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ORIGINAL ARTICLE

Identifying and evaluating suitable tasks for autonomous industrial mobile manipulators (AIMM)

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Abstract This paper investigates the application potential for the technology-push manufacturing technology (TPMT) autonomous industrial mobile manipulation (AIMM), in order to link the conceptual ideas (academia) to actual manufacturing requirements (industry). The approach is based on the proposed TPMT methodology in a comprehensive industrial case study. More than 566 manufacturing tasks have been analyzed according to three main application areas (logistics, assistance, and service) to find their suitability for the AIMM technology. The conducted TPMT analysis shows that AIMM has great potential within the manufacturing industries. More than two thirds of the analyzed manufacturing tasks are solvable with AIMM within the next few years. The AIMM technology, at its current stage, finds most suitable applications within logistics (e.g., transportation and part feeding), moving toward assistance (e.g., (pre)assembly and machine tending), and in the future more service-minded tasks (e.g., maintenance and cleaning). Based on the identified real-world applications, it is possible to raise the AIMM technology to the next levels of industrial maturation, integration, and commercialization.

Keywords Autonomous industrial mobile manipulation (AIMM) · Manufacturing environment · Industry · Applications · Production analysis · TPMT methodology

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1 Introduction

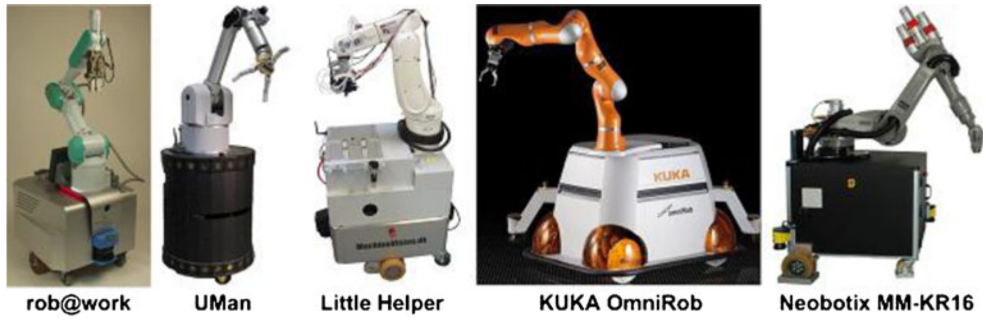
1.1 Autonomous industrial mobile manipulation

Today, robots are widely used in the manufacturing industries to perform dumb, dangerous, dull, and dirty tasks. However, the industrial robots of today are rather inflexible as they are often dedicated and/or fixed. To extend the application prospective of industrial robotics, it is rational to combine locomotion capabilities with manipulation abilities, hereby creating autonomous industrial mobile manipulators (AIMM). The mobility extends the workspace of the robot manipulator, which increments its operational capability and flexibility. Compared to traditional industrial robots, it is easier for mobile manipulators to adapt to changing environments and perform a wide variety of manufacturing tasks [1]. Furthermore, the industrial environments do not have to be altered as in the case of automated guided vehicles, where permanent cable layouts and/or markers are required for navigation [2]. The conventional architecture of AIMM is a robot manipulator mounted upon a mobile platform, extended by a vision and tooling system, respectively [3]. State-of-the-art examples are shown in Fig. 1.

The rationale of AIMM is to seek an optimum between traditional automation and manual labor with the benefits of a compromise between efficiency and flexibility. Furthermore, AIMM robots are intended to be flexible and versatile automation solutions that are simple to use, so they become plug and produce. Thus, AIMM robots must be able to:

- Work with or alongside people
- Operate fully automatic and serve usual manufacturing equipment

Fig. 1 State-of-the-art AIMM examples [4–8]. Integration of mobile platform, robot manipulator, vision, and tooling



- Carry out versatile operations at different workstations in typical industrial environments

In Fig. 2, the general concepts of AIMM are shown in a representative industrial environment. The mobile manipulators carry out their missions by navigating between workstations and performing diverse manufacturing tasks. They avoid any obstacles they may encounter in their paths by using various sensors, e.g., laser scanners, ultrasonic sensors, and/or vision cameras. In order to achieve autonomous use of the mobile manipulators, an a priori layout of the industrial environments must be given, ranging from semi to fully structured [6].

1.2 Potential tasks and applications for AIMM

Despite considerable attention within the academic part of AIMM and definite needs for flexible automation in the industry, deployments of autonomous mobile manipulators in real-world manufacturing environments and applications have been limited to conceptual studies (e.g., [2–4]). The lack of industrial implementations is somehow related to the conservatism in the manufacturing industries, but the main reason is that the research efforts have been technology driven. Therefore, the focus has been on individual technologies (hardware) and specific algorithms (software), while aspects like integration, implementation, and application have been neglected. The underlying ideas of AIMM are in place, and the technology has been tested in several laboratory experiments (e.g., [9, 10]). Now it is time to put the technology to the test in industrial environments to explore the real potential of AIMM. However, there is a need for identification and evaluation of real-world industrial applications for the AIMM technology to link the conceptual ideas (academia) to manufacturing requirements (industry). Already, a large number of research roadmaps have focused on the future use of robotics in home-care, health-care, military, space, and

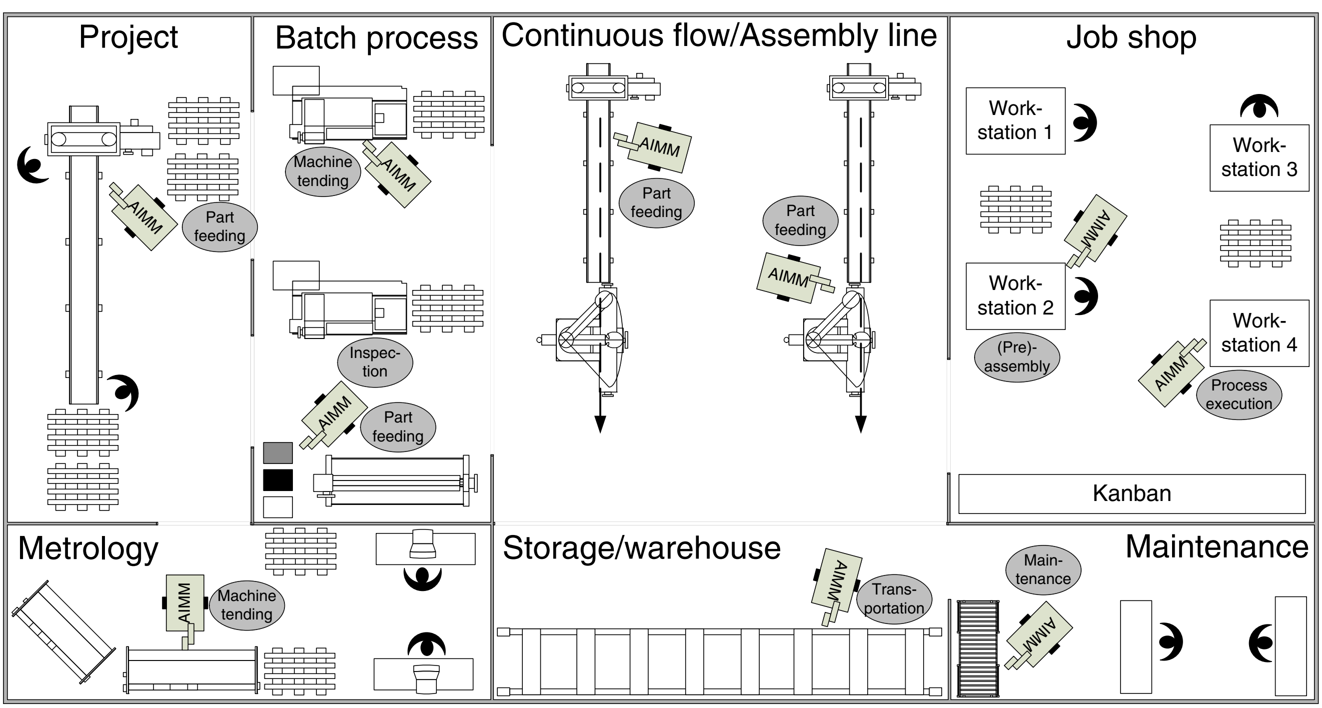


Fig. 2 Context and concepts of AIMM in a representative industrial environment

manufacturing (e.g., [11–13]). Several of these include considerations about promising applications for autonomous mobile manipulators in industrial environments. An overview is provided in Table 1, based on the application categories: assistive, logistics, and service.

In the following, we explore which of the potential tasks and applications are actually most suitable for the AIMM technology in practice. This is based on utilization of the technology-push manufacturing technology (TPMT) methodology in a comprehensive industrial case study. The rest of the paper is structured as follows: The next section presents the proposed TPMT methodology from a theoretical and functional point of view. Section 3 provides an overview of the framework for the industrial case study. Section 4 contains the analyzing part, where the TPMT methodology is applied to the AIMM technology in real-world industrial environments and applications. Section 5 includes the evaluation and interpretation of the case study results with focus on identification and classification of suitable tasks and future trends for the AIMM technology. The final section provides the conclusions and recommendations for future work.

2 The technology-push manufacturing technology methodology

2.1 Motivation

New technologies looking for applications are rather common, and the ability to identify and assess opportunities is seen as a major driver for market success. Many approaches for identifying opportunities and/or applications for technology-push products exist (e.g., [14–18]), but they are primarily related to consumer products. However, within the industrial sectors, approaches for identifying and evaluating applications for technology-push technologies are missing. To identify suitable opportunities and applications for new manufacturing technologies, like AIMM, it is necessary to analyze and explore representative manufacturing facilities. There exist many methodologies for analyzing manufacturing facilities, e.g., learning to see (value-stream mapping) [19], production flow analysis [20], LEAN [21], total productive maintenance [22], and Six Sigma [23]. However, these methodologies are concentrated on production performance. In this paper, we propose the TPMT methodology that can be used for identifying and evaluating applications for new (technology-push) manufacturing technologies in industrial environments. In general, the paper focuses on the manufacturing industry in terms of AIMM, but the TPMT methodology can be used in a broader sense.

2.2 Presentation

The TPMT methodology contributes to the phases of opportunity identification and opportunity analysis in the front end of innovation (FEI) activities (Fig. 3). The methodology provides a practical tool for identifying and evaluating the suitability of applications for technology-push technologies in manufacturing environments, based on

Table 1 Overview of potential AIMM tasks and applications

Assistive tasks	Logistics tasks	Service tasks
Machine tending: the process of loading/unloading materials into machinery for processing. Includes aspects like opening/closing doors, pressing buttons, and turning knobs	Transportation: the process of transporting parts and work pieces between workstations and storages. Transportation tasks contain physical separation larger than the workspace of the robot manipulator	MRO: processes of fixing and retaining the manufacturing equipment. Includes breakdown, preventive and corrective MRO tasks
(Pre)assembly: the process of fitting components together, e.g., into larger or completed parts. Pre-assemblies are typically carried out before assemblies	Multiple part feeding: the process of loading several components at a time into feeders and machines	Cleaning: general processes of cleaning and cleanup. In the context of AIMM, these tasks are related to removal of waste and scrap
Inspection: the process of observing and comparing parts to identify and correct any defects. Includes aspects related to quality and/or process control	Single part feeding: the process of loading components, one at a time, into feeders and machines	
Process execution: processes, where the AIMM is performing the processing part of a manufacturing task. Includes processes like welding, painting, bending, and machining		

MRO maintenance, repair, and overhaul

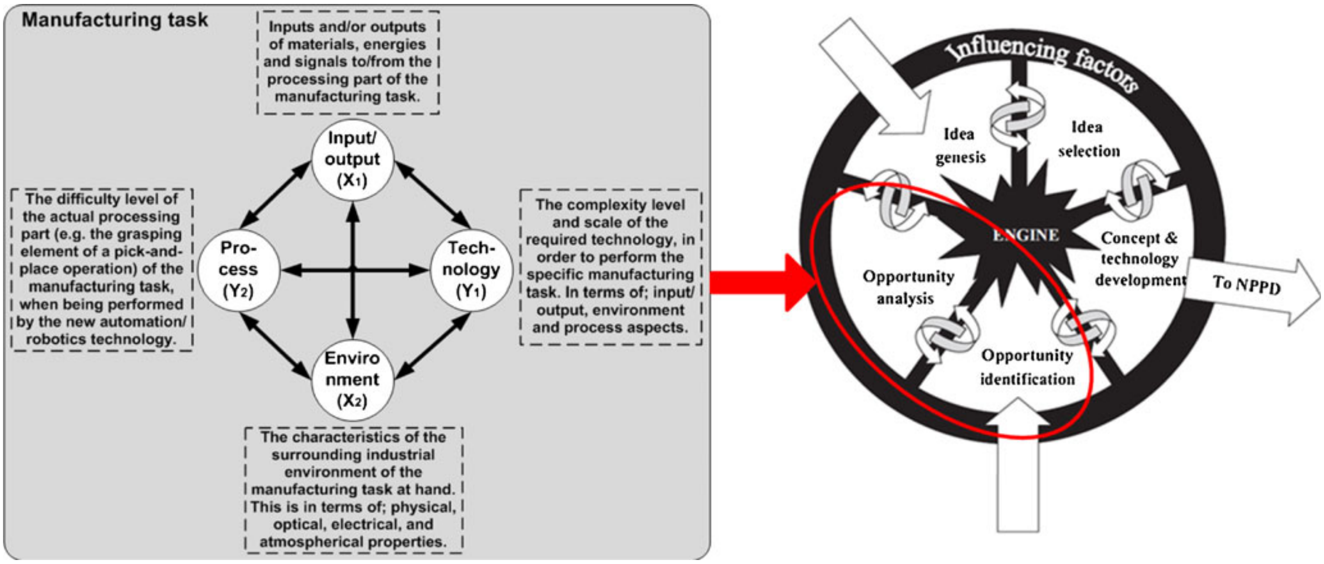


Fig. 3 The TPMT methodology (*left*) and its contributions to the FEI activities of the NCD model (*right*) [24]

a comprehensive analysis at manufacturing task level. In this way, it is possible to map representative manufacturing tasks to a new technology. The methodology considers the complete suitability of manufacturing tasks. Therefore, aspects like cost, time, quality, and environmental impacts are not treated as separate application requirements. This is reasonable, as any (new) manufacturing technology must offer a positive performance ratio on the aspects. To use the TPMT methodology, it is advantageous to gather a group of people with specific knowledge on the new technology and on the manufacturing tasks, respectively. Furthermore, as industrial applications and environments are rather complex, it is necessary to apply both qualitative and quantitative tools in order to obtain a comprehensive and unbiased methodology.

2.3 Modeling

The TPMT methodology is inspired by the theory of technical systems [25] and the general application requirements for automation and robotics [12]. Based on this, the TPMT model consists of four interdependent variables that describe the framework of common manufacturing tasks, see Fig. 3 and Table 2. The variables relate to the manufacturing facilities (the X's) and the new technology (the Y's) to obtain a complete description of the manufacturing task(s).

To make the TPMT methodology operational, it is based on a scoring principle from 1 to 5 and a color-coding scheme (green, yellow, red, and blue) to rank the manufacturing tasks according to their suitability for the new technology:

- 1 (green): very suitable—immediate solvable with the new technology
- 2–3 (yellow): intermediate suitable—solvable with the new technology with modifications applied
- 4–5 (red): not suitable—unsolvable with the current state of the new technology
- X (blue): out of scope

Furthermore, the methodology utilizes the weights α, β, σ, and μ (1–10), which rank the importance of the four variables within the specific domain. It is often the case that new manufacturing technologies must be adaptable to the existing industrial environment to obtain plug-and-produce capabilities. In cases like this, strong emphasis must be put upon the production-related variables (input/output (α) and environment (β)), whereas in other examples strong emphasis is put upon the technology-related variables (process (σ) and technology (μ)). Therefore, the weights represent penalty factors in a minimization-driven approach. Below, the formula used to calculate the general suitability score is shown:

$$\text{Suitability score} = \frac{\alpha X_1 + \beta X_2 + \sigma Y_1 + \mu Y_2}{\alpha + \beta + \sigma + \mu}$$

Based on the suitability score, the manufacturing task is given a time stamp, which is related to the overall implementation horizon (domain specific) of the new automation or robotics technology.

- Suitability score <2→Near-term implementation
- 2=< Suitability score <3→Mid-term implementation
- 3=< Suitability score=<5→Long-term implementation

2.4 Step-by-step procedure

The main purpose of the TPMT methodology is to identify representative applications for new manufacturing technologies. The methodology needs different inputs to assist in the documentation and interpretation process of the ana-

Table 2 Description of the general variables: input/output, environment, technology, and process

Variable	Definition	Factors
Input/output (X_1)	Refers to the inputs and/or outputs of materials, energies, and signals to/from the processing part of the manufacturing task	Factors related to materials, energies, and signals: parts (weight, size, dimensions, orientation, tangibility and frailty), communication (e.g., wireless network), addition/removal of materials (e.g., welding wire and scrap), etc.
Environment (X_2)	Refers to the characteristics of the surrounding industrial environment of the current manufacturing task. This is in terms of physical, optical, electrical, and atmospherically properties	Factors related to aspects like; safety (e.g., man–machine interaction), general working conditions (e.g., OSH), physical properties (structuredness, space, cleanness, dangerousness), etc.
Technology (Y_1)	Refers to the complexity level and scale of the required technology, in order to perform the specific manufacturing task. In terms of input/output, environment, and process aspects. A key question is: can the task be performed with a standardized version of the new automation/robotics technology or is a dedicated one needed?	Factors related to aspects like; communication protocols, human–machine interfaces, safety technologies, end effectors (e.g., manipulation and grasping tools), and technologies related to adaptation, learning, perception, sensing, control, etc.
Process (Y_2)	Refers to the difficulty level of the actual processing part (e.g., the grasping element of a pick-and-place operation) of the manufacturing task, when being performed by the new automation/robotics technology	Factors related to aspects like; positioning, tolerances, tact time, autonomy/intelligence, quality, dependability, processing capabilities (e.g., welding), usage level, etc.

lyzed manufacturing tasks. As a starting point, it is necessary to choose three to seven general application categories for the specific domain under consideration. Furthermore, a description of each manufacturing application (tasks, parts, cycle time, tolerances, quality, etcetera), supported by various forms of documentation (pictures, videos, working procedures, BOM's, statistics, CAD models, etcetera), is required. In Fig. 4 (left), a step-by-step

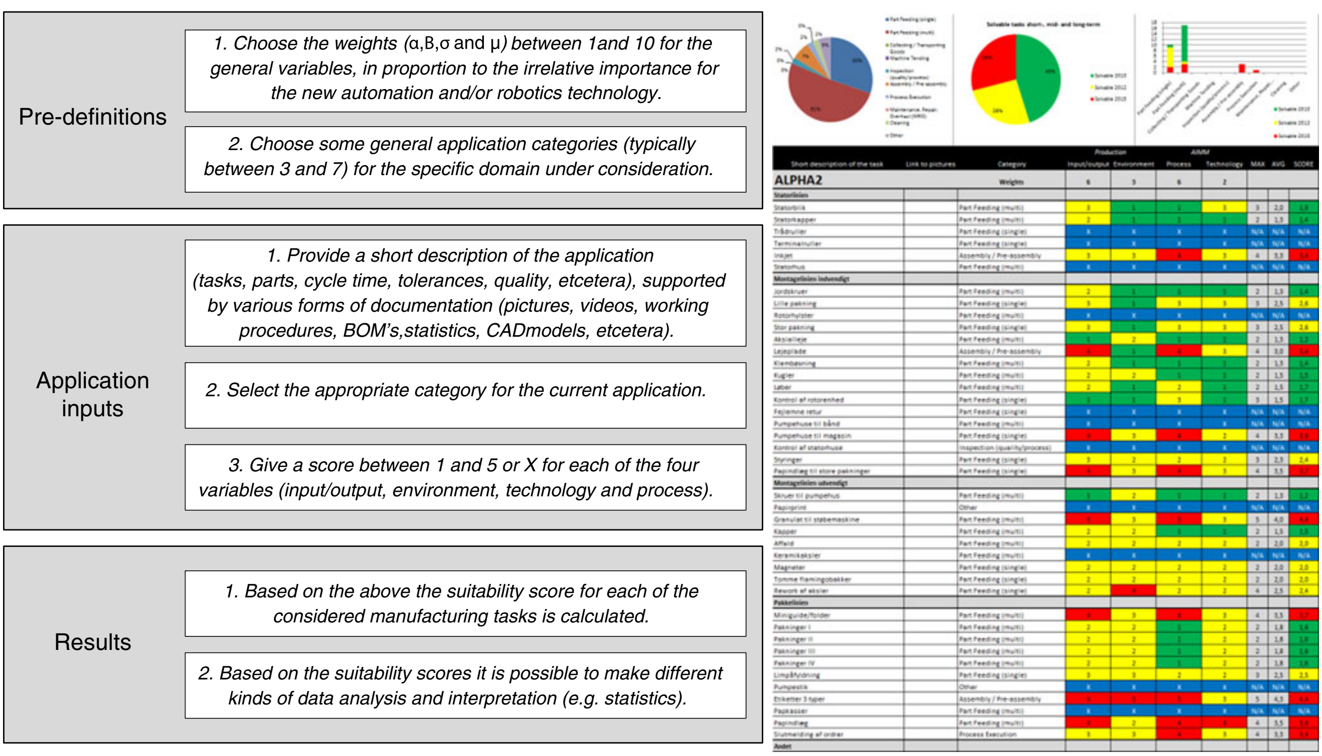


Fig. 4 A systematic procedure (*left*) and interactive spreadsheet (*right*) for the TPMT methodology

Table 3 An application example of the TPMT methodology

Description	Documentation	Category	Input/ output	Environ- ment	Techno- logy	Process	SS
An operator manually puts in part A to machine B in order to perform a punching operation. The task has a cycle time of XXX seconds.		*Machine tending*	*1*	*2*	*2*	*1*	*1.6*
An operator manually assembles part C and D by means of a screw operation. The task has a cycle time of YYY seconds.		*Assembly*	*3*	*2*	*2*	*2*	*2.3*
An operator performs a welding operation in order to join part E and F. The process has a typical cycle time of ZZZ seconds.		*Process execution*	*2*	*4*	*3*	*3*	*3.2*
An operator picks part G from a bin (bin-picking) and puts it on a feeding conveyor. The process has a typical cycle time of QQQ seconds.		*Part feeding*	*X*	*X*	*X*	*X*	*N/A*

procedure is shown, including the three main phases: pre-definitions, application inputs, and results. The first phase contains the aspects that need to be defined in advance (weights and application categories). The second phase contains the inputs that are related to the analysis and assessment of the manufacturing tasks (description, documentation, category selection, and grading). The final phase contains the data interpretation, based on the categories and suitability scores for each manufacturing tasks.

To make the methodology operational in practice, all aspects are embedded in an interactive Microsoft Excel spreadsheet. The user is able to perform customizable analysis by simple entries in pre-defined cells and by choosing values from drop-down-menus. The spreadsheet expands automatically and provides different graphical and statistical outputs, as shown in Fig. 4 (right). The current version of the TPMT spreadsheet template can be downloaded here: www.machinevision.dk/interactive_spreadsheet.

2.5 Application example

To demonstrate the practical use of the TPMT methodology, a general example is presented. As a starting point, the values of the weights are chosen. This example is related to a production adaptive automation technology; therefore, strong emphasis is put upon the production-related variables (input/output and environment), which are controlled by α and β, respectively. This provides the following weighting: $\alpha=6$, $\beta=10$, $\sigma=1$, and $\mu=2$. As this example serves as a clarification of the TPMT methodology, it deals with general manual manufacturing tasks that are typically automated by robotics. The chosen application categories are machine tending, assembly,

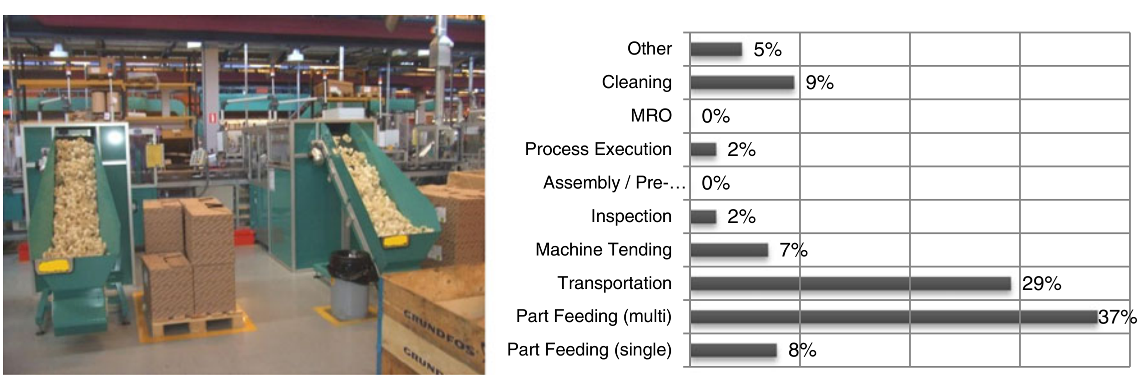


Fig. 5 Overview of the UP factory: the environment (*left*) and the distribution of manual tasks (*right*)

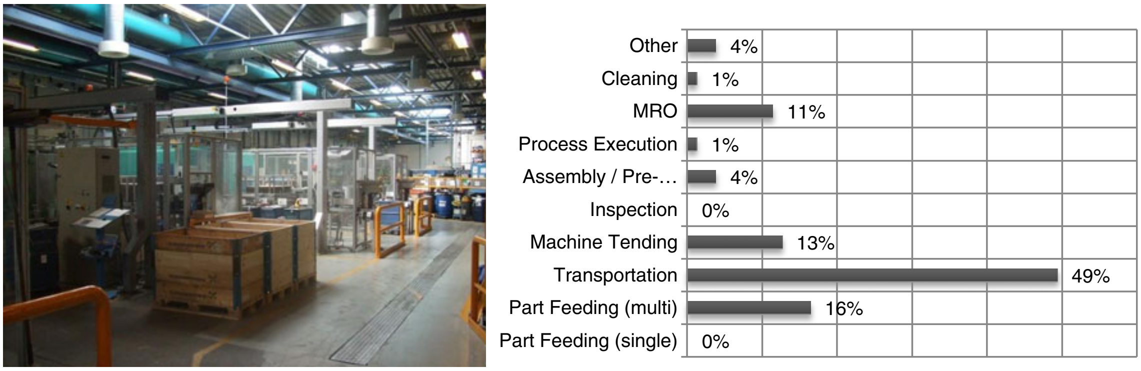


Fig. 6 Overview of the CF factory: the environment (*left*) and the distribution of manual tasks (*right*)

process execution, and part feeding. Calculations for the first manufacturing task are shown below, whereas the remaining part is plotted in Table 3.

$$\text{Suitability score}_{1,1} = \frac{\alpha X_1 + \beta X_2 + \sigma Y_1 + \mu Y_2}{\alpha + \beta + \sigma + \mu} \approx 1.6$$

From Table 3, it is seen that the most suitable manufacturing task for this particular technology is machine tending and the least suitable is a welding operation (process execution). Furthermore, the bin-picking task is out of scope because of an inadequate combination between vision and tooling. Based on this, it is possible to obtain an overview of the new manufacturing technology by use of data interpretation techniques, e.g., statistics. However, more manufacturing tasks are needed to draw a general picture and to make conclusions on the actual potential of the new technology. The complete example is shown in the TPMT spreadsheet template at: www.machinevision.dk/interactive_spreadsheet.

3 Framework for the case study

3.1 Overview

To explore the application potential of AIMM, industrial collaborations representing the general manufacturing industries have been established. This is a reasonable assumption, as the analyzed manufacturing facilities are versatile in relation to process discrepancies, parts variation, and production strategies. Therefore, suitable AIMM tasks identified at these manufacturing facilities are of general relevance. The case study framework includes five distinct factories—CR, CF, SQ, UP, and TC—which develop and produce versatile OEM and consumer products. For the past 2 years, these factories have been analyzed by using the TPMT methodology. In the following, each of the factories is briefly described with focus on setup, environment, and manual manufacturing tasks, based on the categories from Table 1.

3.2 The UP factory—continuous flow and assembly lines (flow shop)

The UP factory consists of several fully automatic production lines, where the primary manual tasks are part feeding, transportation, cleaning, and machine tending. In addition, there exist a series of periodic maintenance procedures. In general, the environment is well structured and it only has few manual manufacturing tasks compared to the high volume. One product is produced at each line with the possibilities of variants by replacing modules. An overview is provided in Fig. 5.

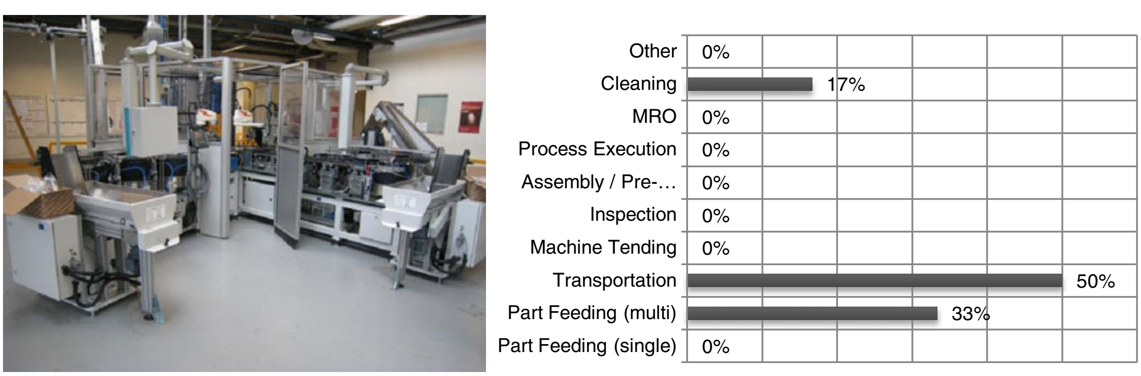


Fig. 7 Overview of the CR factory: the environment (*left*) and the distribution of manual tasks (*right*)

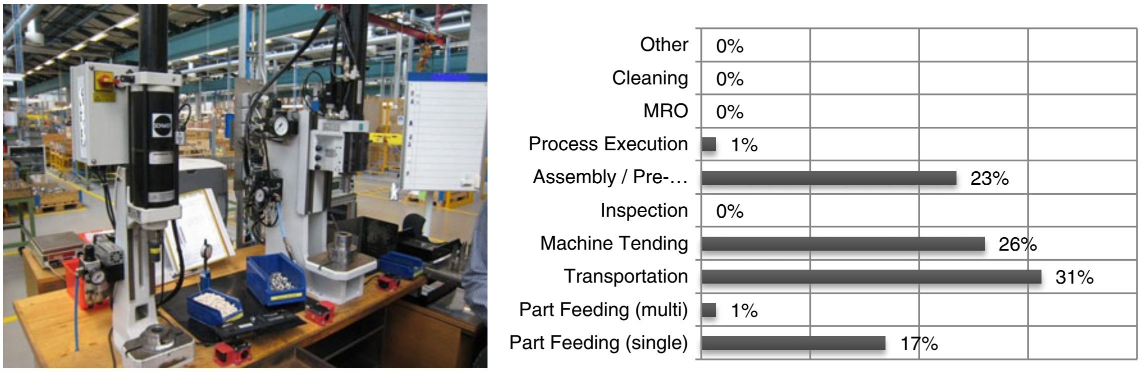


Fig. 8 Overview of the SQ factory: the environment (*left*) and the distribution of manual tasks (*right*)

3.3 The CF factory—large-size batch production

The CF factory produces composite parts and is characterized by large-size batch production. The primary manual tasks are transportation of parts, multiple part feeding, machine tending, and maintenance. The environment consists of several injection-molding machines in a hybrid layout. Furthermore, every machine is easy accessible from a common pathway. An overview is provided in Fig. 6.

3.4 The CR factory—varying batch production

The CR factory is characterized by varying batch production in a cellular layout. The manual manufacturing tasks include transportation, multiple part feeding, and cleaning. The environment is open-spaced and allows easy access to the versatile production equipment. An overview is provided in Fig. 7.

3.5 The SQ factory—job shop

The SQ factory consists of a semi-structured job shop layout with several small work areas (production islands), where different manual and/or semi-automatic tasks take place. Between the work areas, there are small buffers (storages), where sub-assemblies are located until they move on to the next work area. Typical manual manufacturing tasks are transportation, machine tending, and (pre)assembly. An overview is provided in Fig. 8.

3.6 The TC factory—project oriented

The TC factory is project-oriented, as it is concerned with production ramp-up and prototype testing. It constitutes a link between the R&D department and the production facilities. The labor-intensive tasks are part feeding, (pre) assembly, process execution, and assistance (other), e.g., when SAT/FAT tests for new equipment and/or products are carried out. An overview is provided in Fig. 9.

3.7 Overview

An overview of the 566 identified manual manufacturing tasks (immediate potential for AIMM) is shown in Fig. 10. In general, the tasks are dominated by logistics (64%), i.e., part feeding and transportation. These tasks are typically not automated because of either cost or technology.

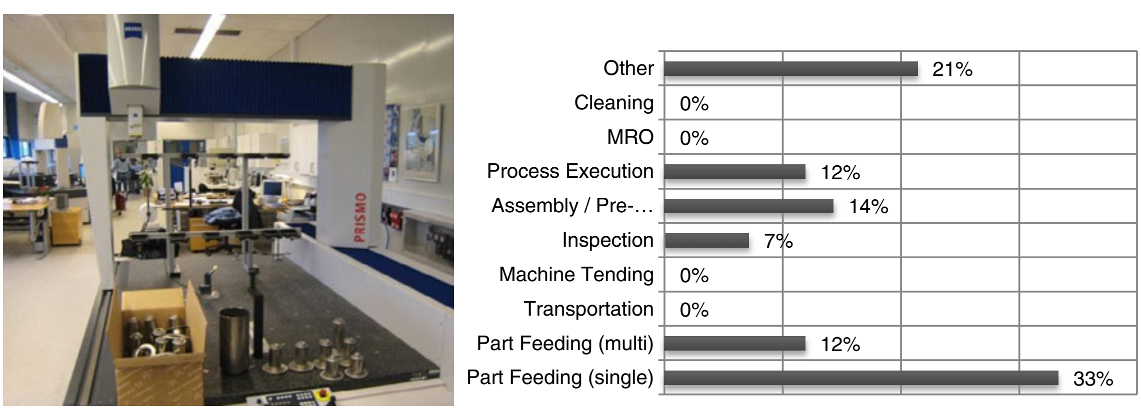


Fig. 9 Overview of the TC factory: the environment (*left*) and the distribution of manual tasks (*right*)

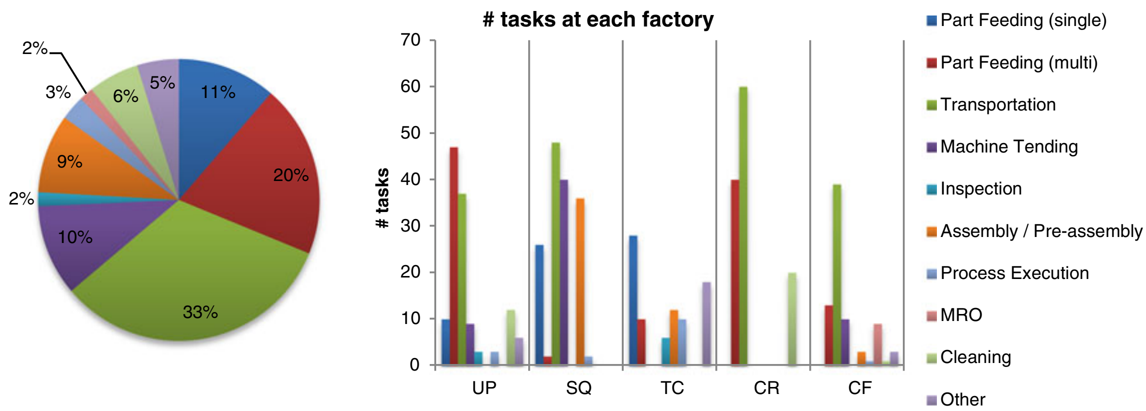


Fig. 10 Total distribution of manual tasks (*left*) and distribution of manual tasks at factory level (*right*)

Furthermore, it is seen that the factories are dominated by diverse application categories related to their production setup and strategy. For example, the UP factory (flow shop) is dominated by transportation and part feeding, the SQ factory (job shop) is characterized by a high amount of machine tending and (pre)assembly, and the TC factory (project oriented) is distinguish by several process execution and assistance tasks. This preliminary investigation forms the basis for utilizing the TPMT methodology for the AIMM technology.

4 The TPMT methodology applied for AIMM

4.1 Introduction

By applying the TPMT methodology at the five factories, a comprehensive analysis is carried out. Based on this, it is possible to identify suitable manufacturing tasks and applications for the AIMM technology and evaluate these in short-, mid-, and long-term implementation goals. As mentioned in Section 2, the TPMT methodology consists of

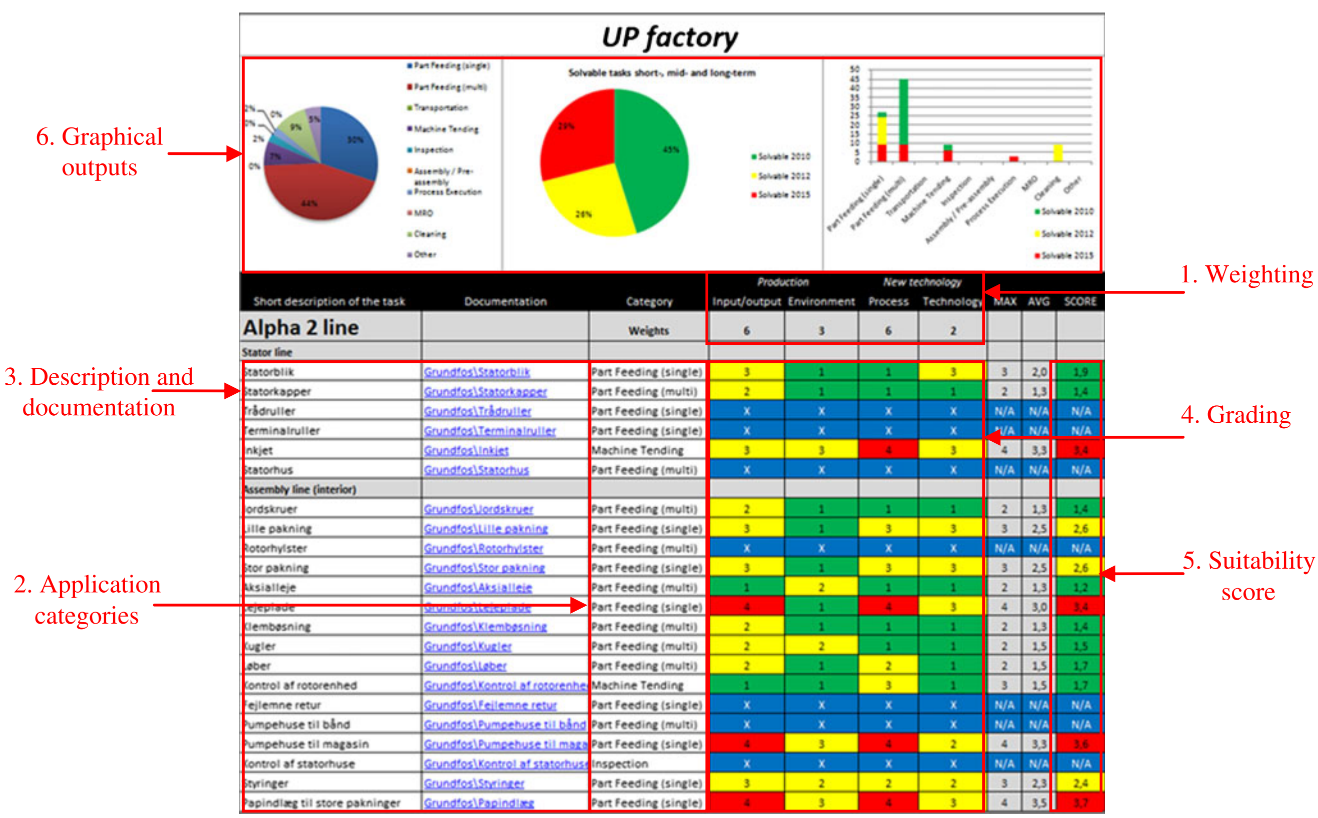


Fig. 11 Spread sheet example (the UP factory) of the data representation according to the TPMT methodology

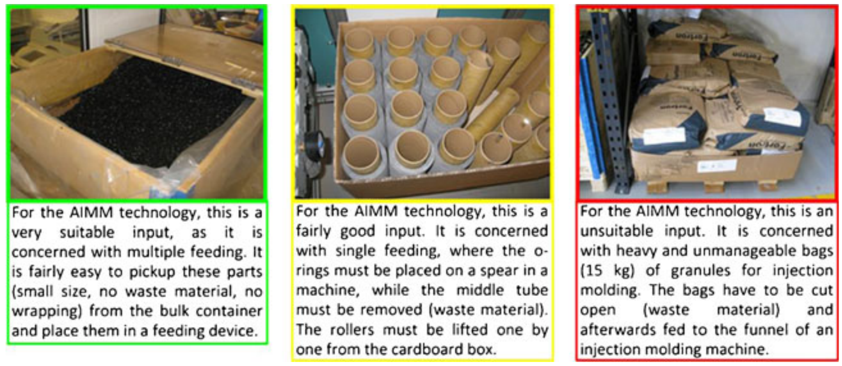


Fig. 12 Real-world examples of the input/output variable

three main phases: pre-definitions (weights and application categories), application inputs (description, documentation, category selection, and grading), and results (data interpretation). In the following, the TPMT methodology is applied to the case study framework presented in Section 3. As a starting point, it is important to setup boundaries and limitations (the general scope) for the specific technology in order to obtain unbiased results. In general, AIMM is a modular and scalable technology. However, there exist hardware and software limitations in aspects like payloads, velocities, tolerances, quality, and safety. These aspects must be considered and revised when utilizing the TPMT methodology.

4.2 Extracts from the analysis

In Fig. 11, an example from the case study is shown, which serves as a general reference for the following review. To further visualize the use of the TPMT methodology, representative examples from the AIMM case study are presented in Figs. 12, 13, 14, and 15. In this way, the methodology is directly mapped to common real-world manufacturing tasks. The examples are intended as references and benchmarks for users of the TPMT methodology. For each general variable, three examples are presented, ranging from very suitable (green) to not suitable (red) for the AIMM technology.

4.3 Pre-definitions

Because AIMM is a production adaptive automation technology, strong emphasis is put on the input/output and process variables. Therefore, the following weighting is chosen:

α=6 (input/output, X_1)
β=3 (environment, X_2)
σ=2 (technology, Y_1)
μ=6 (process, Y_2)

In addition, general application categories for the specific domain under consideration must be chosen. In the case of the AIMM technology, the application categories are provided in advance (see Table 1).

4.4 Application inputs

The application inputs are related to the assessment of the manufacturing tasks. This includes a short description of the task (parts, cycle time, tolerances, quality, etc.) supported by various forms of documentation (pictures, videos, working procedures, BOM's, CAD models, etc.). A folder is made for each manufacturing task, where the description and documentation are stored (see Fig. 11).

Fig. 13 Real-world examples of the environment variable

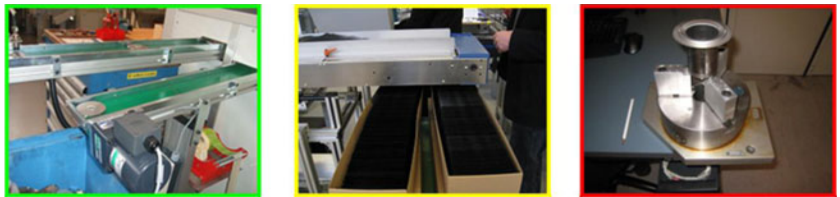


Fig. 14 Real-world examples of the technology variable

After this, the appropriate application category is selected for each manufacturing task. Finally, a score between 1 and 5 or X for each variable is provided for each manufacturing task.

4.5 Results

Based on the pre-definitions and application inputs, the suitability score and implementation horizon for each manufacturing task are calculated (rightmost column of Fig. 11). Furthermore, different graphical and statistical outputs are obtained (top row of Fig. 11). These outputs show the suitability mapping between the AIMM technology and the analyzed manufacturing tasks (general manufacturing industry) based on the application categories. This can be used for further evaluation and interpretation of the actual potential of the AIMM technology, as presented in Section 5.

5 TPMT evaluation and interpretation for AIMM

This section focuses on evaluation and interpretation of the results obtained from the conducted TPMT analysis at the five factories (CR, CF, SQ, UP, and TC). This corresponds to 566 manual manufacturing tasks spread over approximately 2,500 m^2 of manufacturing facilities. The focus is on identification/categorization of suitable tasks and future trends for the AIMM technology. The results are evaluated in three parts. Firstly, an overview of suitable AIMM tasks is provided. Secondly, the focus is on suitability within the different application categories. Finally, the results are evaluated on factory level, in order to investigate the AIMM suitability within different production strategies and domains.

5.1 General overview

In Fig. 16, the general results of the TPMT analysis for AIMM are shown, based on suitability scores and implementation horizons. Manufacturing tasks within the short- and mid-term ranges are of great interest, as they are solvable now or within the next couple of years. The manufacturing tasks within the long-term and out of scope ranges are of less immediate interest. The tasks in the out of scope range are generally not suitable for AIMM, as they require either a different type of automation technology or direct human interference.

From Fig. 16, it is seen that approximately 71% of the identified manual manufacturing tasks are solvable with AIMM within the next few years, and 44% are actually

Fig. 15 Real-world examples of the process variable

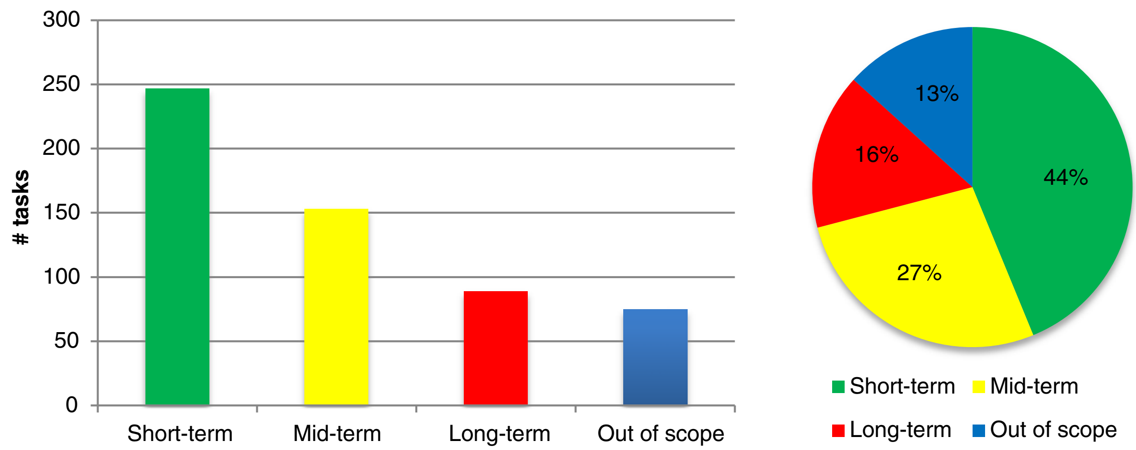


Fig. 16 Results based on solvability: short term, mid-term, long term, and out of scope

solvable with the current state of the technology. Furthermore, 16% of the tasks are currently unsolvable with AIMM, as they require modifications in the production setups or new technologies. Finally, the remaining 13% are out of scope.

5.2 Application categories and areas

In Fig. 17, the AIMM suitability and solvability for the individual application categories are shown, based on the number of tasks (left) and the distribution percentages (right). From Fig. 17, it is seen that the application categories with the highest immediate AIMM potential are transportation and part feeding (multiple and single), respectively. Overall, transportation and part feeding represent 64% of the identified tasks, and the average suitability (short- and mid-term) within these application categories is 74%. In general, transportation and part feeding tasks are either very suited for AIMM (easily manageable work pieces) or out of scope (unmanageable work pieces, e.g., due to large size and/or weight). It is also observed that (pre)assembly, inspection, and process execution tasks are generally not suited for the current state of the AIMM technology. Often, these tasks are tailored for human operators and not suited for automation in general because they require dexterous manipulation skills and experience. Other application categories look promising, e.g., machine tending and cleaning, but they are either short in numbers or low in the general suitability score. Finally, some application categories are generally out of scope, e.g., the maintenance, repair, and overhaul tasks. This application category frequently requires handling of large parts (e.g., injection molds) or task execution in inaccessible areas (e.g., on the backside of manufacturing equipment). In summary, the AIMM technology, at its current stage, finds most suitable applications within the logistics area, moving toward assistive tasks, and in the future more service-minded and other non-production-related tasks.

5.3 Production strategies and domains

In Fig. 18, the AIMM suitability and solvability for the five distinct factories are shown, based on the number of tasks (left) and the distribution percentages (right). The study on factory level is interesting, as the different factories represent diverse production strategies and

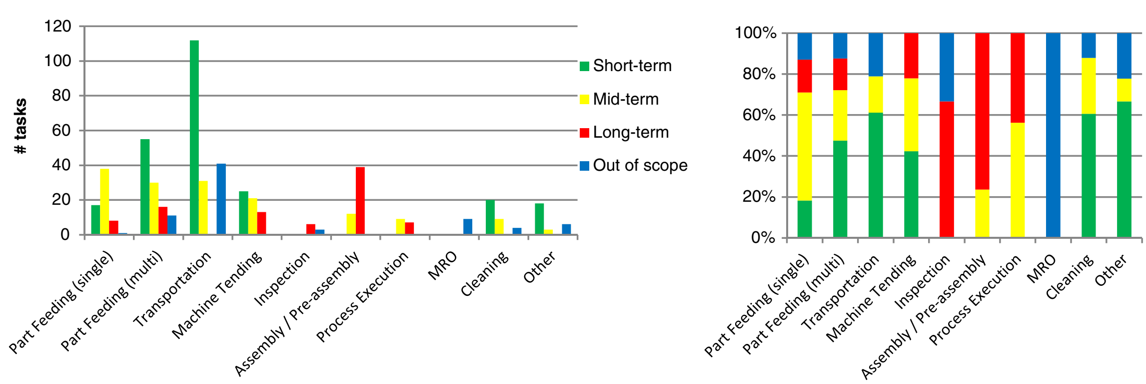


Fig. 17 AIMM suitability and solvability of the individual application categories

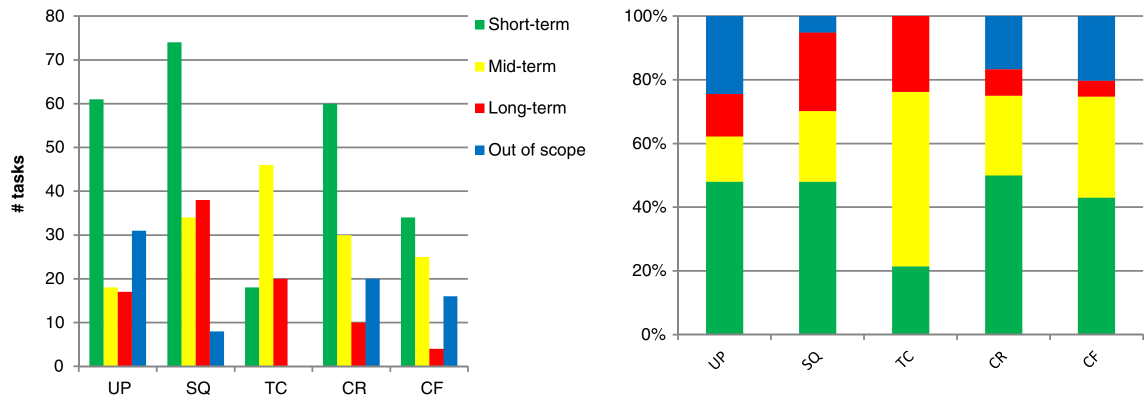


Fig. 18 AIMM suitability and solvability of the different factories: UP, SQ, TC, CR, and CF

domains, ranging from mass production (UP and CF) over mass customization (CR and SQ) down to one of a kind (TC).

From Fig. 18, it is seen that the factories with the highest immediate AIMM potential are SQ (job shop), CR (varying batch), UP (flow shop), and CF (large-size batch), as these factories contain many logistics tasks (see Fig. 10). In contrast, TC (project oriented and prototyping) retains the lowest immediate AIMM potential, as this factory contains many assistive tasks (Fig. 10). Furthermore, the tasks at TC require many transitions and changeovers as they are often one of a kind, whereas the tasks at the other factories all have a certain volume.

6 Conclusions and future work

AIMM is a promising manufacturing technology. In this paper, we have explored its application potential, in order to link the conceptual ideas (academia) to actual manufacturing requirements (industry). By use of the proposed TPMT methodology, an extensive industrial case study has been carried out, which has played a fundamental part in the exploration of suitable tasks and applications for the AIMM technology. More than 566 manual manufacturing tasks have been analyzed according to three main application areas: logistics, assistive, and service to find their suitability for the AIMM technology. In general, the results from the TPMT analysis show great potential for the use of AIMM in manufacturing environments. More than two thirds of the analyzed manufacturing tasks are solvable with AIMM within the next few years. The AIMM technology, at its current stage, finds most suitable applications within logistics (e.g., transportation and part feeding), moving toward assistive tasks that naturally extend the logistic tasks (e.g., (pre)assembly and machine tending), and in the future more service-minded and non-production-related tasks (e.g., maintenance and cleaning). This represents a balanced and stepwise implementation process. Based on the identified applications, it is possible to raise the AIMM technology to the next levels.

In the future, we will focus on developing general application and implementation scenarios for AIMM. As a starting point, continuous part feeding has been selected as pilot project for a full-scale implementation. By utilizing AIMM-based part feeding, it is possible to obtain a fully automatic production setup, increased equipment uptime (OEE), and utilization of LEAN strategies (e.g., minimization of inventories). Furthermore, we will modify the AIMM technology according to platform strategies to accommodate the different application requirements in a cost-effective manner.

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