \ldots, K\} \tag{4.1}$$

The expected operating time at the end of the entire planning horizon is the sum of the expected operating times. From a maintenance planning point of view, the operating time until the end of each k^{th} cycle can be divided into three stages: From a maintenance planning point of view, the operating time until the end of each k^{th} cycle can be divided into three stages:

- total operating times before the last planned maintenance was performed $(\sum_{m=1}^{\zeta_i^k} \Delta_i^m)$
- operating times from the last planned maintenance to the last cycle before the current $(\sum_{n=\zeta_i^k}^{k-1} \Delta_i^n)$
- expected operating times in the current cycle (Δ_i^k)

During the maintenance planning process, it is essential to consider the impact of planned maintenance activities, as a result of which the tool regains its new-like condition. The cycle in which the tool has been maintained determines which stages of the tool's history should be taken into account when calculating the probability of failure. In this approach, the aforementioned phases are modeled by expected effective operation times, similar to the concept of effective age [123]. The formula for the expected effective operating time up to a given cycle k is defined as follows:

$$\tau_i^k = \begin{cases} \Delta_i^1 \left(1 - y_i^1\right), & \text{if } k = 1, \quad \text{(Case 1)} \\ \left(\sum_{m=1}^{\zeta_i^k} \Delta_i^m\right)\left(1 - y_i^k\right) + \left(\sum_{n=\min(\zeta_i^k, k-1)}^{k-1} \Delta_i^n\right)\left(1 - x_i^k\right), & \text{if } k > 1, \quad \text{(Case 2).} \end{cases} \tag{4.2}$$

Note that the second summation over n is only meaningful in the general case of $k > 1$ in the Case 2 formula. Therefore, it is necessary to distinguish the edge case from the general case, because in the case of $k = 1$, the running index in the second summation operator would include a term with an undefined $k - 1$. Since there are no prior cycles to consider in the second summation, the expression for $k = 1$ should be evaluated directly (Case 1).

x_i^k is a decision variable that takes a value of 1 if the i^{th} tool is selected for planned maintenance in the k^{th} cycle, otherwise, it takes 0. y_i^k is an auxiliary variable that tells if there was maintenance up to and including cycle k:

$$y_i^k = \begin{cases} 0, & \text{if } \sum_k x_i^k = 0 \\ 1, & \text{if } \sum_k x_i^k > 0 \end{cases} \qquad \forall i \in T, \forall k \in \{1, \ldots, K\} \tag{4.3}$$

and ζ_i^k denotes when the last maintenance was performed from the perspective of the k^{th} cycle.

$$\zeta_i^k = \begin{cases} l, & \text{if } x_i^l = 1 \ \ \& \ \ x_i^{l+1} = 0, \quad \forall i \in T, \forall l = 1, \ldots, k-1 \\ k, & \text{if } x_i^k = 1, \quad \forall i \in T, \forall k \in \{1, \ldots, K\} \\ 0, & \text{if } \sum y_i^k < 1, \quad \forall i \in T, \forall k \in \{1, \ldots, K\} \end{cases} \tag{4.4}$$

This formula is to select the last cycle when x_i^k was 1 and in the next cycle was 0.

To illustrate how the effective operating time formula works, consider the following example. The example scenario is that there are seven production orders (planning cycles). A given tool is not required for the production of the third and seventh cycles, so the tool can be selected for maintenance only in these cycles. Assume that it has already been decided that the tool will be maintained in the third cycle, and the decision whether it will be maintained or not in the seventh cycle should be made. If maintained, then $x_i^7 = 1$, so $y_i^7 = 1$ and $\zeta_i^7 = 7$. Substituting these into the expected effective operating time formula (Equation 4.2) yields $\tau_i^7 = 0$. In other words, at the beginning of the seventh week, a tool in like-new condition is available.

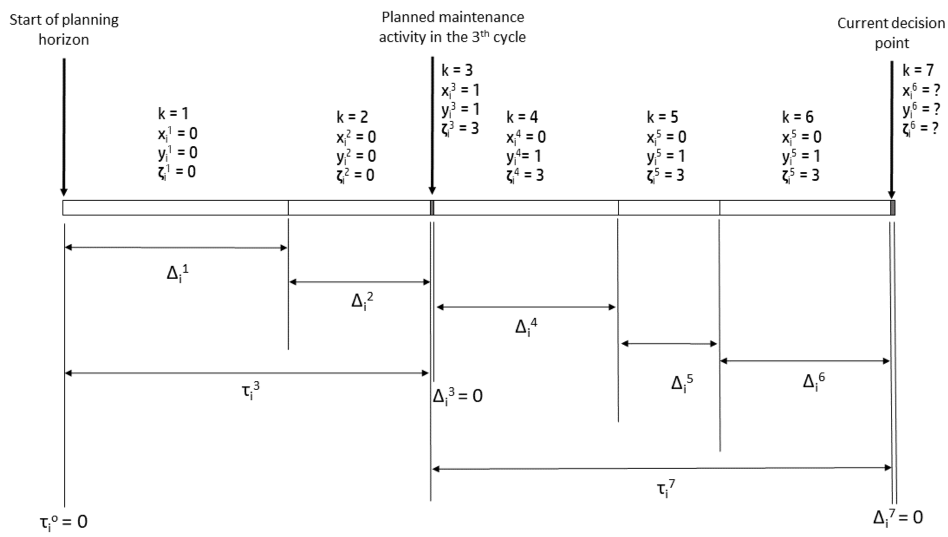

FIGURE 4.2: Illustration of the expected effective operating times. The length of the operating times in each cycle Δ_i^k depends on the type of product and the quantity to be produced N_j^k, and the planned maintenance activities determine which production cycles should be considered during planning.

If the tool is not maintained, the variables take the following values: $x_i^7 = 0$, $y_i^7 = 1$, and $\zeta_i^7 = 3$. By substituting these into Equation 4.2, then $\tau_i^7 = \Delta_i^3 + \Delta_i^4 + \Delta_i^5 + \Delta_i^6$ (in which Δ_i^3 is equal to zero because it is not required for that production). That is, it is as if we started working with a new tool from the third cycle (Figure 4.2).

The formula is designed so that τ_i^k always contains only the expected operating times from the last maintenance to the $k-1^{th}$ cycle.

4.1.3 Reliability, availability and maintainability models of tools

Reliability and availability models are applied to deal with the likelihood of undesirable events. The operational reliability model expresses the probability that a tool will perform without failure over a specified period of use. Using this model and the probability distributions of repair times, we can estimate the availability of tools in each production cycle.

4.1.3.1 Reliability model of tools

Since the degree of tool degradation depends not only on the amount of time the tool has been used, but also on the operating conditions, tool reliability is modeled using the AFT model.

Suppose the active life of the i^{th} tool consists of the durations of the operating times to failure and the repair times. Let t stand for the operation time to failure, which is assumed to be an independent random variable, following the Weibull distribution. The Weibull distribution is well suited for reliability modeling because it is customizable through two parameters that letting adjust its scale and shape (Figure 4.3). The Weibull reliability function of a tool is expressed by the following formula:

$$R_i(t) = exp\left(-\left(\frac{t}{\eta_i}\right)^{\beta_i}\right) \tag{4.5}$$

Where β is the shape parameter, η is the scale parameter, and i is the lower index indicating that it belongs to the i^{th} tool.

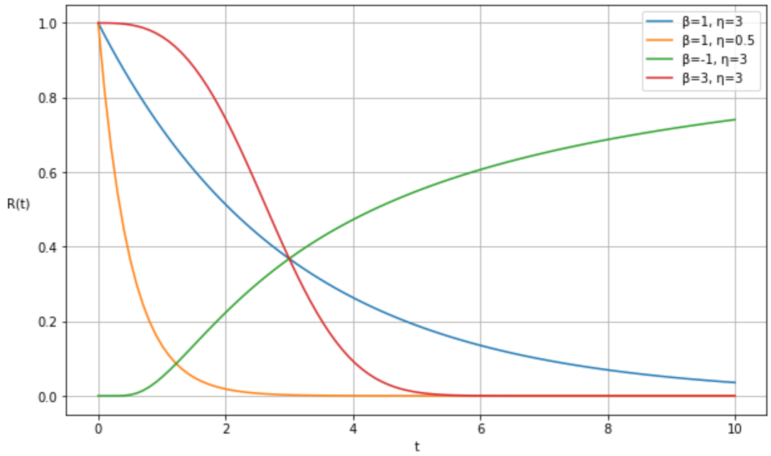

FIGURE 4.3: Weibull reliability curves in case of different shape and scale parameters

The baseline Weibull hazard function, which is the probability of the failure occurring during any given time point t is described as follows:

$$\lambda_i^0(t) = \frac{\beta_i}{\eta_i}\left(\frac{t}{\eta_i}\right)^{\beta_i - 1} \tag{4.6}$$

In the case of a Weibull distribution, the AFT model is equivalent to the Proportional Hazard (PH) model [133]. Assume d different type of operation conditions. In PH models, a baseline hazard function is multiplied by a functional term $exp\left(\mathbf{z}^T\boldsymbol{\gamma}\right)$, which is an exponential function of a vector of covariates and a vector of coefficients:

$$\lambda_i(t|\mathbf{z}) = \frac{\beta_i}{\eta_i}\left(\frac{t}{\eta_i}\right)^{\beta_i - 1} exp\left(\mathbf{z}^T\boldsymbol{\gamma}\right) \tag{4.7}$$

The covariates $\mathbf{z} = [z_1, ..z_d]$ represent the effect of different conditions on the rate of tool degradation, and the coefficients $\boldsymbol{\gamma} = [\gamma_1, ...\gamma_d]$ represent the magnitude of these effects.

Let the covariates of the operating conditions of the different production processes be denoted by $\mathbf{z}_i^k$. To study tool reliability over time, the time-dependent nature of the covariates must be expressed by a mapping function that indicates which covariate associated with a given cycle is valid for the i^{th} tool at a given time:

$$\mathbf{z}_i(t) = \mathbf{z}_i^k, \quad \text{if} \quad \tau_i^k < t \leq \tau_i^k + \Delta_i^k \tag{4.8}$$

Based on the above, the hazard function of the Weibull AFT model can be expressed as:

$$\lambda\left(t|\mathbf{z}_i(t)\right) = \frac{\beta_i}{\eta_i}\left(\frac{t}{\eta_i}\right)^{\beta_i - 1} exp\left(\mathbf{z}_i^T(t)\boldsymbol{\gamma}(t)\right) \tag{4.9}$$

Where T is the vector transposition, not to be confused with the number of tools.

The cumulative hazard function $\Lambda(t|\mathbf{z})$ represents the cumulative risk of failure over time under varying conditions. It is defined as the integral of the hazard function $\lambda(t|\mathbf{z})$ from time 0 to time t.

$$\Lambda(t|\mathbf{z}_i(t)) = \int_0^t \lambda(u|\mathbf{z}_i(u))du \tag{4.10}$$

Substituting the baseline hazard function and the time-varying covariates, we obtain:

$$\Lambda\left(t|\mathbf{z}_i(t)\right) = \int_0^t \frac{\beta_i}{\eta_i}\left(\frac{u}{\eta_i}\right)^{\beta_i - 1} exp\left(\mathbf{z}_i^T(u)\boldsymbol{\gamma}(u)\right)du \tag{4.11}$$

The conditional reliability of the tool for a given covariate sequence will be determined by the exponential of the negative cumulative hazard [134]:

$$\begin{aligned} R_i\left(t|\mathbf{z}_i(t)\right) &= exp(-\Lambda(t|\mathbf{z})) = \\ &= exp\left(-\int_0^t \frac{\beta_i}{\eta_i}\left(\frac{u}{\eta_i}\right)^{\beta_i - 1} exp\left(\mathbf{z}_i^T(u)\boldsymbol{\gamma}(u)\right)du\right) \end{aligned} \tag{4.12}$$

This function essentially expresses how tool reliability evolves with varying intensity of use. Figure 4.4 illustrates a reliability curve in the case of a tool that operates under different conditions in each cycle. The sections delimited by the grey vertical lines, the different production cycles. It can be seen that the slope of the reliability curve differs for each stage due to the different $\mathbf{z}_i^k$ covariates.

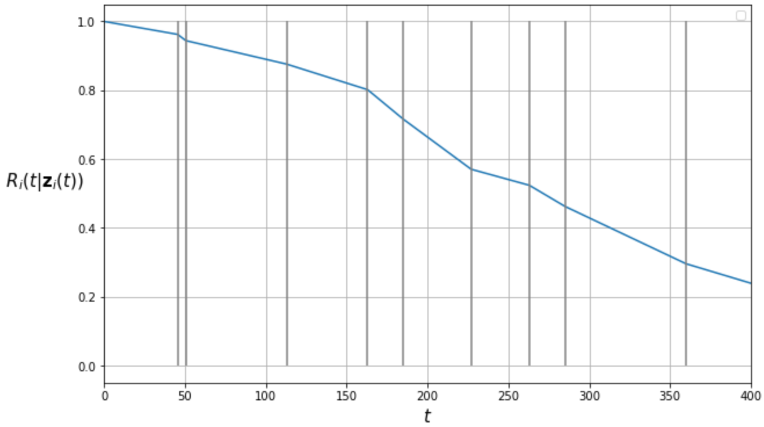

FIGURE 4.4: Illustration of the reliability evolution of a tool that works at different intensities during each production cycle.

The cumulative distribution function or failure function $F_i(t)$ expresses the probability that this tool will fail before t, which is the complement of the reliability function $R_i(t)$:

$$F_i(t|\mathbf{z}_i(t)) = 1 - R_i(t|\mathbf{z}_i(t))$$

Finally, the conditional probability that the tool will fail in cycle k^{th}, given that the failure has not occurred before, can be expressed as the difference between the probability of failure at the beginning and end of the cycle divided by the reliability at the beginning of the cycle [118]:

$$\phi_i^k = \mathbb{P}(t \leq \tau_i^k + \Delta_i^k | \tau_i^k \leq t, \mathbf{z}_i(t)) = \frac{F_i(\tau_i^k + \Delta_i^k | \mathbf{z}_i(t)) - F_i(\tau_i^k | \mathbf{z}_i(t))}{R_i(\tau_i^k | \mathbf{z}_i(t))} \tag{4.13}$$

4.1.3.2 Repairability and availability models of tools

In the context of risk assessment, it is important to consider the availability of tools, as failure may result in production downtime. The knowledge of the reliability model and the probability distribution of repair times can be employed to gain insight into the availability of a tool in a specific period. Availability is calculated as the ratio of operational time and total time. Generally, it is expressed in terms of the ratio of asymptotic mean time between failures $MTBF$ and mean time to repair $MTTR_{rm}$. These indicators use calendar time, which can be useful when the utilization of different assets is equal and continuous. Using the mean operation time between failures $MOTBF$ would be a more appropriate indicator of hectic tool use, but there is a limitation to this indicator, which is that it applies to a time interval from 0 to ∞. The failure rate increases with time, and thus examining the period between τ_i^k and $\tau_i^k + \Delta_i^k$, the average uptime between two failures takes on a different value than if it were examined from the initial startup to the end of the entire lifecycle. The mean resiudal operation times are also different for the different cycles (Figure 4.5). For these reasons, we are interested in a mean operational time only over a specific production cycle, which is bounded by $\mathcal{T}_i^k$ and $\mathcal{T}_i^k + \Delta_i^k$. To calculate the average operating time of a tool in a given cycle, Interval Mean Operation Time (IMOT) is defined, which is calculated in a manner analogous to the restricted residual mean [135]:

$$\begin{aligned} IMOT_i^k &= \mathbb{E}\left(min\left(t, \tau_i^k + \Delta_i^k\right) - \tau_i^k | \tau_i^k < t, \mathbf{z}_i(t) \right) = \\ &= \frac{\int_{\tau_i^k}^{\tau_i^k + \Delta_i^k} R_i(u|\mathbf{z}_i(u))d(s)}{R_i(\tau_i^k|\mathbf{z}_i(\tau_i^k))} \end{aligned} \tag{4.14}$$

The integral in the numerator does not have an analytical solution, but numerical methods can approximate it.

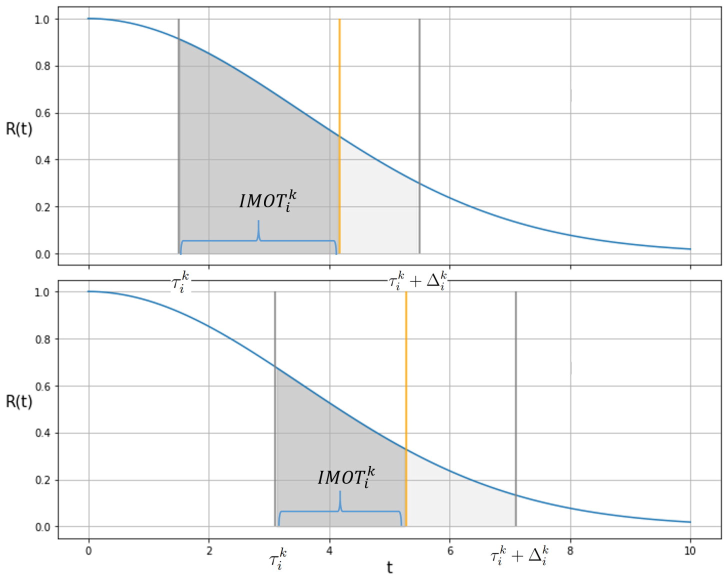

FIGURE 4.5: Illustration of the Interval Mean Operation Time in two difference cycles. The orange vertical lines represent the IMOT values. It can be seen that the IMOT is lower in a cycle when the tool reliability is lower.

Let t^{rm} stand for the repair time of a tool, which is also assumed to be an independent random variable, following a lognormal distribution. The mean repair time of a tool can be obtained as the expected value of this lognormal distribution. However, availability is only relevant within the current production cycle. Therefore, the mean should be calculated as a right-censored distribution. The right truncation point in each k^{th} cycle, is obtained as the sum of the expected operation times of all tools in each cycle:

$$\Delta^k = \sum_{i \in T} \Delta_i^k, \qquad \forall k \in \{1, \ldots, K\} \tag{4.15}$$

Based on the mean value of the truncated lognormal distribution [136], Interval Mean Repair Time $IMR_{rm}T$ indicator can be defined for each k^{th} cycle (Figure 4.6):

$$\begin{gathered} IMR_{rm}T_i^k = \mathbb{E}\left(t^{rm} | t^{rm} < \Delta^k\right) = \\ exp\left(\mu_i^{rm} + \frac{\sigma_i^{rm^2}}{2}\right) \frac{\Phi\left[\frac{ln(\Delta^k) - \mu_i^{rm} - \sigma_i^{rm^2}}{2}\right]}{\Phi\left[\frac{ln(\Delta^k) - \mu_i^{rm}}{2}\right]} \end{gathered} \tag{4.16}$$

where μ_i^{rm} is the location parameter, σ_i^{rm} is the shape parameter, $\Phi(.)$ is the CDF of normal distribution, and rm superscript refers to the repair time distribution.

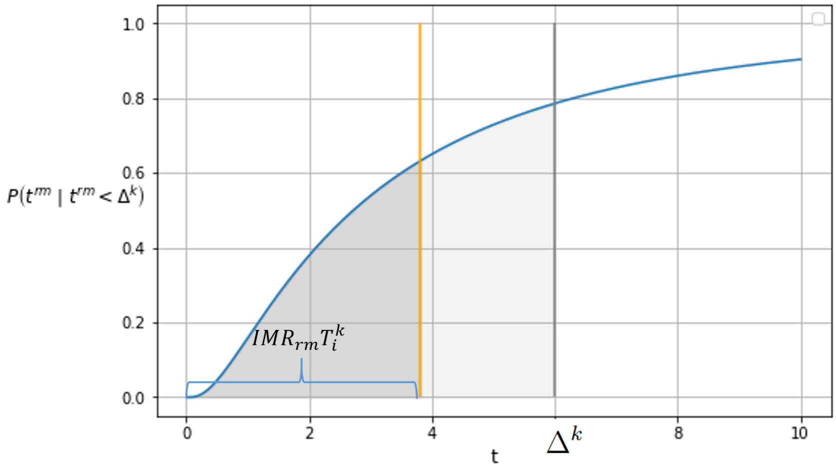

FIGURE 4.6: Illustration of the Interval Mean Repair Time. The orange vertical line represents the $IMR_{rm}T_i^k$value.

On the basis of the expected values presented above, the availability indicator of the i^{th} tool during the k^{th} cycle is expressed as follows:

$$A_i^k = \frac{IMOT_i^k}{IMOT_i^k + IMR_{rm}T_i^k} \tag{4.17}$$

This can be interpreted as the predicted value of the availability indicator of OEE in the k^{th} cycle.

4.1.3.3 Maintenability model of tools

Typically, there is a limited amount of time available to perform maintenance activities. Therefore, it is necessary to model the time requirements of these activities.

Let t^{pm} denote the planned maintenance or replacement time of a tool, which is assumed to be also an independent variable with lognormal distribution. The mean time demand of the planned activity in the interval of k^{th} cycle can be expressed similarly to the $IMR_{rm}T$ (Equation 4.16):

$$IMR_{pm}T_i^k = \mathbb{E}\left(t^{pm}|t^{pm} < \Delta^k\right) = \\ exp\left(\mu_i^{pm} + \frac{\sigma_i^{pm^2}}{2}\right) \frac{\Phi\left[\frac{ln(\Delta^k)-\mu_i^{pm}-\sigma_i^{pm^2}}{2}\right]}{\Phi\left[\frac{ln(\Delta^k)-\mu_i^{pm}}{2}\right]} \tag{4.18}$$

where pm superscript refers to the context of planned maintenance or replacement time distribution.

4.1.4 Formulation of risk-based tool maintenance selection as an optimization problem

This section presents the proposed risk evaluation and optimization model for the risk-based selection of tools to maintain. Based on the available production program, system information, and the expected values derived from the probability models described above, a cost function is defined that incorporates the financial risks of both under and over-maintenance.

4.1.4.1 Risk evaluation model

The risk evaluation model has two inputs. One is the probabilities of undesired events, such as failure and downtime, represented by expected values including the conditional probabilities of tool failure in the k^{th} cycle, conditional on the tool having previously operated without failure ϕ_i^k, and the predicted availability indicators in the k^{th} cycle A_i^k. These probabilities are estimated using the reliability model (Subsection 4.1.3.1), availability model (Subsection 4.1.3.2), and maintainability model (Subsection 4.1.3.3). They depend on the predicted operating times derived from the production plan (τ_i^k, Δ_i^k), the maintenance decisions x_i^k (represented in matrix form by $\mathbf{X}$ with dimensions $K \times T$), and the historical operating conditions encoded in the covariate vectors $\mathbf{z}_i^k$ and their associated coefficients $\boldsymbol{\gamma}$.

The other input set represents the criticality of the consequences of the undesired events. This is determined by two factors: on the one hand, the financial costs, including the prices of the products pr_j and the maintenance costs c_i^r and c_i^p, and on the other hand, the available production-related information, including the operating times of the tools on each product p_{ji}, the product quantity N_j^k to be produced in each k^{th} week. To quantify the financial cost of downtime, unit production values are derived from product prices. Unit production values are the ratio of the price of the product to the sum of the required processing times:

$$r_j = \frac{pr_j}{\sum_{i \in T} p_{ij}}, \quad \forall j \in P \tag{4.19}$$

The output of the model is the total risk of the system in each production cycle. The risk function has four components. The first represents the risk of production losses in the current cycle. It is essentially the product of the unit production values and production time increments due to stoppages:

$$\begin{gathered} \mathcal{R}_{1,i}^{k}\left(\mathbf{X}\right) = \sum_{j \in P} \left(1 - A_i^k\right) p_{ji} N_j^{(k)} r_j, \\ \forall i \in T, \forall k \in \{1, \ldots, K\} \end{gathered} \tag{4.20}$$

The second term represents the reactive maintenance risk, which is the product of the failure probability (which corresponds to the repair probability) and the repair cost:

$$\mathcal{R}_{2,i}^{k}\left(\mathbf{X}\right) = \phi_i^k c_i^r \tag{4.21}$$

The third component is the risk of over-maintenance in the current cycle. The binary decision variable x_i can also be interpreted as the probability of selection. Multiplied by the maintenance cost, this term can be interpreted as the financial risk of the planned maintenance:

$$\mathcal{R}_{3,i}^{k}\left(\mathbf{X}\right) = x_i^k c_i^p \tag{4.22}$$

The time window available for planned maintenance is determined by the duration of the k^{th} production cycle. Thus, the sum of the average planned maintenance activity times of the selected tools should not exceed the sum of the expected operating times of the working tools in this cycle. The maintenance time that extends into the next cycle reduces the availability in that cycle. Therefore, a loss function is defined as the product of the availability reduction of the next cycle and the production value of the next cycle that should be produced by the tools being maintained in the current cycle:

$$\mathcal{R}_{4,i}^{k}(\mathbf{X}) = \begin{cases} 0 & \text{if } \Delta_i^{k+1} = 0 \\ \sum_{j \in P} \max\left(0, \frac{\sum_i IMR_{pm} T_i^k x_i^k - \Delta^k}{\Delta_i^{k+1}}\right) x_i^k p_{ji} N_j^{(k+1)} r_j & \text{if } \Delta_i^{k+1} \neq 0 \end{cases} \tag{4.23}$$

The third and fourth terms represent the financial losses due to the over-maintenance. The risk function for a given cycle is obtained by summing the above expressions for each tool:

$$\mathcal{R}^k(\mathbf{X}) = \sum_{i \in T} \left(\mathcal{R}_{1,i}^k + \mathcal{R}_{2,i}^k + \mathcal{R}_{3,i}^k + \mathcal{R}_{4,i}^k \right) \tag{4.24}$$

4.1.4.2 Risk-based optimization for tool selection

The objective of the proposed method is to find the selection solution that minimizes overall risk over the entire planning horizon. The mathematical formulation for this optimization problem is presented below:

$$\min_{\mathbf{X}} \mathcal{R}(\mathbf{X}) = \sum_{k \in K} \left(\mathcal{R}^k(\mathbf{X}) + q^k(\mathbf{X}) \right) \tag{4.25}$$

subject to:

$$x_i^k = 0 \quad \text{if} \quad p_{ji} \neq 0 \tag{4.26}$$

$$y_i^k = 0 \quad \text{if} \quad \sum x_i^k = 0 \tag{4.27}$$

$$y_i^k = 1 \quad \text{if} \quad \sum x_i^k > 0 \tag{4.28}$$

$$z_i^k = k \quad \text{if} \quad x_i^k = 1 \tag{4.29}$$

$$z_i^k = 0 \quad \text{if} \quad \sum y_i^k < 1 \tag{4.30}$$

$$z_i^k = \max\{l | x_i^l = 1 \quad \text{and} \quad x_i^{l+1} = 1 \quad \text{for} \quad l = 1, 2, ..., k-1\} \tag{4.31}$$

where $q^k(\mathbf{X})$ is a penalty function associated with soft constraint. The risk of any production job does not exceed the maximum acceptable risk R_{max} at any cycle, and therefore, a loss function is defined for each k^{th} cycle to penalize it:

$$q^k(\mathbf{X}) = \max\left(0, \mathcal{R}^k(\mathbf{X}) - R_{max}\right) \tag{4.32}$$

The first constraint (Equation 4.26) ensures that tools required for production in a given cycle are not selected for maintenance in that same cycle. The second and third constraints (Equations 4.27 and 4.28) define the binary variable y_i^k, which indicates whether planned maintenance has occurred up to and including cycle k. The fourth, fifth, and sixth constraints (Equations 4.29, 4.30, and 4.31) determine the value of z_i^k, which stores the index of the last cycle in which the i^{th} tool was maintained prior to or during cycle k.

The proposed objective function accounts for both the operational role and criticality of each tool as defined by the production plan. As such, it enables maintenance scheduling to adapt dynamically to the changing conditions of a flexible manufacturing environment over the planning horizon.

4.1.5 Finding the best solution by genetic algorithm

In this optimization problem, each point in the search space represents a possible tool maintenance assignment plan.

GA, which is a population-based metaheuristic algorithm that approximates the optimum by applying the mechanics of natural selection and evolution [137], is chosen to find the best solution in this method because of the following reasons:

- Non-linear and and discontinuous functions are involved in the model. The GA can optimize these complex functions without requiring differentiability.
- The solution space is made up of discrete decisions. GA works well with discrete representations of potential solutions, making it ideal for combinatorial optimization problems where decisions are not continuous but categorical or binary.
- Multiple objectives conflict with each other (think about preventive or reactive costs of maintenance). GA is well-suited for multi-objective optimization as it can maintain a diverse population of solutions that represent different trade-offs among objectives.

The operation of the algorithm is described as follows:

The operation starts with a random initial population, which is an N_{pop} number of possible solutions called individuals or genomes/chromosomes. A genome is represented by a vector of independent variables, whose elements are called genes. A fitness function evaluates each individual with respect to the objective function and assigns a fitness score that represents reproductive potential. Individuals are selected for reproduction with probability corresponding to their fitness score in the selection process. The selection operator can be implemented in several ways, such as roulette wheel selection or tournament selection. Next, the genetic information of pairs of selected individuals, called parents, is recombined to create a new population using the crossover operator. Several approaches are available, including single-point, multi-point, and shuffle crossover. The selection operator does not guarantee the selection of the fittest individuals, so the elitism operator is used to ensure the convergence of the algorithm by retaining the fittest individuals at each generation. The mutation operator aims to maintain diversity in the populations in order to avoid getting stuck in local optima by randomly varying the genes with a low probability denoted by p_{mut}. Bit flipping and inversion are commonly used mutation operators. The algorithm iterates for a predefined number of generations N_{gen} or until it reaches a predefined termination criterion.

Determining the appropriate individual representation is a crucial task in GA. The most common choice is binary encoding. In this scheme, the genome is a string composed of binary values, where each bit represents the characteristics of a solution.

In our problem, binary encoding is obvious because the decision variable x_i^k is also binary. A binary vector $\mathbf{x}$ of length $k \times i$ can be obtained by the vectorization of $\mathbf{X}$. However, due to the constraint that the selection of tools used in a given cycle is forbidden, not all elements in $\mathbf{x}$ can be freely modified. This constraint can lead to invalid solutions during mutation.

To ensure feasible solutions, the search space should be restricted. We encode only the elements of $\mathbf{X}$ as genes where maintenance decisions can be freely made. Based on the expected operating times Δ_i^k we define a mask matrix $\mathbf{M}$ with $k \times i$ dimensions such that:

$$\mathbf{M}_{i,k} = \begin{cases} 0 & \text{if } \Delta_i^k \neq 0 \\ 1 & \text{if } \Delta_i^k = 0 \end{cases} \tag{4.33}$$

Using the mask, the binary vector $\hat{\mathbf{x}}$ is formed by selecting elements of $\mathbf{X}$ corresponding to the 1's in $\mathbf{M}$. Let I be the index set where $\mathbf{M}$ is 1:

$$I = \{(i,k) \mid \mathbf{M}_{i,k} = 1\} \tag{4.34}$$

Thus, the binary vector $\hat{\mathbf{x}}$ is:

$$\hat{\mathbf{x}} = \{x_{i,k} \mid (i,k) \in I\} \tag{4.35}$$

This formalization ensures that the genom $\hat{\mathbf{x}}$ only includes feasible decision variables, maintaining the integrity of the solution space.

Let g superscript be the generation counter and h be the index of an individual. New genomes $\hat{\mathbf{x}}^{(g+1,h)}$ are created by performing genetic operators on the members of the previous generation $\hat{\mathbf{x}}^{(g,h)}$. Prior to the evaluation, the values of the vector $\hat{\mathbf{x}}^{(g+1,h)}$ are substituted back into $\mathbf{X}$, while the other entries are set to zero.

$$\begin{aligned} x_{i,k\notin I}^{(g+1,h)} &= 0 \\ x_{i,k\in I}^{(g+1,h)} &= \hat{x}_{i,k}^{(g+1,h)} \end{aligned} \tag{4.36}$$

The newly formed $\mathbf{X}^{(g+1,h)}$ is assessed using the risk function as defined in Equation 4.24. The fitness of the genome is calculated on the basis of the evaluation. The fitness function must ensure that the fitness score takes a higher value in the case of a lower risk. Therefore, the fitness function of the h^{th} genome $\hat{\mathbf{x}}^{(g,h)}$ in the g^{th} generation can be calculated based on the reciprocal of the risk. The numerator is set to 10^6 to ensure that the fitness value is between 1 and 10.

$$\mathcal{F}_{(g,h)} = \frac{10^6}{\mathcal{R}(\mathbf{X}^{(g,h)})} \tag{4.37}$$

where $\mathbf{X}^{(g,h)}$ is the decision matrix formed based on $\hat{\mathbf{x}}^{(g,h)}$ and $h = 1, ..., N_{pop}$.

4.2 Demonstration of the proposed maintenance optimization method through a numerical example

The application study of the proposed methodology is demonstrated using a numerical example. In the example, we simulate a manufacturing environment where 26 metalworking machine tools are used to produce 20 different products. Probability distribution models associated with the tools are generated on the basis of relevant models found in the literature by adding zero-centered, low-variance normal distributions to the model parameters found in the studies listed below. Machine tool reliability model parameters are generated based on the model in Ref. [138]. The factors that accelerate aging in this model are cutting force and the number of tool changes. The parameters of the repair time distribution models are generated based on the model in Ref. [139]. The parameters of the planned maintenance activity time distribution models are generated based on the model in Ref. [140]. Data on product tooling requirements comes from real machine tools in a metalworking shop. Production information, prices, and costs were not available, so their values are arbitrary. The production plan contains $K = 100$ production orders. The maximum acceptable risk value $\mathcal{R}_{max}$ is chosen so that for an average tool model, average operating conditions, and average production value, the risk remains below this value for at least 10 production cycles.

Figure 4.7 illustrates the evolution of the reliability of a specific tool as an example, given the model parameters applied and the production plan. The vertical gray lines indicate the endpoints of the production cycles. On the reliability curve, breaks can be observed at the endpoints of the cycles, as the rate of decrease in reliability varies with changing manufacturing conditions in each cycle.

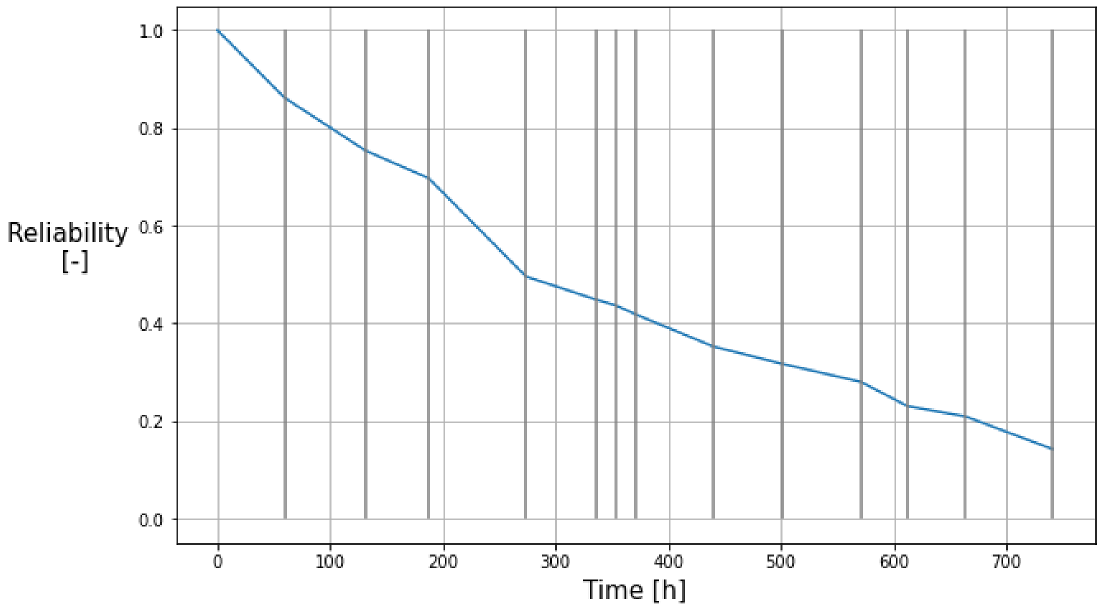

FIGURE 4.7: Reliability evolution of the 16^{th} tool according the planned production sequence.

To provide a point of reference, the proposed method is compared against a reactive and a static threshold-based scheduling approach inspired by reliability-centered maintenance (RC). [127] In the reactive approach, risk is calculated under the assumption that no planned maintenance occurs. In the RC approach, maintenance is scheduled in the first feasible cycle following a drop in reliability below a given threshold. In other words, maintenance is triggered once reliability falls below a predefined level. This comparison serves two purposes. First, it allows us to highlight the advantages of the genetic algorithm in capturing dynamic and system-wide interdependencies. Second, it demonstrates that the proposed risk evaluation model can also guide simpler decision rules in static settings, thus underlining its flexibility and broader applicability beyond optimization contexts.

Thresholds are set as integers from 0 to 100, where 0 corresponds to the reactive approach. The total risk is calculated for each threshold.

In the best-performing RC scenario, the proportion of applied planned maintenance actions was low. This insight was used to inform the initialization of the GA, accelerating its convergence. Specifically, the probability of assigning a value of one in the binary solution vectors was set to 10%.

The parameters used for the GA were:

- Population size (N_{pop}): 100 Number of generations (N_{gen}): 4000
- Mutation probability (p_{mut}): 0.01

Roulette wheel selection was used as the selection method. A single-point crossover operator was applied, with the crossover point selected randomly and uniformly. The bit-flipping mutation operator was employed, randomly inverting one bit in the genome. Elitism was also applied, preserving the two fittest genomes in each generation.

4.2.1 Results of the application of the method

First, the risk was calculated as a function of different reliability threshold settings (Figure 4.8). The curve suggests that excessive maintenance can lead to significantly higher financial costs.

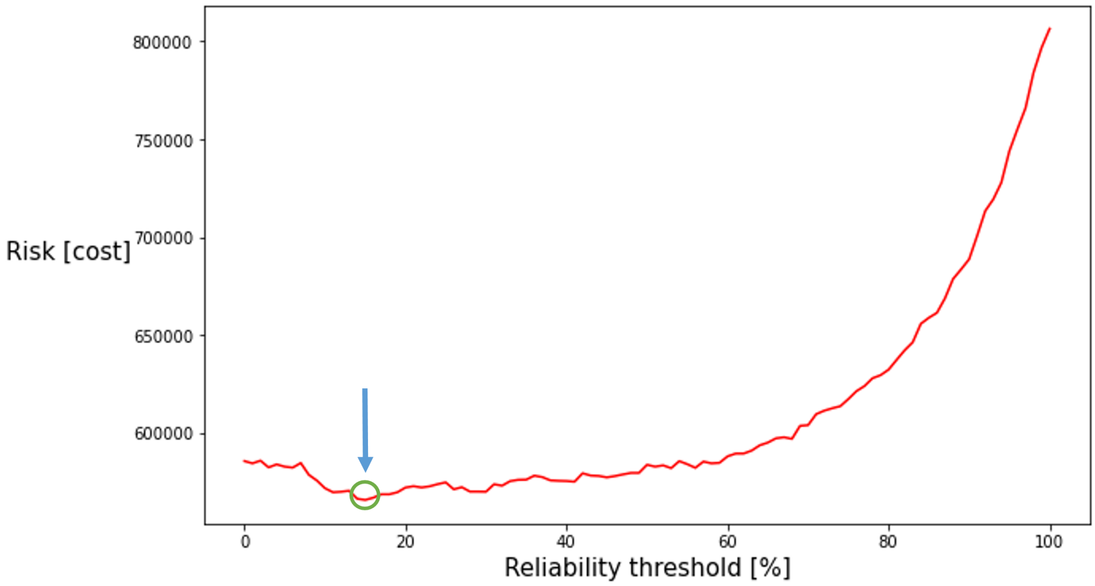

FIGURE 4.8: Evolution of risk value in the case of planned maintenance triggered by different reliability thresholds. The green marker indicates the minimum of the curve.

As can be seen on the figure, the best choice was to set the threshold to 15%. In this case, the total risk would be 565768. A heatmap (Figure 4.9) illustrates which tool maintenance is scheduled in which production cycle for this strategy. In total, 16 tool maintenance events are scheduled in the planning horizon.

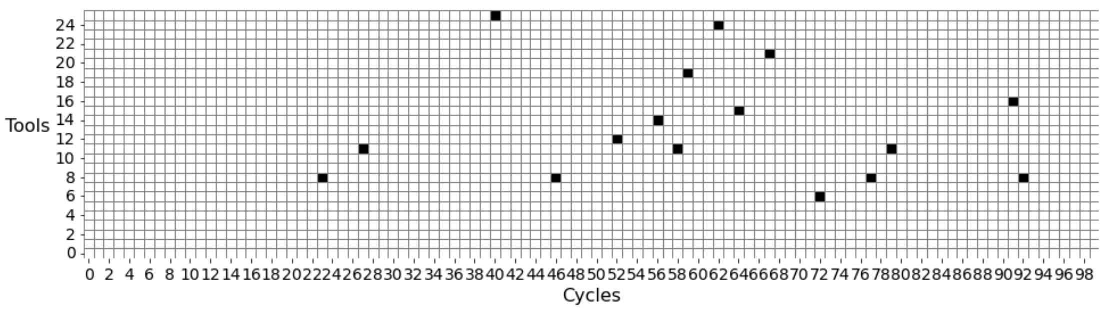

FIGURE 4.9: Heatmap showing the assignment of planned tool maintenance events (cells with black filling) to opportunity cycles in the case of a 15% reliability threshold triggered maintenance strategy.

Next, the optimization was performed. Figure 4.10 shows the evolution of the population fitness during the evolutionary optimization process. The plot shows that there is no significant increase in the best fitness values after the 1000^{th} generation, while the population diversity increases.

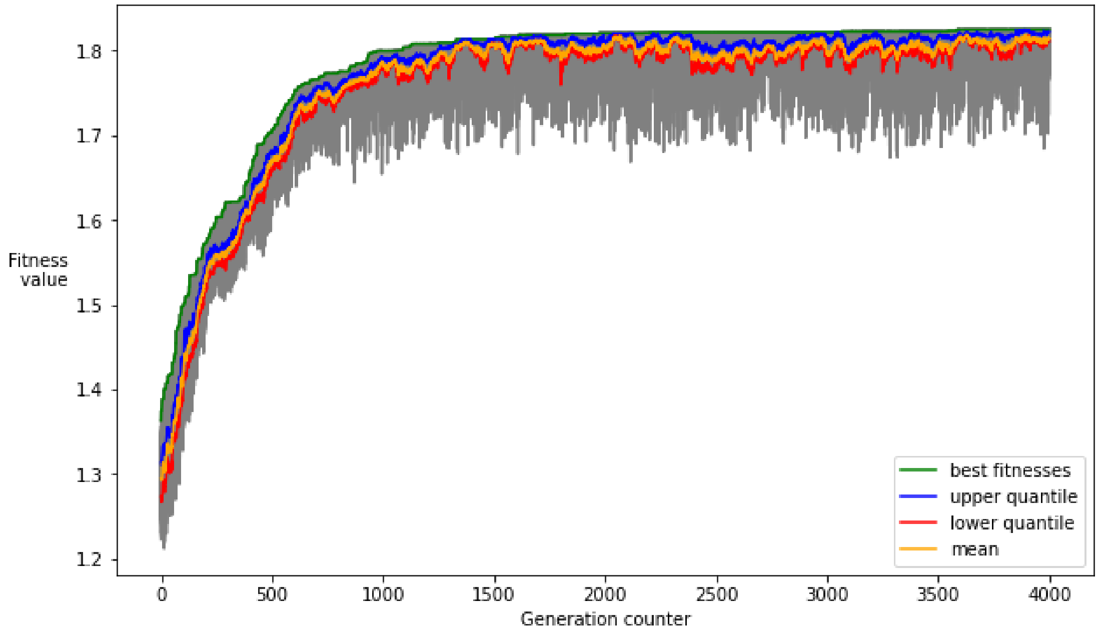

FIGURE 4.10: Illustration of the evolution of the population fitness during the genetic process. The gray lines show the fitness of the individuals.

The risk associated with the best solution found by the genetic algorithm was 548145. A heatmap illustrates the assignment of maintenance work to tools in different cycles (Figure 4.11). In total, 26 tool maintenance events are scheduled in the planning horizon according to this solution.

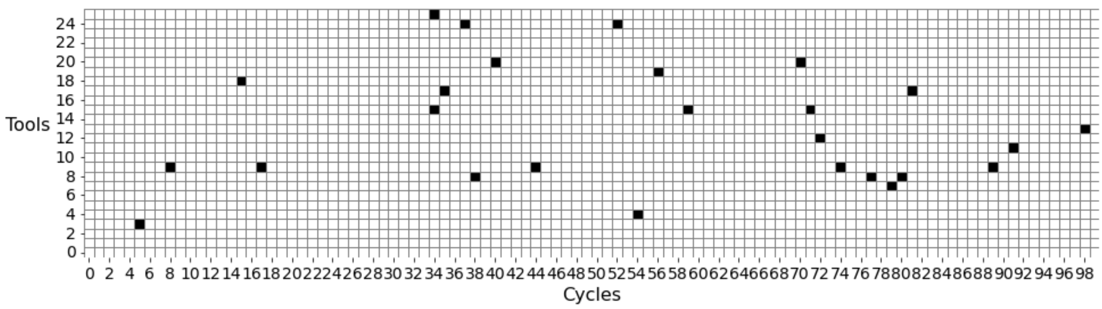

FIGURE 4.11: Heatmap showing the assignment of planned tool maintenance events (cells with black filling) to opportunity cycles in the case of the GA-optimized maintenance strategy.

This selection resulted in 3% less financial risk even compared to the best RC setting. This selection prescribes more planned maintenance activity. This can be explained by the fact that the algorithm finds those cases where the cost of unexpected failures exceeds the cost of prevention. This could be due to several reasons: the price of the product to be manufactured is higher, its manufacture requires more processing time, or the planned maintenance cost is lower in the case of that tool.

The results also suggest that a selection strategy based on a single reliability threshold can result in significant savings while being more advantageous in terms of computational requirements. The proposed dynamic risk evaluation function is suitable for determining the optimal reliability threshold, thus supporting a predictive reliability-centered maintenance strategy.

4.3 Concluding remarks and future directions

In a dynamic manufacturing environment, the utilization and criticality of tools, and therefore their risk profile, is constantly changing. When planning maintenance, risks must be evaluated dynamically, taking into account the impact of the production plan on the probability of failure and the consequences of failure.

The research proposes a method for selecting maintenance tasks that employs a dynamic risk evaluation formula, which takes the current production schedule into account. The formula quantifies the risks associated with both inadequate and excessive maintenance, including the potential for production losses and the costs associated with maintenance. An objective function is formulated based on the risk evaluation function and applied in a genetic algorithm to assign tool maintenance activities to different maintenance opportunity windows, thus minimizing the total risk to the system.

The proposed method is demonstrated through a numerical example. The optimal tool maintenance assignment is determined using data from a model manufacturing environment. The result of optimization was compared with a reliability-centered maintenance strategy at different reliability thresholds. The work order selection determined by the optimization resulted in a lower risk than that achievable with a uniform reliability threshold-induced maintenance strategy. The risk assessment formula can also be used to fine-tune the threshold levels.

The study has some limitations. In the absence of real production and maintenance data, the model is tested only on a simulated example with arbitrarily generated data. Testing its application on real data would be beneficial to refine and validate these approaches in production environments. Future work should focus on bridging the gap between academic research and practical implementation, ensuring that this methodology contributes to real-world efficiency gains. The model considers only one failure mode. If domain-specific knowledge is available, it can be used to extend the model with other failure modes. To reduce complexity, the method applies the two "extreme" maintenance models, perfect repair and minimal repair. In practice, however, the effectiveness of repair activities lies between these two. It would be worth exploring the possibility of incorporating improvement factor or other maintenance models into the risk model. In real-world scenarios, tool degradation results in increasing scrap rates before the tool loses its ability to perform its function. By using probability distributions of defective production and its expected values, the risk model could be extended to include quality loss.

Chapter 5

Conclusions and thesis findings

This research aims to develop machine learning-based methods to support tool management. Tool management is a complex task that must manage many interdependencies, constraints, and stochastic processes. The primary role of tool management is to ensure that the right tool is in the right place at the right time to keep the production running smoothly. This can be achieved through proper planning of tool allocation and maintenance. A well-designed maintenance system guarantees that tools are available in the right condition and able to perform their function. Thoughtful allocation ensures that they are in the right place at the right time where they are needed. Monitoring tool utilization is also an important part of tool management. The awareness of a detailed tool life history is a prerequisite for an optimized maintenance plan. It helps to highlight the shortcomings of the current tool allocation plan allowing for continuous improvement. Moreover, monitoring the activity and usage of production tools helps to gain insight into manufacturing processes and understand their business value. By replacing traditional, data-sparse, manual decision-making processes with probabilistic, data-driven prediction and optimization approaches, tool management can ensure the flexibility and adaptability of the manufacturing enterprise. Based on this motivation, methodologies for tool allocation, tool monitoring, and tool maintenance are proposed.

As a graphical summary, Figure 5.1 represents the discussed theoretical and practical sections of my research.

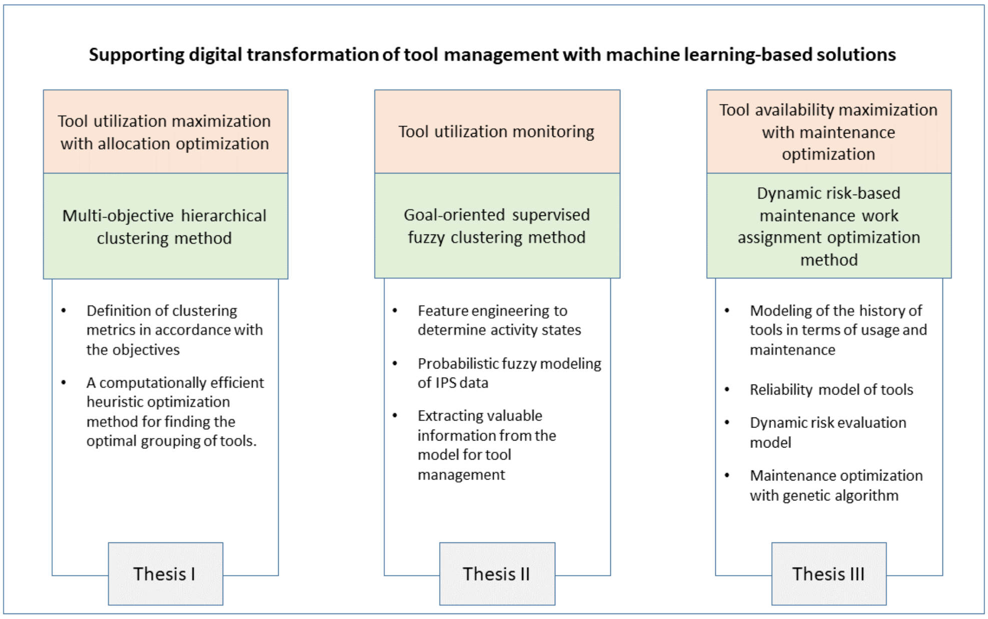

FIGURE 5.1: The graphical summary of thesis findings. The orange boxes represent the problem areas and the green boxes represent the solutions developed for them. Gray boxes indicate which thesis (see below) belongs to which area.

Reducing the number of changeovers and increasing asset utilization can be achieved by optimizing tool allocation. I introduced a multi-objective hierarchical clustering method suitable for tool allocation optimization. After a brief introduction to the topic, the problem is formulated and mathematically formalized in two ways. First, it is formalized as a bin-packing problem, and then the proposed heuristic optimization-based clustering is presented, describing the defined clustering metrics and applied heuristic rules that form the basis of the method. The two approaches are then demonstrated through an industrial example of a metalworking manufacturer and contrasted in terms of allocation effectiveness and computational efficiency. The advantages of the proposed method over the traditional one are highlighted.

Reliable utilization monitoring techniques are critical to improving tool-related processes. I presented a supervised fuzzy clustering method suitable for identifying relevant places on the shop floor and estimating the utilization of assets at those locations. The problem formulation, the feature engineering procedure, the description of the probabilistic modeling, the description of how the probabilistic approach forms the basis of fuzzy clustering, and a description of the business-oriented interpretation of the results are presented. The applicability of the proposed method is demonstrated through an industrial example of a wire harness factory.

In the case of a flexible manufacturing system, tool maintenance planning must take into account the changing production and demand. I proposed a risk-based optimization method that can be used to find the most opportune times to perform tool maintenance tasks under varying production conditions. After a brief introduction to the topic, the maintenance assignment task is formulated. Models of tool life history and tool condition are introduced. A risk assessment function is presented that takes into account the dynamic factors of the manufacturing environment. The risk-based genetic optimization technique for finding the best maintenance task assignment is described. A numerical example is used to demonstrate the application of the proposed method.

The following list summarizes my scientific results in three thesis findings:

Thesis I.

I developed a heuristic multi-objective optimization-based clustering method for the tool allocation problem, which provides a feasible solution that approximates the result of the full optimization algorithm with lower computational requirements [64].

> Due to the limited tool magazine capacities of machines, time-consuming tool changeovers result in inefficient equipment utilization. A method is developed to minimize the changeovers by optimizing the allocation of the tools to the machines. The proposed algorithm is efficient as it approaches the tool assignment task as a multi-objective hierarchical clustering problem where the products are grouped based on the similarity of the tool demands. During the agglomerative clustering process, two objectives are pursued: the size of the resulting product group should be as small as possible, and the overlap between the tool requirements of the group members should be as large as possible. The novelty of the goal-oriented agglomerative clustering algorithm is that it is based on the Pareto optimal selection of the merged clusters. The tool assignment problem has also been formulated as a bin-packing optimization task, and the results of the related linear programming were used as a benchmark reference. The comparison highlighted that the proposed method provides a feasible solution for large real-life problems with low computation time.

Thesis II.

I developed a location-based utilization monitoring methodology that can be implemented based on position data, using information revealed by clustering algorithms [65].

Indoor positioning systems allow real-time tracking of tool locations. Tool utilization can be calculated based on positional data of the storage and manufacturing areas. Due to the uncertainty of the position measurements, estimation of the state of the tools is problematic when the distance between the examined zones is less than the estimation error. I proposed a goal-oriented supervised fuzzy clustering algorithm that utilizes the activity state of the tool, as the algorithm simultaneously maximizes the spatial distribution probability and the probability of a specific activity state occurring in a cluster. By weighting the data points according to the time spent in the associated states and positions, valuable information can be extracted. The resulting clusters represent relevant locations on the shop floor. They can be categorized based on the temporal probabilities of different activity states of the cluster. The temporal probability of finding a tool in an active state can be interpreted as its utilization, which can be calculated both in general and for location.

Thesis III.

I developed a maintenance optimization methodology that can optimize maintenance under changing manufacturing conditions with a risk evaluation model that considers dynamic failure probability and criticality.

Flexible manufacturing systems represent a rapidly changing environment in which a large number of manufacturing tools are used for production, with multiple interdependencies between them. As a result, the improper condition of any tool can pose a significant risk to the performance and availability of the system. Risk-based maintenance approaches seek to minimize the risks of both over- and under-maintenance. Traditional methods assume that the assessed risks are constant, which in many cases does not reflect the dynamic nature of flexible manufacturing systems. On the one hand, the probability of adverse events increases due to tool wear which is a function of the operating times and conditions, and on the other hand, the severity of the consequences of these events depends on the current production schedule. I proposed an optimization algorithm to find the optimal selection and allocation of maintenance work that minimizes the overall risk. The objective function includes the probabilities of adverse events, obtained from tool reliability models, and the costs of lost production, over-maintenance, and under-maintenance as a result of these events, taking information about the system and current production orders into account. A genetic algorithm is used to find the best solution, where the fitness function is based on the risk evaluation function.

This research has contributed to developing machine learning-based Industry 4.0 solutions for tool management, specifically in tool allocation, monitoring, and maintenance planning. These methodologies can be utilized in flexible manufacturing systems (FMSs) to improve efficiency, reduce downtime, and optimize resource allocation. The multi-objective hierarchical clustering approach for tool allocation could support manufacturers in better scheduling and utilization of tools, while the goal-oriented supervised fuzzy clustering method enhances real-time monitoring in production environments. The risk-based maintenance planning approach offers a dynamic and adaptive method for scheduling maintenance, which can significantly reduce unexpected failures and costs.

In terms of real-world applications, these methods can be integrated into smart manufacturing systems, Manufacturing Execution Systems (MES), and Computerized Maintenance Management Systems (CMMS). Further collaborations with industry partners could facilitate real-world validation and deployment.

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