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Operational production planning in smart factories

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***Abstract* - Proclaiming a revolution before it has even started is keen. This is what the German government did when calling for a 4th one in the industry sector. Accompanied by the help of information and communication technology, industrial supply chains at all levels are expected to increase efficiency through smart factories, digital twin, and big data analytics. At the end there is a paradigm shift where smart factories share information with each other to steer themselves autonomously. Many questions still need to be answered on this rocky road. For this purpose, we address an operational production planning problem in smart factories in this paper. A brief overview on current state of the art literature in the field is given first. Then, we identify challenges stemming from smart factory principles and include them in a mixed-integer programming model. Finally, the model is validated through a set of scenarios and some results are presented.**

***Keywords* – Operational production planning, Industry 4.0, Smart factory, Mixed-integer programming**

1 INTRODUCTION

The term Industry 4.0 (I4.0) has no unique definition. It refers to a paradigm shift in industry standards, which is pronounced as the 4th industrial revolution. While there is no uniform perception for what can be considered as I4.0 standard, extensive usage of information and communication technology is manifested within its spectrum and is a useful tool to achieve mass personalization (MP). However, the satisfaction of customers through MP creates challenges for today's production standards. Producing personalized items on masse requires a highly flexible production line. For that reason, the principle of modular, and therefore flexible, production is favoured within I4.0, which enables a convertible factory, that can adapt to demand variations [BMWK, nd].

Furthermore, the extensive use of data from external and internal sources interconnected through cloud technologies shall steer a production and moreover a supply chain autonomously. For this, machines and other entities act as cyber-physical systems (CPS) and are connected together in the Internet of Things (IoT), where they generate and process information in real-time. Products receive a memory which enables them to orchestrate their way to completion. The role of human workers is of central significance within the autonomous production flow. Their value as the most flexible and adaptive entity qualifies them for a wide range of tasks ranging from monitoring to verifying production strategies instructed by the system. These technologies and principles ultimately pave the way towards, which is depending on the geographical location named, a smart factory, smart manufacturing, or real-time manufacturing [Strozzi et al., 2017].

The explosion in the availability and accessibility of data in smart value chains and breakthrough advances in machine learning (ML) approaches [Gopal, 2019] boost I4.0 research. Information must be adequately leveraged towards data-driven decision models along with efficient and fast solution algorithms in order to promote real-time/smart decision-making in modern supply chains (SC). A recent survey [McKinsey & Company, 2019] reveals that 61% of executives report decreased costs and 53% report increased revenues as a direct result of introducing AI into their SCs. While the vision is clear and components as well as data are available, modular production lines and ranging workforce tasks unfold new challenges for decision-makers. Therefore, real-time manufacturing is yet to be investigated to achieve peak efficiency within smart factories.

Literature on operations research (OR) topics within the scope of smart factories is quite scant and the clear link to new challenges is often neglected. Therefore, we investigate operational planning in smart factories with the goal to overcome pending new challenges stemming from its inherent paradigm shift. More precisely, we focus on a digital and smart manufacturing network comprising of an assembly facility and a set of vertically integrated component\sub-assembly facilities that are connected to a cloud manufacturing environment. Each manufacturing facility in this SC is comprised of automated, digitally-connected and reconfigurable machines equipped with a wide range of sensors along with a fleet of partially trained workforce. Therefore, real-time data in terms of the condition of machines and production capacities is shared on the cloud. Ultimate goal is to unite these aspects in an integrated decision-making model.

This paper is structured as follows. Section 2 gives a brief overview of the current literature. Section 3 presents the problem as well as the mathematical model. Section 4 follows with some interpreted results before section 5 concludes the paper.

2 LITERATURE REVIEW

Decision models for smart factories

An increasing number of research publications appeared in the past couple of years that mainly focus on the conceptual design of smart SCs [Dolgui et al., 2020, Ivanov et al., 2016, 2021]. Further, research around smart factory is often focused on managerial aspects and changing requirements of production at a conceptual level [Strozzi et al., 2017]. Guo et al. [2020b] present a roadmap for conditioning fixed-position assembly islands (FPAI) for I4.0, by applying the graduation-inspired assembly system, called Graduation Manufacturing Systems (GMS), proposed by Guo et al. [2020a]. The requirements for flexibility and customization are challenging for FPAI, resulting in configuration and production dilemmas. Through the adaption of GMS to FPAI, the traditional assembly line can be "retrofitted" for I4.0 principles. In the same vein, Li and Huang [2021] investigate an assembly line balancing problem within the context of GMS and I4.0. The authors show how demanding production-intralogistics processes can be optimized by leveraging I4.0's real-time data collection and analytics.

To the extent of the authors' knowledge, quantitative and data-driven approaches for I4.0 supply chain management (SCM) are not explored to their full extent in the literature, but the topic receives growing attention. Katoozian and Zanjani [2022] investigate supply network design within the context of MP by proposing a mixed-integer programming (MIP) model. The authors consider different design complexity levels for elements of the BOM. Furthermore, batch sizes and their impact on the choice of suppliers is modelled via considering piece-wise linear cost functions.

Ohand Jeong [2019] propose a real-time single-period SC tactical planning model for smart manufacturing SCs. In particular, a deterministic model with discrete demand is developed in which re-planning during a lead-time is permitted to adapt the SC to a changing environment. To create stability in performance, upper bounds for the utilization rates of manufacturers and distributors and lead time are introduced. Consequently, to approximate real-time decision-making, the minimization of lead time is considered besides maximizing profit. Perraudat et al. [2022] introduce a tactical capacity planning problem set in a flexible manufacturing environment. In their model, machines must be qualified to process a product. The goal is to minimize the total costs of performed qualifications, while still meeting demand and capacity constraints. The authors first propose a deterministic version, which is transformed into a robust model to cope with uncertain demand.

Malladi et al. [2020] investigate a dynamic mobile multi-location production-inventory control problem. The authors consider a reconfigurable and mobile production system, which can be transported between several locations to adapt production capacities. Since the number of locations and horizon let the model exponentially grow, approximate dynamic programming is used to solve the problem. Several heuristics with different model simplifications are introduced and compared. Ivanov et al. [2016] investigate SC dynamic scheduling for smart factories. The idea is that operation execution and machine availability are dynamically distributed in time over the planning horizon, such that not all operations and machines are involved in the decision making at the same time. For that, the authors use optimal program control to dynamically decompose the NP-hard scheduling problem. Coordinated scheduling in SCs under dynamic market conditions is addressed in Jamrus et al. [2020]. The authors consider fluctuations in production time and solve the problem with an integrated hybrid particle swarm optimization and genetic algorithm.

In summary, researchers acknowledge the potentials of I4.0. This is demonstrated by the wide range of conceptual studies about implementing I4.0 within existing manufacturing structures or how to prepare established settings for I4.0 implementation to facilitate a successful transition. Also, some operational aspects, such as assembly line balancing or production-inventory problems, are partially covered in a handful of studies. Additionally, research on incorporating I4.0 aspects into production planning and other operational-level planning problems is still quite scant.

Predictive & condition-based maintenance

Maintenance is a big share of the total manufacturing costs. The goal of predictive maintenance is thereby, among others, to predict the remaining useful life of a machine, by collecting data from multiple sensors. Zonta et al. [2020] recently reviewed predictive maintenance in I4.0. The authors state among the most used ML algorithms in the most current literature are Neural Networks (NN) and DL approaches. They also highlight that research often is restricted to simple alert monitoring, leaving it open whether maintenance actions are subsequently conducted or not. Applying predictive maintenance can consequently be a powerful tool to boost CBM. CBM combines data-driven reliability models with sensor data and aims to reduce unnecessary maintenance actions [Alaswad and Xiang, 2017] and has received considerable attention within the context of I4.0. Kumar et al. [2018] provide a big data driven framework to accurately predict remaining machine life and thereby exploit the benefits of CBM. Ghaleb et al. [2021] consider the joint optimization of maintenance planning and production scheduling in smart manufacturing systems. The authors consider uncertain event, such as the arrival of new jobs and due date changes. Furthermore, the production rate of a machine is affected by its current deterioration state and random machine breakdowns can occur at any degradation state. Deterioration, failure, and repair rates to recover machine performance are assumed to be constant and follow an exponential distribution. The authors introduce a two-stage hybrid genetic algorithm to solve the problem. van Staden and Boute [2021] investigate the cost optimal policy given a set of available information from machine sensors. To formulate the problem, the authors use a partially observable Markov decision process in which the true state of the monitored system is only stochastically related to the monitoring process. Depending on the believed underlying deterioration state of the system, a decision-maker has the choice to keep monitoring with only internal data, acquire extended information from external data sources, or initiate preventive maintenance actions. In general, maintenance receives significant attention in the literature. Proven concepts, such as CBM, benefit from the support of ML in form of predictive maintenance. However, current research on predictive maintenance is often focused on alert monitoring, neglecting the question of how to embed it in decision-making and draw optimal conclusions from the information provided.

Given the elaborated gaps, this paper aims to answer the question on how to represent specific challenges prevalent to operational production planning in smart factories in a mathematical decision model. As such, we investigate the impact of incorporating machine degradation states, captured

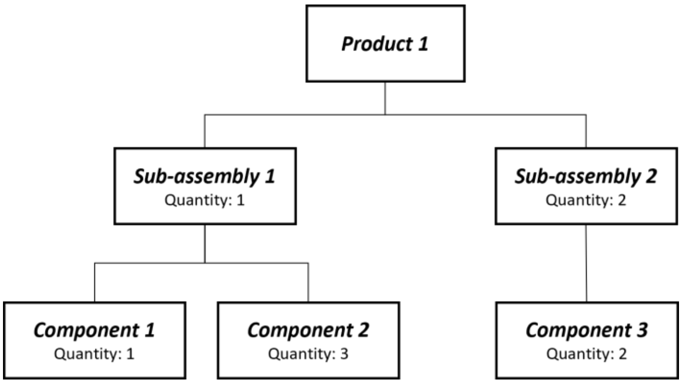

Figure 1. Exemplary BOM of a product

from sensors into the production planning process in smart manufacturing settings.

3 Problem description and formulation

3.1 Problem description

I4.0 pledges to change manufacturing in a fundamental way. One driving factor is the demand for product customizability. The satisfaction of customers through MP creates challenges for today's production standards in a way, that it has to deal with vast number of products inheriting complex bill-of-material (BOM), similar to the one depicted in figure 1, and simultaneously small batch sizes.

To manifest that, a pivotal aspect is the realization of a modular manufacturing setup. Machines are not arranged in a fixed structure, but flexible and mobile. This allows to activate or deactivate a number of machines, depending on the demand and BOM of a certain product within a short period. Accordingly, products are processed through the facilities in a predefined, but not standardized path, as shown in figure 2. However, the flexibility gained is also subject to some challenges and limitations. While planning for space already plays a vital role in strategic facility layout planning, it now becomes an additional and new aspect for operational level production planning. What and how much can be produced in a day heavily relies on which machine groups and how many machines within that group are activated and necessary for the BOM of the items to be produced. The physical space within a manufacturing facility is thereby a natural limitation to that everyday decision. Besides time, activating and deactivating machines flexibly additionally requires manpower with matching skill sets. They are further required to set up machines correctly and accordingly to the specific requirements of the items scheduled on them. Due to MP, where many different products with unique BOMs

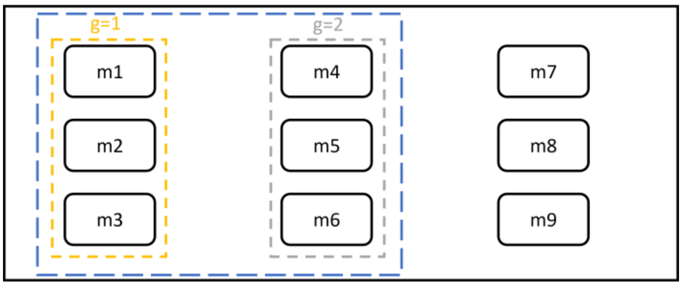

Figure 3. Machine groups

coexist, assigning qualified workers to these tasks is necessary. Even if a worker is qualified to process a machine, additional training might be needed regularly to run different, individualized items on that machine. Tracking and training skills of highly qualified workforce therefore becomes a crucial aspect of efficient operational planning.

Another key aspect of I4.0 is its self-steering characteristic. For that, items need to be aware of their state at any time in a way that the know which machines are available as well as which are required for their production. Figure 3 exemplary depicts the machine groups. The blue frame is the subset of machines needed to process the item. Machines framed by the yellow and gray lines are the subsets of machines with identical operational tasks. In that case, processing an item would require scheduling it on at least one machine of the yellow and gray subset. Simultaneously, in smart factories, machines are typically equipped with smart sensors, which track, trace and send information to the cloud in real-time. They allow to monitor the current condition and degradation status of a machine. This development enables condition-based maintenance (CBM). We are assuming, that this information is available and incorporate it by considering a random deterioration factor affecting the state of a machine. Consequently, decisions about maintenance actions (partial or full maintenance) are made based on the actual machine state, allowing to conduct more preventive and precise maintenance actions in a shorter time.

3.2 Problem formulation

3.2.1 Notation

Sets

M: Set of modular machines *m*
G: Set of machine groups *g* conducting the same tasks
I: Set of items *i*
K: Set of workers *k*
F: Set of facilities *f*
T: Set of time periods *t*

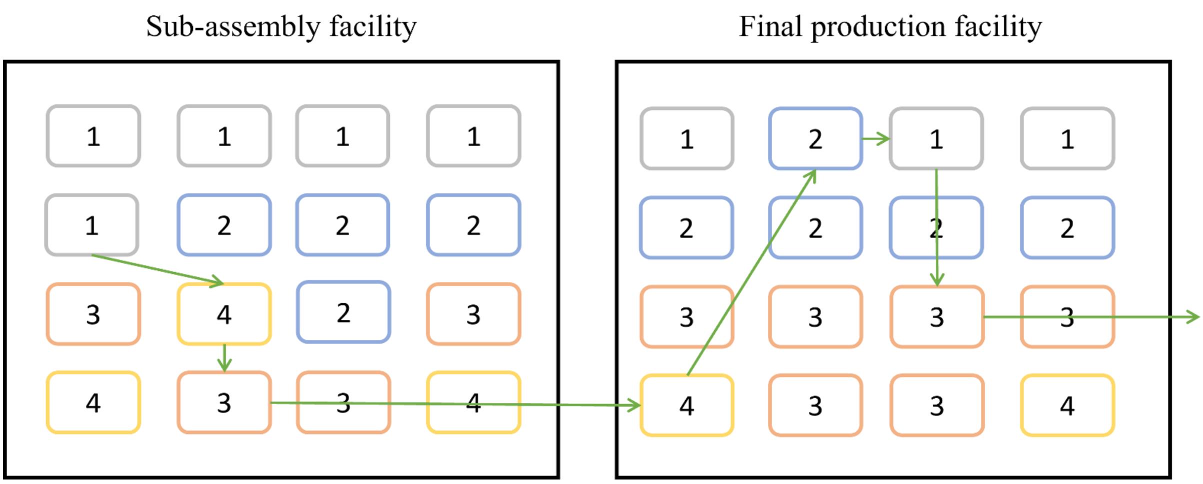

Figure 2. Two echelon SC with modular production facilities

Subsets

I^P: Subset of final product i
I^A: Subset of sub-assemblies i
I^C: Subset of components i
$I(f)$: Subset of items i produced in facility f
$S(i)$: Subset of superordinates of item i in the BOM
$G(i)$: Subset of machine groups g required to produce item i
$K(f)$: Subset of workers k in facility f
$M(f)$: Subset of machines m in facility f
$M(i)$: Subset of machines m associated to item i
$M(i,g)$: Subset of machines m of machine group g required to produce item i
$M(f,i,g)$: Subset of machines m of machine group g in facility f required to produce item i

Parameters

d^t_i: Demand for item i in period t
c_i: Cost of producing item i
a_m: Cost of activating machine m
c_n: Cost of maintenance action n
h_i: Inventory holding cost of item i
b_i: Penalty cost for backorder of item i
pt_n: Process time of maintenance action n
lt: Nominal capacity
λ_{si}: Amount of item i required to produce superordinate item s
e_{gi}: Cost of training a worker on machine group g for processing item i
α^t_m: Random deterioration rate between [0.03,0.1] of machine m in period t
sp_f: Available space in facility f
β_{im}: Capacity consumption of item i on machine m
σ_m: Space consumption of machine m
r_n: Restored level of machine state when undertaking maintenance action n
ws_{gi}: Required time to training a worker on machine group g for processing item i
M: Random very large number
B^0_i: Initial amount of backorder of item i
I^0_i: Initial amount of inventory of item i
D^0_m: Initial deterioration level of machine m
Sk^0_{gki}: Initial qualification of worker k to process item i on machine group g

Decision variables

Q^t_i: Number of produced items i in period t
Q^t_{im}: Number of produced items i on machine m in period t
B^t_i: Amount of backorder of item i at the end of period t
I^t_i: Amount of inventory of item i at the end of period t
Ca^t_m: Capacity of machine m in period t
D^t_m: Deterioration level of machine m in period t
H^t_{kim}: Percentage of a regular shift that worker k is assigned to process item i on machine m in period t
Pl^t_m: Whether machine m is activated in period t
Sk^t_{gki}: Whether worker k is qualified to process item i on machine group g in period t
Tr^t_{gki}: Whether worker k is trained to process item i on machine group g in period t
X^t_{nm}: Whether maintenance action n is applied to machine m in period t
Z^t_m: Auxiliary decision variable for linearizing constraint (7)
Y^t_{nm}: Auxiliary decision variable for linearizing constraint (14)

3.2.2 Mathematical formulation

$$\min \sum_t^T \Big(\sum_i c_i Q_i^t + \sum_i h_i I_i^t + \sum_i b_i B_i^t + \sum_m a_m Pl_m^t + \sum_n \sum_m c_n X_{nm}^t + \sum_g \sum_k \sum_i u_{gi} Tr_{gki}^t \Big) \quad (1)$$

$$I_i^t - B_i^t = I_i^{t-1} - B_i^{t-1} - d_i^t + Q_i^t \quad t = 2, \dots, T, \forall i \in I^P \quad (2)$$

$$I_i^t - B_i^t = I_i^0 - B_i^0 - d_i^t + Q_i^t \quad t = 1, \forall i \in I^P \quad (3)$$

$$I_i^t - B_i^t = I_i^{t-1} - B_i^{t-1} - \sum_{s \in S(i)} \lambda_{si} Q_s^t + Q_i^t \quad t = 2, \dots, T, \ \forall I \in I^A \cup I^C \quad (4)$$

$$I_i^t - B_i^t = I_i^0 - B_i^0 - \sum_{s \in S(i)} \lambda_{si} Q_s^t + Q_i^t \quad t = 1, \ \forall I \in I^A \cup I^C \quad (5)$$

$$\sum_{m \in M(i,g)} Q_{im}^t = Q_i^t \quad \forall t \in T, \forall i \in I^P \cup I^A, \forall g \in G(i) \quad (6)$$

$$\sum_{i \ in \ I(f)} \beta_{im} Q_{im}^t \le Ca_m^t Pl_m^t \ \ \forall t \in T, \forall m \in M(f), \forall f \in F \quad (7)$$

$$\sum_{m \in M(f)} \sigma_m Pl_m^t \le sp_f \ \ \forall t \in T, \forall f \in F \quad (8)$$

$$\sum_{k \in K(f)} Q_{kim}^t = Q_{im}^t \ \ \forall t \in T, \forall f \in F, \forall i \in I(f), \ \forall m \in M(f) \quad (9)$$

$$\beta_{im} Q_{kim}^t \le lt H_{kim}^t \ \ \forall t \in T, \forall f \in F, \forall m \in M(f), \ \forall i \in I(f), \forall k \in K(f) \quad (10)$$

$$\sum_{m \in M(i,g)} H_{kim}^t \le Sk_{gki}^t - \frac{ws_{gi}}{lt} Tr_{gki}^t \ \ \forall t \in T, \ \forall g \in G, \forall k \in K, \forall i \in I^P \cup I^A \quad (11)$$

$$Sk_{gki}^t = Sk_{gki}^{t-1} + Tr_{gki}^t \ \ t = 2, \dots, T, \forall g \in G, \forall k \in K, \ \forall i \in I \quad (12)$$

$$Sk_{gki}^t = Sk_{gki}^0 + Tr_{gki}^t \ \ t = 1, \forall g \in G, \forall k \in K, \forall i \in I \quad (13)$$

$$D_m^t = D_m^{t-1} - \alpha_m^t Pl_m^t + \sum_n X_{nm}^t (r_n - D_m^{t-1} + \alpha_m^t) \quad t = 2, \dots, T, \forall m \in M \quad (14)$$

$$D_m^t = D_m^0 - \alpha_m^t Pl_m^t + \sum_n X_{nm}^t (r_n - D_m^0 + \alpha_m^t) \quad t = 1, \forall m \in M \quad (15)$$

$$Ca_m^t = lt D_m^{t-1} - \sum_n pt_n X_{nm}^t \quad t = 2, \dots, T, \forall m \in M \quad (16)$$

$$Ca_m^t = lt D_m^0 - \sum_n pt_n X_{nm}^t \quad t = 1, \forall m \in M \quad (17)$$

$$\sum_{k \in K(f)} \sum_{i \in I(f)} H_{kim}^t \le Pl_m^t \ \ \forall t \in T, \forall m \in M(f), \ \forall f \in F \quad (18)$$

$$\sum_{i \in I(f)} \sum_{m \in M(i)} H_{kim}^t \le 1 \ \ \forall t \in T, \forall k \in K(f), \forall f \in F \quad (19)$$

$$\sum_n X_{nm}^t \le 1 \ \ \forall t \in T, \forall m \in M \quad (20)$$

$$0 \le D_m^t \le 1 \ \ \forall t \in T, \forall m \in M \quad (21)$$

$$0 \le H_{kim}^t \le 1 \ \ \forall t \in T, \forall k \in K, \forall i \in I, \forall m \in M \quad (22)$$

$$Pl_m^t, Sk_{gki}^t, Tr_{gki}^t, X_{nm}^t \in \{0,1\} \ \ \forall t \in T, \forall i \in I, \ \forall n \in N, \forall g \in G, \forall k \in K, \forall m \in M \quad (23)$$

$$Q_i^t, Q_{im}^t, I_i^t, B_i^t, Ca_m^t \ge 0 \ \ \forall t \in T, \forall i \in I, \forall m \in M \quad (24)$$

The objective function (1) minimizes costs of production, inventory, and backorder of items, maintenance actions, activation of machines, and workforce training. The inventory balance for all products is defined by constraint (2) as the level of inventory from the previous period minus the difference of produced products and demand. Constraint (3) defines the inventory for all products for the initial period. Constraints (4) and (5) define the inventory for all sub-assemblies and components for the respective periods. Constraint (6) ensures that the total production of an item is equal to the total production within each machine group that is required for that item. Constraint (7) limits the machine capacity, which is only available if a platform is activated for a machine. Constraint (8) limits the number of activated machines by the sum of their respective space consumption. Constraint (9) equals the number of produced items on a machine under the supervision of several workers to the total amount of produced items on that machine. Constraint (10) is the capacity constraint depending on the available time of assigned workforce. Constraint (11) allows a workers' assignment to a machine depending on the workers' skill. If a worker has not the required skill to work on a machine group and/or to process an item on that machine group, training can be scheduled. Constraints (12) and (13) update the workers' skills for the respective periods depending on their previous skills and scheduled training. Constraints (14) and (15) describe the deterioration level of the machines at the end of the respective periods. It is composed of the deterioration status of the previous period minus the random factor α plus a term equalizing the deterioration when maintenance r_n is conducted. Accordingly, machine deterioration is affected by the decision on whether a machine is activated, and maintenance is scheduled. Constraint (16) defines the capacity per period, which is affected by multiplying the deterioration level of the end of the previous period with the working hours per day minus the required time for conducting a maintenance action. Consequently, the capacity of a machine dynamically relies on the decisions considering maintenance actions as well as machine activation. Constraint (17) defines the initial capacity of a machine. Constraint (18) limits the sum of proportional assigned workers and items to a machine. Constraint (19) limits the sum of assigned machines and items to a single worker to one. Constraint (20) restricts the amount of maintenance tasks per period and machine to one. Constraints (21) - (24) are domain constraints. Additionally, the right-hand side of constraints (7), and (14) are linearized by using auxiliary decision variables and the Big-M method.

New set of constraints replacing constraint (7) where M is a random very large number:

$$\sum_{i\in I(f)} \beta_{im} Q_{im}^t \le Z_m^t \ \ \forall t \in T, \forall m \in M(f), \forall f \in F$$
$$Z_m^t \le M * Pl_m^t \ \ \forall t \in T, \forall m \in M$$
$$Z_m^t \le Ca_m^t \ \ \forall t \in T, \forall m \in M$$
$$Z_m^t \ge Ca_m^t \ - M * (1 - Pl_m^t) \ \forall t \in T, \forall m \in M$$
$$Z_m^t \ge 0 \ \ \forall t \in T, \forall m \in M$$

New set of constraints replacing constraint (14):

$$D_m^t = D_m^{t-1} - \alpha^t Pl_m^t + \sum_n (X_{nm}^t (r_n + \alpha^t) - Y_{nm}^t)$$
$$t = 2, \dots, T, \forall m \in M$$
$$Y_{nm}^t \le M * X_{nm}^t \ \ t = 2, \dots, T, \forall n \in N, \forall m \in M$$
$$Y_{nm}^t \le D_m^{t-1} \ \ t = 2, \dots, T, \forall\, n \in N, \forall m \in M$$
$$Y_{nm}^t \ge D_m^{t-1} - M * (1 - X_{nm}^t) \ \ t = 2, \dots, T, \forall n \in N, \forall m \in M$$
$$Y_{nm}^t \ge 0 \ \ t = 2, \dots, T, \forall n \in N, \forall m \in M$$

4 RESULTS

All problem instances are solved by CPLEX 20.1 and run on a Core i7 CPU 2.90 GHz computer equipped with 16 GB RAM under Windows 10.

Table 1. Scenario settings ; P = Final-product level ; A= Sub-assembly level

Setting	Products	Machines		Workforce	
		P	A	P	A
High	4	18	54	6	18
Medium	3	12	39	5	13
Low	2	9	27	3	9

Table 1 presents the different settings chosen for different scenarios in our experimental settings. Columns 2 - 4 define respectively the number of products, machines, and workforce for each setting in column 1. The model was tested for a planning horizon of T = 4 days and demand randomly created between [30,50] for each period and product. The deterioration state was randomly initialized between [0.7,0.9] for each machine.

Table 2 presents the results of model (1)-(19) under different scenarios settings, defined in table 1. The scenario choice primarily serves the purpose of validating the proposed model. Our goal is to investigate how the model behaves under extreme

Table 2. Scenario results

Scenario	# of products	# of machines	Workforce size	Backorder		Inventory		Maintenance		Training	
				P	A	P	A	P	A	P	A
1	Low	Low	Low	0	0	0	0	0	4	0	0
2	Medium	Medium	Medium	1	0	2	18	0	6	0	0
3	Medium	Medium	Low	278	0	0	0	0	1	0	0
4	Medium	Low	Medium	278	0	0	0	0	1	0	0
5	Medium	Low	Low	347	2	0	0	0	6	0	0
6	High	High	High	15	2	0	11	0	5	0	0
7	High	High	Medium	279	0	0	18	0	4	0	0
8	High	Medium	High	3	0	0	6	0	8	0	0
9	High	Medium	Medium	251	2	0	5	0	2	0	0
10	High	Low	Low	742	0	0	1	0	9	3	0
11	High	Low	High	621	0	0	0	0	9	2	0
12	High	High	Low	622	0	0	0	0	0	0	0
13	High	Medium	Low	613	3	0	4	0	0	1	1
14	High	Low	Medium	623	3	0	0	0	9	0	0
6*	High	High	High	253	15	0	1593	0	18	0	0

situations in terms of key parameters. Columns 5 - 8 present optimal decisions on backorder, inventory, maintenance, and training, further subdivided into the final product and sub-assembly levels. The columns for backorder and inventory present respectively the accumulated amount of all items across the planning horizon. The columns for maintenance and training present the accumulated amount of scheduled maintenance actions and workforce training respectively across the planning horizon.

It is worth mentioning that workforce training is conducted only in scenarios 10, 11, and 13, all configured with a high number of products. Training in scenario 10 and 13 can be explained by the low amount of available workforce in the beginning of planning horizon, making the training inevitable. Interestingly, scenario 11 is configured with a high initial level of workforce. As explained in section 3, labor skills are defined per machine group and product, making it possible that a worker is qualified to run a machine group, but not for every product. For that reason and due to the high number of products, it is possible that additional training is needed to receive an optimal result under this scenario.

Some maintenance actions can be observed in most scenarios on the sub-assembly level, whereas there is no maintenance action on the final production level. A deeper analysis of scenario 8 showed, that the highest machine group utilization averaged over the planning horizon T at the final product level is 45% compared to 85% at the sub-assembly level. It can be concluded that the sub-assembly facility is in general the bottleneck and maintenance actions are of higher importance. The absence of maintenance actions in scenarios 12 and 13 can further be explained by the configurations, as less labors than machines are available and machines are accordingly interchanged.

In contrast to backorder decisions, only little inventory decisions can be observed on the sub-assembly level and vanishingly little on the final product level. A factor can be the rather constant demand over the planning horizon T. To further investigate this, scenario 6* was tested with a randomized demand between [10,20] in the first two periods, and a considerable larger demand of 100 in the last two periods for each product. Consequently, the model builds up inventory at the sub-assembly level in the early periods, to compensate the larger demands in following periods. Backorder decisions are very rare at the sub-assembly level. On the contrary, backorder only occurs at the final production level. Except for the balanced scenarios 1, 2, and 6, backorder commonly occurs. This is also due to the fact that machine and workforce configurations are either on the same level or lower than the number of products in these scenarios. Surprisingly, scenario 8 shows very little backorder, even though the number of machines is set as medium, and the number of products is high. When comparing with scenario 9, it can be seen that the backorder is much higher, most likely due to the medium workforce size. Other scenarios, e.g. when comparing scenarios 2 and 4, show the effect of different machine configurations on the amount backorders. Furthermore, scenario 13 records less backorders compared to scenario 12, even though less machines are available. The same can be observed when comparing scenarios 7 and 9. This can be explained by the respective BOMs of products and accordingly required machine groups. Given that the level of workforce and products are similar in the compared scenarios, the model might allow more total backorder when more machines are available in favor of producing a product with a higher unit backorder cost, in order to minimize total costs.

5 CONCLUSION

This paper presented a MIP operational production planning model incorporating features stemming from smart factory principles which are crucial to operational production planning. Goal was to fill in the gap and need for decision-making models that bridge and support the challenging transition from existing production facilities towards a smart factory. Several numerical experiments were conducted and the behavior of the model evaluated by interpreting the results. The model showed that it can act as a valuable decision-support tool as is possible to adapt to different kinds of scenarios.

Yet, there is a number of enhancements that could be addressed in our future work. It is desirable to test the model at larger instances, e.g. for a longer time period as well as for a larger number of products with more complex BOMs. Yet, its inherit complexity requires an efficient decomposition algorithm to cope with considerably larger instances. Finally, the inclusion of uncertain parameters can be valuable additions to the model. Creating robust models for smart factories can therefore be a promising research avenue for future smart factory applications.

6 REFERENCES

Alaswad, S. and Xiang, Y. (2017). A review on condition-based maintenance optimization models for stochastically deteriorating system. Reliability Engineering & System Safety, 157:54–63.

BMWK (n.d.). What is industrie 4.0? https://www.plattform-i40.de/IP/Navigation/EN/Industrie40/WhatIs Industrie40/what-is-industrie40.html. Last checked on 31.01.2023.

Dolgui, A., Ivanov, D., and Sokolov, B. (2020). Reconfigurable supply chain: the x-network. International Journal of Production Research, 58(13):4138–4163

Ghaleb, M., Taghipour, S., and Zolfagharinia, H. (2021). Real-time integrated production-scheduling and maintenance-planning in a flexible job shop with machine deterioration and condition-based maintenance. Journal of Manufacturing Systems, 61:423–449.

Gopal, M. (2019). Applied Machine Learning. McGraw-Hill Education and McGraw Hill, New York, N.Y., 1st edition.

Guo, D., Zhong, R. Y., Lin, P., Lyu, Z., Rong, Y., and Huang, G. Q. (2020a). Digital twin-enabled graduation intelligent manufacturing system for fixed-position assembly islands. Robotics and Computer-Integrated Manufacturing, 63:101917.

Guo, D., Zhong, R. Y., Ling, S., Rong, Y., and Huang, G. Q. (2020b). A roadmap for assembly 4.0: self-configuration of fixed-position assembly islands under graduation intelligent manufacturing system. International Journal of Production Research, 58(15):4631–4646.

Ivanov, D., Dolgui, A., Sokolov, B., Werner, F., and Ivanova, M. (2016). A dynamic model and an algorithm for short-term supply chain scheduling in the smart factory industry 4.0. International Journal of Production Research, 54(2):386–402.

Ivanov, D., Tsipoulanidis, A., and Schönberger, J.

(2021). Digital supply chain, smart operations and industry 4.0. In Ivanov, D., Tsipoulanidis, A., and Schönberger, J., editors, Global Supply Chain and Operations Management, Springer Texts in Business and Economics, pages 521–581. Springer International Publishing, Cham.

Jamrus, T., Wang, H.-K., and Chien, C.-F. (2020). Dynamic coordinated scheduling for supply chain under uncertain production time to empower smart production for industry 3.5. Computers & Industrial Engineering, 142:106375.

Katoozian, H. and Zanjani, M. K. (2022). Supply network design for mass personalization in industry 4.0 era. International Journal of Production Economics, 244:108349.

Kumar, A., Shankar, R., and Thakur, L. S. (2018). A big data driven sustainable manufacturing framework for condition-based maintenance prediction. Journal of Computational Science, 27:428–439.

Li, M. and Huang, G. Q. (2021). Production-intralogistics synchronization of industry 4.0 flexible assembly lines under graduation intelligent manufacturing system. International Journal of Production Economics, 241:108272.

Malladi, S. S., Erera, A. L., and White, C. C. (2020). A dynamic mobile production capacity and inventory control problem. IISE Transactions, 52(8):926–943.

McKinsey & Company (2019). Global ai survey: Ai proves its worth, but few scale impact. https://www.mckinsey.com/featured-insights/artificial-intelligence/global-ai-survey-ai-proves-its-worth-but-few-scale-impact. Last checked on 31.01.2023.

Oh, J. and Jeong, B. (2019). Tactical supply planning in smart manufacturing supply chain. Robotics and Computer-Integrated Manufacturing, 55:217–233.

Perraudat, A., Dauzère-Pérès, S., and Vialletelle, P. (2022). Robust tactical qualification decisions in flexible manufacturing systems. Omega, 106:102537.

Strozzi, F., Colicchia, C., Creazza, A., and Noè, C. (2017). Literature review on the 'smart factory' concept using bibliometric tools. International Journal of Production Research, 55(22):6572–6591.

van Staden, H. E. and Boute, R. N. (2021). The effect of multi-sensor data on condition-based maintenance policies. European Journal of Operational Research, 290(2):585–600.

T. Zonta, C. A. Da Costa, R. Da Rosa Righi, M. J. de Lima, E. S. Da Trindade, and G. P. Li. Predictive maintenance in the industry 4.0: A systematic literature review. Computers & Industrial Engineering, 150:106889, 2020. ISSN 03608352. doi: 10.1016/j.cie.2020.106889