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RESEARCH ARTICLE-MECHANICAL ENGINEERING

Design and Development of Best Class Discrete Production Model for Distributed Manufacturing under Industry 4.0

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Abstract

Global competitiveness creates a challenge for manufacturing companies to maintain their market share with dynamic customer requirements. Capital investment in machinery does not allow facility expansion to accommodate large orders from customers but to reconfigure the manufacturing enterprise. Distributed manufacturing (DM) is embraced in order to increase facility utilization by decentralizing production. An enterprise in charge of a DM network allows customers to choose the best manufacturers available for their order based on their track record, which is available through historical and online performance data. Furthermore, manufacturers as members of this network may receive orders based on their past performance. Industry 4.0 with all necessary Industrial Internet of Things (IIoT) enables the online monitoring of production key parameters of manufacturers subscribed to a DM network. We develop a new network model of manufacturers teamed under specific terms and conditions to support a group of customers who have specific needs. The proposed model, known as the continuous supervised model, is created with the ARENA simulation software. We demonstrate the effectiveness of our model by contrasting it with the standard practice approach. To ensure the best possible performance, we continuously monitor the cost, quality, delivery time, and production rate indicators of the various manufacturers and update their performance ranking for current and future orders. Furthermore, using the analytic hierarchy process (AHP) approach, a single performance measure based on the four indicators is developed. Implementing the proposed model showed an improvement in the average performance by 51.3%.

Keywords Distributed manufacturing · Discrete production model · Production line · Supply chain · International load sharing (ILS) system

Abbreviations

AHP	Analytic hierarchy process
Avg.	Average
CA	Conveying agent
DM	Distributed manufacturing
I 4.0	Industry 4.0
ILS	International Load Sharing
MA	Machining agent
MCDM	Multi-criteria decision making
PA	Product agent
RFID	Radio frequency identification
WH	Warehouse

Symbols

a	Importance factor of cost
a_{ij}	Number of production attempts by ith manufacturer with the jth assigned order
A	Production allowance time
AC_i	Average production cost of manufacturer i
AD_i	Average delivery time of manufacturer i
APM_i	Average performance measure of the ith manufacturer
AP_i	Average productivity of manufacturer i

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AQ_i	Average quality of manufacturer i
b	Importance factor of quality
c	Importance factor of delivery time
c_i	Cost of single production attempt by the ith manufacturer
C_{ij}	Product cost of the ith manufacturer with the jth assigned order
$\mathrm{CI_{ij}}$	Cost indicator of the ith manufacturer with the jth assigned order
C_{th}	Cost indicator threshold above which assigned order is shifted
d	Importance factor of productivity
D_{ij}	Delivery time of the ith manufacturer with the jth assigned order
DI_{ij}	Delivery time indicator of the ith manufacturer with the jth assigned order
D_{th}	Delivery time indicator threshold above which assigned order is shifted
g_{ij}	Number of goods produced by the ith manufacturer with the jth assigned order
i	Represents the ith manufacturer
j^{th}	Represents the jth assigned order
K	Currently delivered batch by a manufacturer
M	Batch size of good item produced by manufacturer
N	Number of registered manufacturers in the DM network
NAM	Number of assigned manufacturers for an order
NS_i	Total number of assigned orders to the ith manufacturer
PM_{ij}	Performance measure of the ith manufacturer with the jth assigned order
PI_{ij}	Productivity indicator of the ith manufacturer with the jth assigned order
PM_j	Performance measure for the jth assigned order
P_{ij}	Productivity of the ith manufacturer with jth assigned order
P_{th}	Productivity indicator threshold above which assigned order is shifted
Q	Order size
Q_T	Total number of orders placed
Q_{ij}	Quality of the ith manufacturer with the jth assigned order
QI_{ij}	Quality indicator of the ith manufacturer with jth assigned order
Q_{th}	Quality indicator threshold above which assigned order is shifted
R_{ij}	The jth ordered quantity assigned to manufacturer i
SAC	System average cost
SAD	System average delivery time
SAP	System average productivity
SAPM	System average performance
SAQ	System average quality
S_{th}	Threshold of remaining parts for shifting order
TBO	Time between orders or time frequency for online order
TB_{ijk}	Time at which the manufacturer i completed the production of the kth batch of good items for the jth assigned order
T_{Ci}	Time for cleaning the part of the ith manufacturer
T_{Fi}	Time for minor failure (maintenance time) of the ith manufacturer
T_{Ii}	Time for inspection of part of the ith manufacturer
T_{Mi}	Time for machining the part of the ith manufacturer
T_{MFi}	Time for major failure of the ith manufacturer
T_{MTi}	Time for material ordering of the ith manufacturer
T_{ij}	Time at which manufacturer i start production for jth assigned order
T_{now}	Current time
w_c	Weight for cost
w_d	Weight for delivery
w_p	Weight for productivity
w_q	Weight for quality

1 Introduction

In recent years, the concept of distributed manufacturing (DM) emerged in production planning and operations. In DM, the main idea is centered around the load sharing of a manufacturing facility among different manufacturers (suppliers) to accomplish the planned order in reduced time according to the specified standards [1]. The authors have surveyed large production lines in various factories serving local large users. The expected large number of parts in thousands was difficult to meet initial specs including time delivery, cost and recently covid-19 effects.

DM are the scenarios needed to support the discrete production. Continuous production has obvious routing with very little decision and transport time. Challenges faced by discrete manufacturing, such as increased globalization, market volatility, workforce shortages, and mass personalization have necessitated scalable solutions that improve the agility of production systems. These challenges have driven the need for better collaboration and coordination in production via improved integration of production systems across the product life cycle. It becomes important to motivate the research and development needed for distributed production in discrete manufacturing. Initially, more advanced approaches seek to successfully link shop floor operations to their front-end systems, such as ERPs (Enterprise Resource Planning) and SCM (Supply Chain Management) applications. But even these approaches do not successfully provide a holistic solution in which all relevant internal and external information, from the topmost business system all the way down to the shop floor, can be shared, in real time. Hence, the need for international load distribution (ILS) in DM.

Dynamic selection of the right manufacturer available for the right product is a challenging task for companies. Customers look for quality products with minimal cost and appropriate lead time when ordering manufacturing parts. In general, a quality product comes at a higher cost or larger lead time. DM helps in providing the production process control by utilizing the latest technologies in monitoring and sensing [2]. Furthermore, it increases the utilization of manufacturing facilities by adopting a continuous improvement strategy of their productivity to keep competitive in the market. Globalization amplified the need for distributed production across different manufacturers possibly located in different countries. The DM concept results in the load sharing of needed production using different approaches and methodologies. In DM, a new recent paradigm was introduced in 2019 and named as international load sharing (ILS) system by Mekid and Akbar [3].

In this paper, they defined the protocols and architecture to facilitate the local and global production load sharing system aimed at maximizing the machines utilization and improving productivity. Also, they have clearly shown the detailed relationship between the proposed ILS and I4.0 as it is tightly related.

A distributed/load sharing manufacturing system reduces the centralization and the rigidity of a manufacturing system while increasing flexibility, reconfiguration, and scalability [4]. For a decentralized decision/control, it is incumbent that all participants in the system have access to the relevant information and efficiently communicate with each other. The benefit of decentralized decisions is just-in-time actions with less computational time and superior services. To share the DM resources for achieving good performance, two multi-agent systems are built named as enterprise multi-agent system and enterprise alliance multi-agent system [5]. For load balancing and efficient production, a smart structure is proposed with top and bottom loops. The top loop contains the users' layer and is networked with a cloud assistance layer. The bottom loop contains the resource interaction layer and is connected to the cloud assistant layer [6]. In this smart manufacturing network, agents are divided into three categories: machining agent (MA), conveying agent (CA), and product agent (PA). MAs are responsible for machining, storing, testing, and processing, while CAs are responsible for loading, unloading, conveying with manipulators and automatic guided vehicles. PA defines and identifies the product with RFID and microcontroller tags for storage information.

The implementation of DM requires all elements in a smart factory to be fully integrated and connected in real-time. The network of machines consists of data networks, data servers, sensors, actuators, and control components [7]. The historical data of previous years can be analyzed to forecast future demand. This also helps in predicting the machine's failure and communicating with the responsible operator to fix it proactively before failure occurrence [8, 9]. This system allows collecting the accurate information of ongoing manufacturing tasks, whereas in traditional manufacturing, manufacturers can manipulate and falsify the production status. This facilitates the timely taking actions and saves not only time but also the cost of late delivery to customers [10, 11]. The production information of a complete cycle from ordering to delivery in ILS is presented in Fig. 1 [3]. Customers order online through a website/application for the parts to be manufactured by uploading the computer-aided design (CAD) file and the manufactured products are delivered by the production company after inspection and packing.

The DM advantages consist of access to global business, profitability, spare capacity utilization, access to recent trends, and ease of communication with manufacturers. Similarly, the benefits for customers are easy access to manufacturing companies, competitive cost, better quality, access to real-time information, and instant coordination and communication [12]. Smart manufacturing, robotics, M2M (machine-to-machine) communication, and smart supply chain involve production in batches to optimize cost and time, and use of sensors to record, account, share, and analyze the data in an effective way [13]. Decisions are made digitally by collecting the data by smart sensors and analyzing it to make meaningful decisions [14]. These are all terms illustrated in Industry 4.0 (I4.0) to obtain maximum effectiveness. The effectiveness is not only the target, ILS enabled by I4.0 also widely promote the traditional relationships among producers, suppliers, and its consumers. Implementation of advanced manufacturing and artificial intelligence technologies has positive effects and opens new ways for manufacturing. The completion time, cost, and quality of the manufacturing tasks have been considered in the study for flexible configuration of distributed manufacturing resources [15]. In the DM literature, there is a lack of detailed studies on the operation sequences, and the performance calculation of production line in manufacturing industries. This article focuses on the performance evaluation of ILS with multiple machining orders from one customer (or multiple) by selecting the suitable manufacturers to be assigned and the online monitoring of their performance. Discrete-event simulations in ARENA software are performed to gain insight on the model behavior as function of the inputs. In addition, one overall performance measure is introduced to cover the four indicators on cost, quality, production rate, and delivery time. This is used to systematically guide the decisions on the production of each manufacturer for the sake of an efficient DM setup. The result of this activity helps

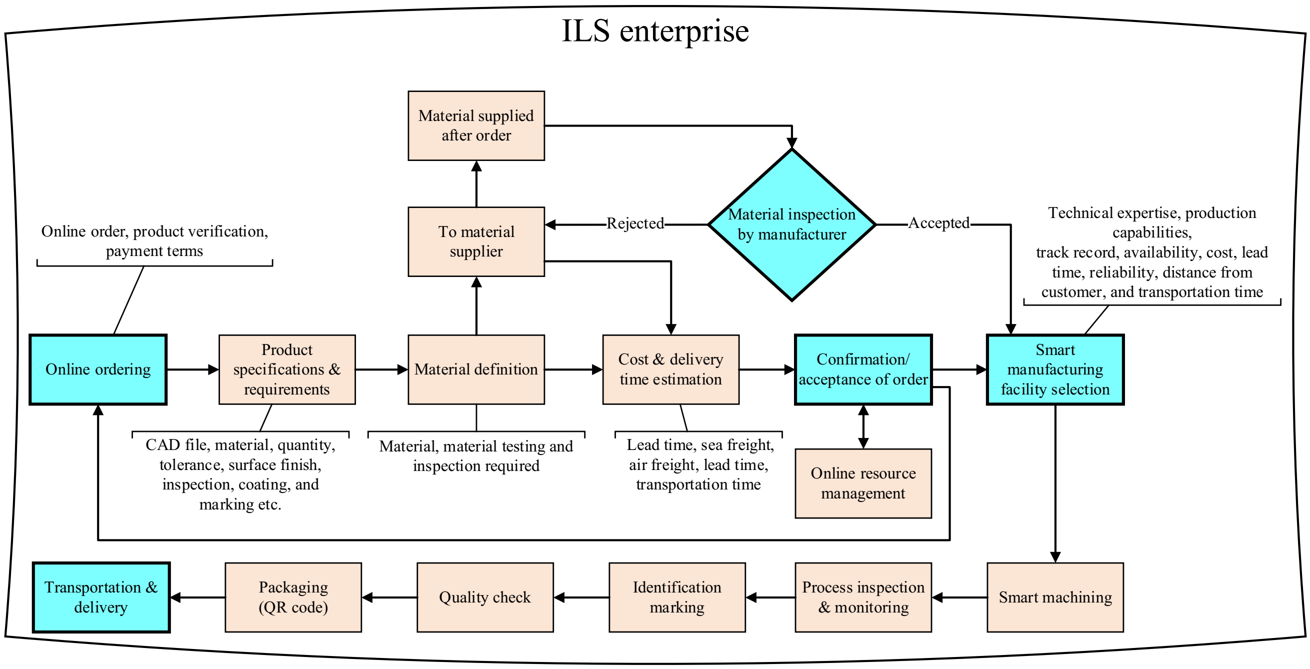


Fig. 1 Part ordering cycle and steps involved for ordering in an international load system

the customer to select the best manufacturer available worldwide/countrywide. Manufacturer with higher performance on records will always be on top to be selected.

The evaluation and selection of the right supplier at the right time becomes important here. This can be either for the material suppliers or parts manufacturing suppliers. The selection of a supplier with minimum cost criteria is not effective in advanced supply management [16]. The multi-criteria decision making (MCDM) method is now commonly used in assessing and selecting suppliers with important criteria, e.g., quality, cost, delivery time, performance, technical capability, communication and coordination, geographical location, attitude, financial position, repair services, certifications, and reputation [17]. Several methods are reported in the literature such as AHP [18], fuzzy AHP [19], VIKOR [20], fuzzy axiomatic design [21], fuzzy TOPSIS [22], TODIM [23], fuzzy grey relational analysis [24], fuzzy analytic network process (ANP) [25], and data envelopment analysis (DEA) [26]. These models can be used in a stand-alone as well as combined ways to achieve the selection of the best possible supplier by evaluating the different criteria.

One of the powerful software for conducting discrete-event simulations as a first approach is ARENA. This software helps in considering the stochastic nature of real-life systems. Many researchers have used it to perform simulations and solving problems in manufacturing, production, supply chain, and materials handling. This software gives access to the user to enter values and blocks, as well as user-defined functions as per the requirements for each activity of the system. Awasthi et al. in [27] proposed the framework of modeling and simulations for part selection and routing in automated guided vehicle (AVG) systems using ARENA. Berman et al. also simulated the management system of AVGS by using this software. For the systems that are complex to build and systems with a long time to complete, simulation is one of the best ways to evaluate and predict the performance by varying numerous parameters [28]. The simulation is not only used to check the system behavior, but also to expedite the system development and optimization. In [28], a study was performed for a manufacturing system prone to failures and optimized to reduce the cost by controlling the production rates of different machines. This failure-prone manufacturing system (FPMS) was simulated in ARENA and optimized using a simulated annealing algorithm. In [29], a case study was presented of tires manufacturing company by simulating the model in ARENA to find the bottleneck, processing time, and the non-value-added activities. Machine modification was proposed after root cause analysis to increase productivity and eliminate the bottleneck point [30].

The proposed new network model is based international load sharing supported by the availability of necessary performance data through I4.0 a membership condition required for each company to be in the network. The overall performance of this proposed model has several components including productivity, quality, cost, and delivery time. This model secures continuous production to meet worldwide orders on time. Examples of usefulness are critical stocks

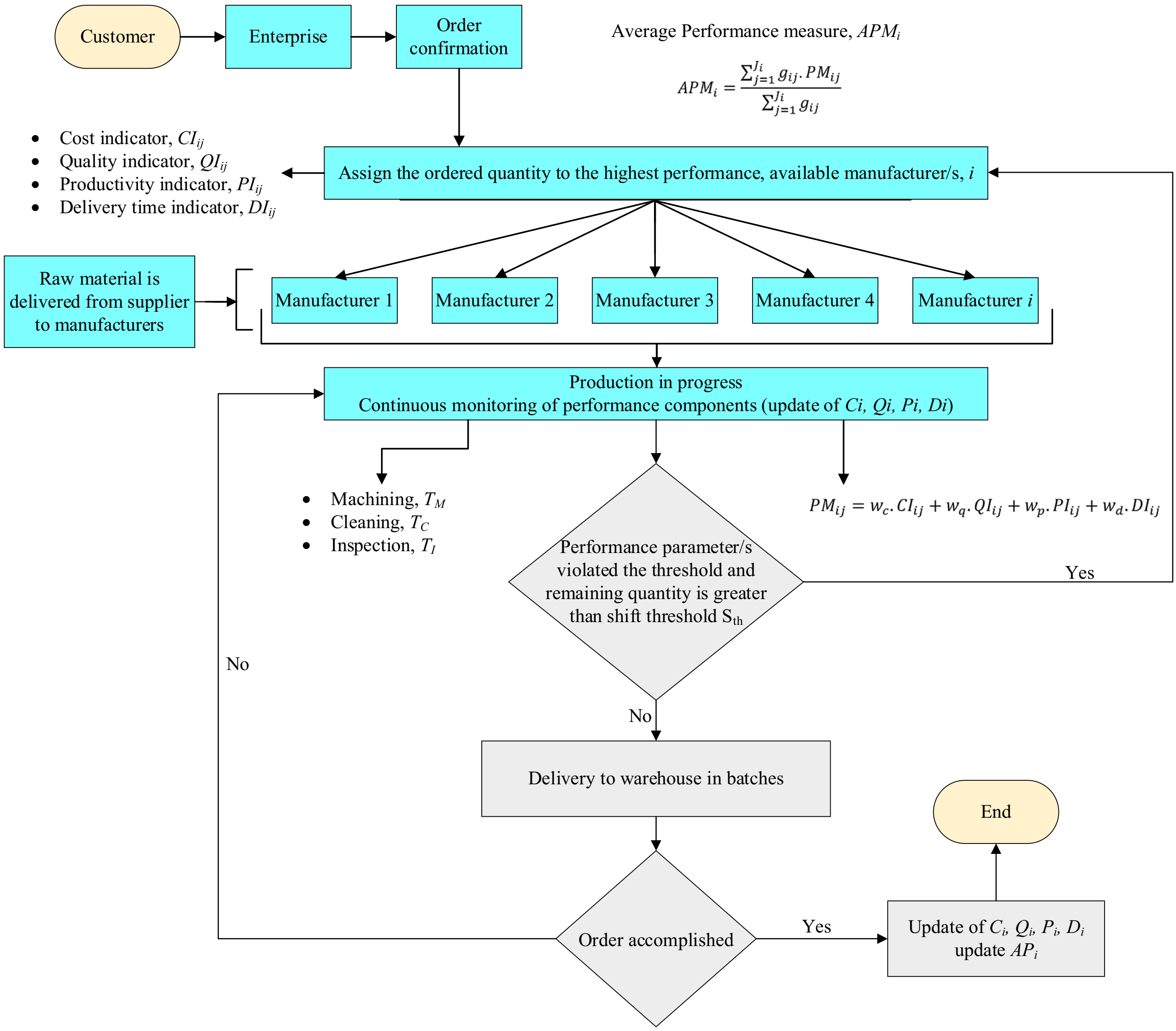


Fig. 2 Description of continuous supervised model for distributed manufacturing network

fulfilled for immediate assemblies. The comparison with traditional system has shown an improvement for specific cases by an average of 50%—refer to Figs. 5 and 6. The superiority of the proposed model is exhibited through the comparison with conventional techniques with very clear novelty since no similar work was found in the open public literature.

This paper presents the proof of concept of the continuous supervised ILS model by showing its superior performance using simulations. The simulation is based on the workflow of a production load-sharing environment as described in Fig. 2. In the continuous supervised model, significant indicators are considered as productivity, quality, cost, and delivery time. The preference in selection of manufacturers is merely dependent on performance measure which considers all indicators jointly.

The rest of the paper is structured in four sections. Section 2 is dedicated to detailed description and assumptions of the proposed continuous supervised model. Section 3 contains the model formulations to describe the performance measures and indicators. In Sect. 4, the results generated by the model are represented and compared with traditional manufacturing. The results demonstrate that the continuous supervised model has higher performance measure in terms of quality, cost, productivity, and delivery in comparison with other models. Lastly, Sect. 5summarizes the importance of the proposed model in the form of conclusions and potential applications in global manufacturing industries.

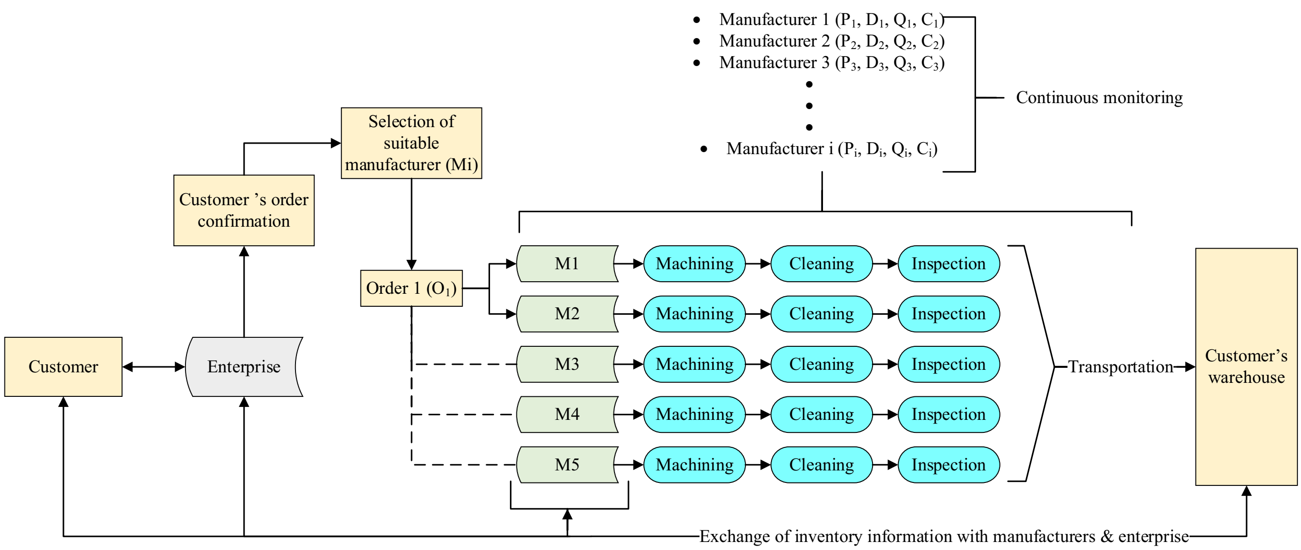


Fig. 3 Typical arrangement of the workflow

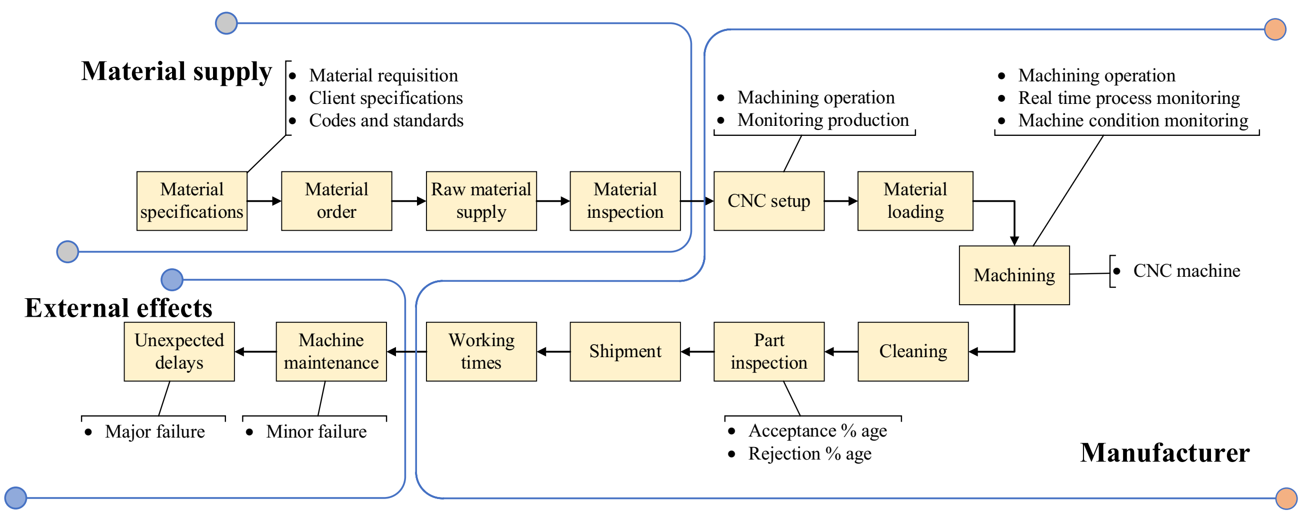


Fig. 4 Typical representation of flow activities in a manufacturing unit

2 Model Description: Continuous Supervised Model (Case 1)

We consider a production problem in an enterprise where the selection of manufacturers is based on their performance with continuous monitoring of the production activities. The continuous supervised model presented seeks to take timely actions to improve the overall efficiency of production. Consider a DM network consisting of N registered manufacturers. Once a customer places an online order of size Q through the enterprise, it will be assigned to a number of the available manufacturer/s (NAM) with the highest average performance measure APM_i. The selected manufacturers will order the required raw materials from a supplier S_i. Once the raw materials are delivered by the supplier, the manufacturer starts production, and the performance of the manufacturer is monitored and continuously updated. The performance measure is defined for a manufacturer i for order j based on four indicators namely cost (CI_{ij}), quality (QI_{ij}), productivity (PI_{ij}), and delivery time (DI_{ij}). These indicators are combined in one performance measure to help managers in the selection decision. Toward this end, weight should be assigned to each indicator; the weights are calculated based on the analytic hierarchy process (AHP). The indicators of the manufacturers are continuously monitored and updated. So, if the current manufacturer is violating one of the indicators defined thresholds (C_{th}, Q_{th}, P_{th}, or D_{th}) and the remaining quantity is greater than a shift threshold, S_{th}, the remaining order will be shifted and assigned to another available manufacturer with higher performance. If the order is fulfilled and produced parts are of good quality, then items will be

Table 1 Manufacturer's data for the simulation

	Machining time, T_{Mi}	Cleaning time, T_{Ci}	Inspection time, T_{Ii}	Time between failures for machine, T_{Fi}	Maintenance time for machine failure	Time between major failures, T_{MFi}	Recovery time from major failure
	mints	mints	mints	mints	mints	mints	mints
Manufacturers (M1 to M10)	Normal (μ, 0.1)	Normal (μ, 0.05)	Normal (μ, 0.05)	Exponential (λ)	Normal (μ, 5)	Exponential (λ)	Normal (μ, 30)
	μ	μ	μ	$1/\lambda$	μ	$1/\lambda$	μ
M1	2.5	0.3	2	160	60	50,000	5000
M2	2.6	0.3	2	160	60	48,000	5200
M3	2.7	0.3	2	160	60	46,000	5400
M4	2.8	0.3	2	150	60	44,000	5600
M5	2.9	0.3	2	150	60	42,000	5800
M6	3.0	0.3	2	150	60	40,000	6000
M7	3.1	0.3	2	140	60	38,000	6200
M8	3.2	0.3	2	140	60	36,000	6400
M9	3.3	0.3	2	140	60	34,000	6300
M10	3.4	0.3	2	130	60	32,000	6400

sent to the customer in batches of size M by the manufacturers. Manufacturers will continue their production until the required order size is met. At the end of the manufacturing activity, the manufacturer indicators will be updated for the next order. The whole process of the continuous supervised model is shown in Fig. 2 for a distributed manufacturing network. The details and descriptions of parameters used in model are defined in Sect. 3.

In this paper, we consider one product type, and all manufacturers are using the same production flow, but they are different in the production line characteristics such as machinery speed, probability of having defective items, failure rate, and cost. Continuous monitoring enables the customer to see the effect of the early mentioned characteristics on the performance. A typical part will be manufactured with computerized numerical control (CNC) followed by an inspection of the final product. Products are shipped in batches of size M items per batch. Therefore, once a batch is ready it will be shipped directly to the customer. Figure 3 shows a schematic diagram for the system including customer warehouse, manufacturers, and enterprise.

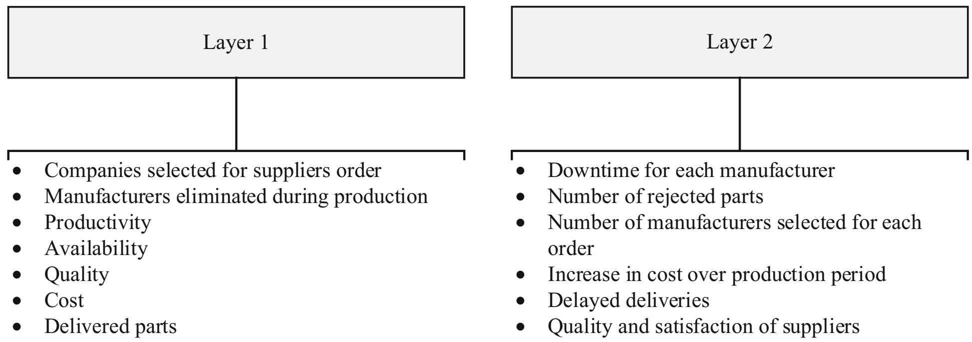
Once the manufacturer is chosen for an order, the raw material is ordered from the supplier. The time for material procurement includes time spent for defining specifications (based on material requisition, customer/client specifications, international codes, and standards), ordering, supply, and inspection of material. The shipment/transportation time is directly proportional to the required quantity and the distance between the supplier and the manufacturer. On the other hand, manufacturers may produce imperfect items that will be excluded, and each manufacturer has a different probability of having an imperfect item out of production attempt. The imperfect items are identified through an error-free inspection process. The proportion of imperfect items is merely depending on the condition of the machine, cutting tool, and machining conditions. The flow of activities and factors affecting the production process is shown in Fig. 4.

The advantages of continuous supervised model are as follows:

- On time actions are taken without any delay in the case when a manufacturer violates the performance thresholds agreed upon, the assigned order will be shifted to a new manufacturer with better performance.
- Implementing the proposed model will increase the system performance. According to numerical results, the timely actions improved the performance by 51.3%. For more details see Table 2.
- Continuous supervised model enhances the visibility and transparency in supply chains and this will force the manufacturers to improve their production performance aspects such as quality, cost, productivity, and delivery time.
- Improve the production planning adherence of large assets manufacturer by making sure the critical subassemblies are readily available.

In addition to the manufacturers performance, many other input parameters and decisions making are there to highly affect the system under study. Managers need to consider the following factors in order to secure best performance.

Fig. 5 Data collection layer description for production activities by each manufacturer



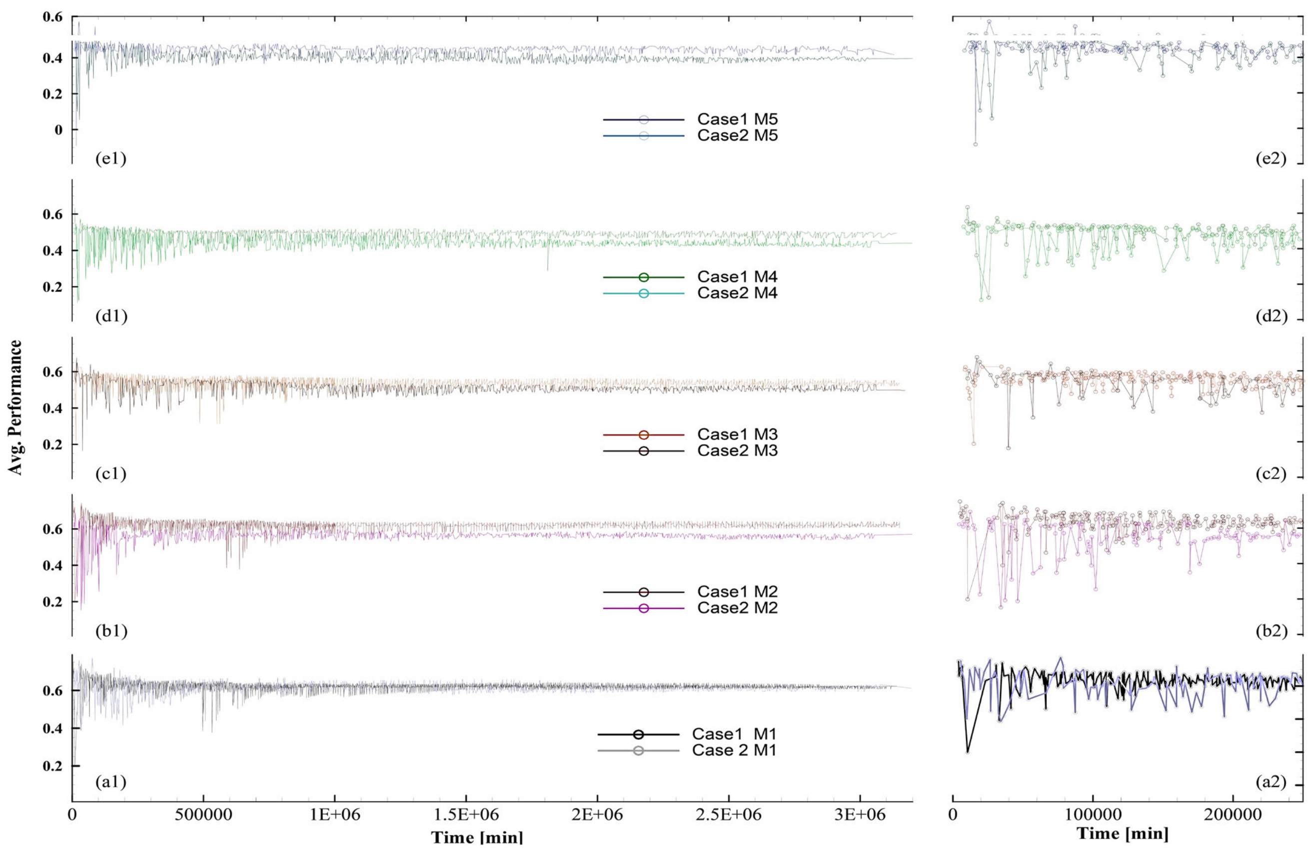


Fig. 6 Avg. performance for case 1 and case 2 (a1 and a2)- manufacturer 1, (b1 and b2)- manufacturer 2, (c1 and c2)- manufacturer 3, (d1 and d2)- manufacturer 4, and (e1 and e2)- manufacturer 5

1. Order's variability: covering variability in both quantities ordered and ordering frequency.
2. The number of assigned manufacturers (NAM) for a single order. This is mainly depending on the productivity of the manufacturers included, the quantities ordered, and the variability of the orders.
3. Indicator's thresholds (C_{th}, Q_{th}, P_{th}, $and\, D_{th}$) these thresholds should be defined reasonably based on the performance of the set of manufacturers registered in the network.
4. Shift threshold, S_{th}: the system must include shift threshold as the minimum remaining quantity below which no shift for order from a current manufacturer even if indicators thresholds are violated. Consider a case at which a manufacturer fails to satisfy one or more of the indicators thresholds then the remaining ordered quantity is shifted to another manufacturer. But the remaining quantity could be small, and the newly assigned manufacturer has to order the raw material from supplier and has a required setup. The time needed for such activities can

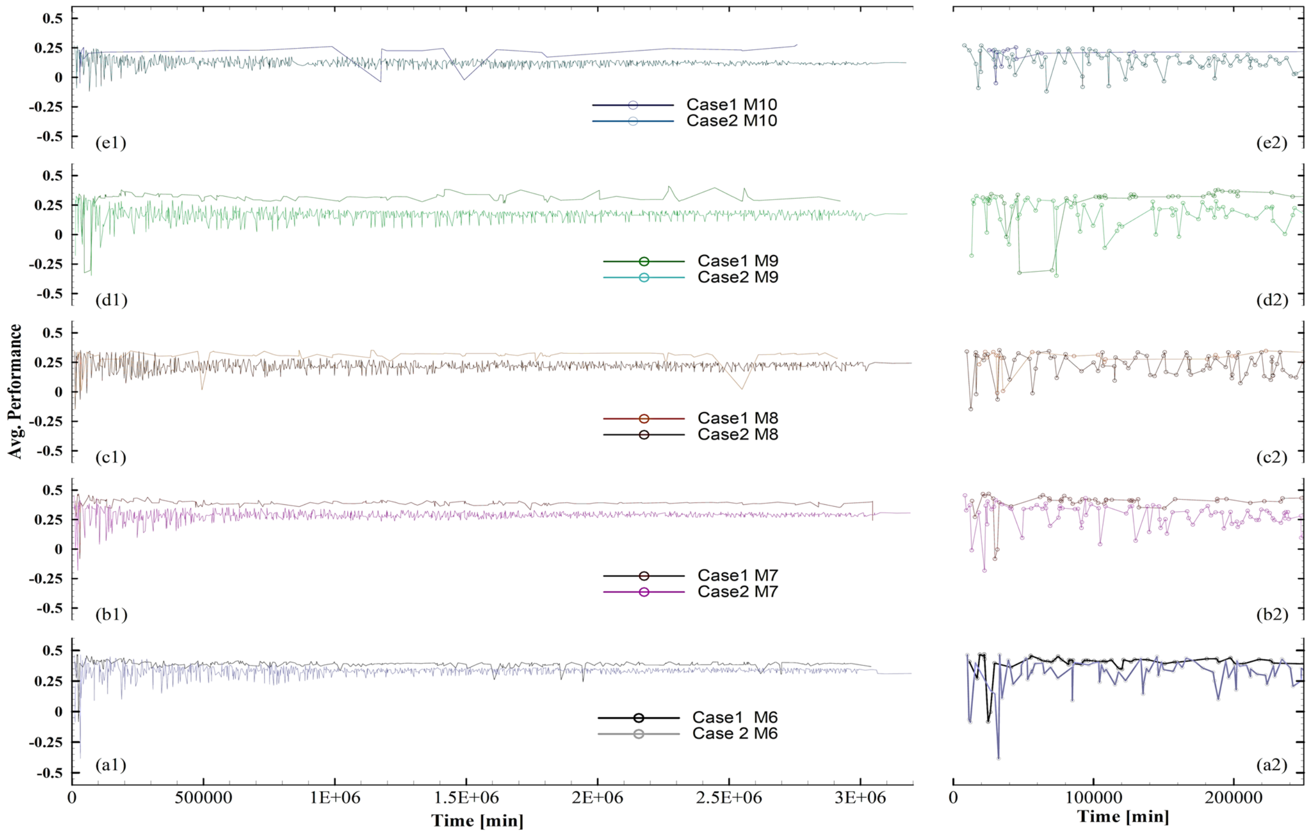


Fig. 7 Avg. performance for case 1 and case 2 (a1 and a2)- manufacturer 6, (b1 and b2)- manufacturer 7, (c1 and c2)- manufacturer 8, (d1 and d2)- manufacturer 9, and (e1 and e2)- manufacturer 10

be greater than the time needed for the current manufacturer to finish the order and there is no guarantee on the new performance indicators to be better than the older ones. On the other hand, this threshold could represent the minimum ordered quantity accepted by a manufacturer such that manufacturers are not accepting orders less than this threshold because of profit issues.

5. WH delivery batch size, M: this represents the minimum batch of good items produced to deliver to WH.
6. Production allowance time, A: Usually in real life it is fair enough to give the manufacturer some time at the beginning before start applying decisions based on the monitored performance.

3 Model Formulation

The selection of the proper manufacturer i for a customer order is based on the average performance measure (APM_i) that needs to be high when the manufacturer is selected. APM_i represents the average performance of a manufacturer depending on all previous experience (completed orders) with that manufacturer. Whenever a manufacturer finishes from the j^{th} assigned order, the performance measure (PM_{ij}) and the average performance measure (APM_i) are updated. PM_{ij} should cover the four indicators: cost, quality, productivity, and delivery. Hence, it is calculated as per Eq. (1);

$$PM_{ij} = w_c.CI_{ij} + w_q.QI_{ij} + w_p.PI_{ij} + w_d.DI_{ij} \tag{1}$$

where w_c, w_q, w_p, and w_d are the weights for cost, quality, productivity, and delivery, respectively.CI_{ij}, QI_{ij}, PI_{ij} and DI_{ij} are performance indicators for cost, quality, productivity, and delivery, respectively. In order to identify the indicators, their respective thresholds are taken as a reference. Hence, for the cost and delivery the smaller is the better but for quality and productivity the larger is the better. The performance indicators for cost, quality, productivity, and delivery are normalized using Eqs. (2), (3), (4) and (5), respectively, and are monitored and updated.

$$CI_{ij} = \frac{C_{th} - C_{ij}}{C_{th}} \tag{2}$$

$$QI_{ij} = \frac{Q_{ij} - Q_{th}}{Q_{th}} \tag{3}$$

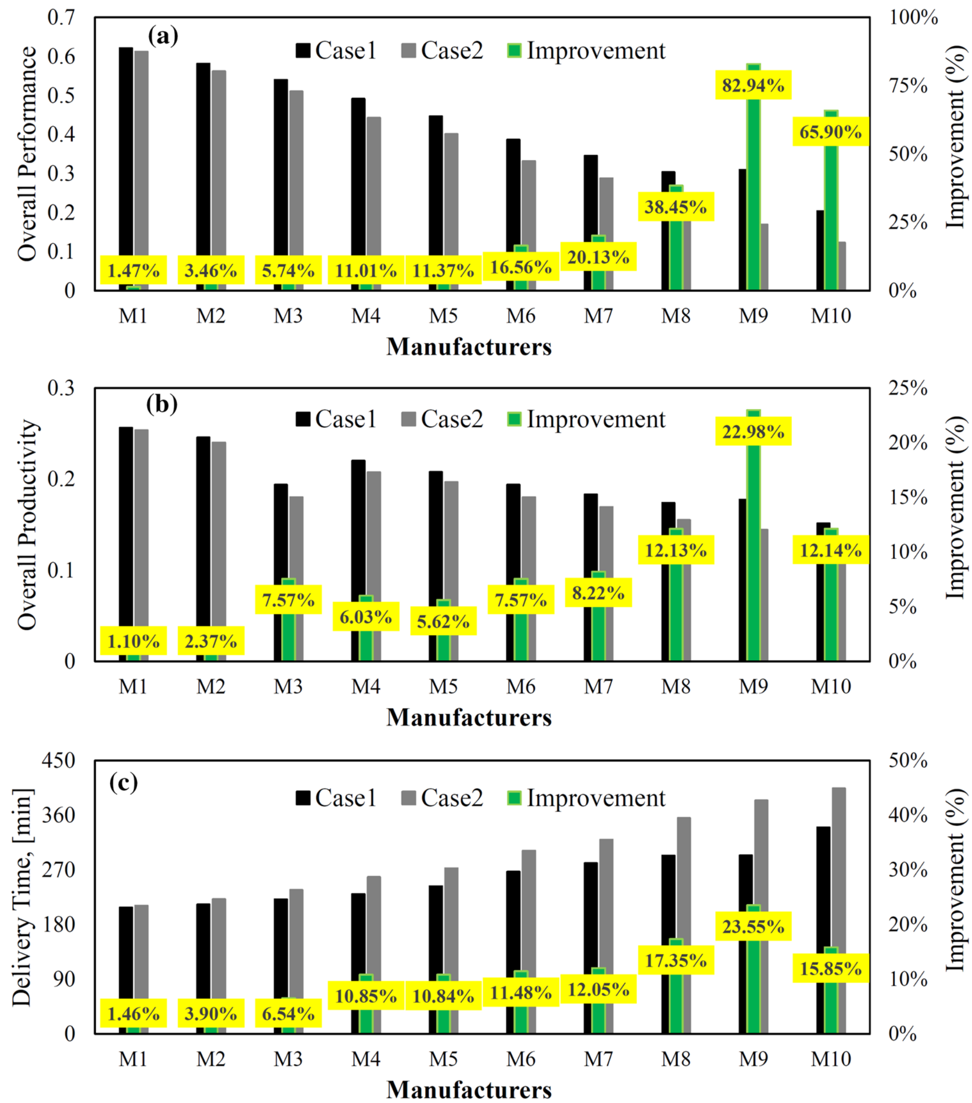


Fig. 8 Percentage improvement comparison of (**a**) overall performance, (**b**) overall productivity, and (**c**) delivery time for 10 manufacturers in case 1 and case 2

Table 2 Sum performance of all manufacturers (M1 to M10) for case 1 and case 2

Result description	No. of simulation replications	Manufacturers	Case 1	Case 2
System average performance ($\boldsymbol{SAPM}$)	10	M1 to M10	0.56	0.37
System average cost ($\boldsymbol{SAC}$), [$]	10	M1 to M10	2.18	2.24
System average quality ($\boldsymbol{SAQ}$)	10	M1 to M10	0.95	0.89
System average productivity ($\boldsymbol{SAP}$)	10	M1 to M10	0.24	0.19
System average delivery ($\boldsymbol{SAD}$), [min]	10	M1 to M10	219.29	293.22
System average order waiting time $\boldsymbol{OWT}$, [min]	10	M1 to M10	6631.13	8050.48

$$PI_{ij} = \frac{P_{ij} - P_{th}}{P_{th}} \tag{4}$$

$$DI_{ij} = \frac{D_{th} - D_{ij}}{D_{th}} \tag{5}$$

Next, we propose a simple approach to update these indicators. All parameters are time dependent but to avoid clumsy notations, the time index is excluded from the notations. We assume that the profit margin is the same for all manufacturers. Hence, the cost parameter is represented by the cost of producing a good item. Production process may yield imperfect items. So, the cost of total production attempts will be assigned to the good items produced. The cost of a good item

Table 3 Values set for optimization of average performance and order waiting time

Values set	Variable	Type	Low bound value	Step size	Upper bound value	Simulation runs	Objective	Constraints
Set No. 1	*NAM*	Discrete	1	1	4	168	Max (*APM*) & Min. (*OWT*)	–
	A (min)	Discrete	300	100	800			
	S_{th}(parts)	Discrete	200	50	500			
Set No. 2	c_w	Discrete	0.125	0.125	0.5	31	Max (*APM*) & Min. (*OWT*)	$c_w + p_w + q_w + d_w = 1$
	p_w	Discrete	0.125	0.125	0.5			
	q_w	Discrete	0.125	0.125	0.5			
	d_w	Discrete	0.125	0.125	0.5			
Set No. 3	*NAM*	Discrete	1	1	3	1134	Max (APM) & Min. (OWT)	$\frac{Q-Q_{\text{dev}}}{\text{NAM}} > S_{th}$
	S_{th}(parts)	Discrete	100	100	700			
	Q	Discrete	900	300	2400			
	TBO (min)	Discrete	1800	300	4200			

produced by manufacturer i is formulated as per Eq. (6);

$$C_{ij} = \frac{c_i * a_{ij}}{g_{ij}} \tag{6}$$

where c_i is the cost of a single production attempt for manufacturer i, a_{ij} is the number of production attempts done by manufacturer i for the j^{th} assigned order, and g_{ij} is the number of good items produced by manufacturer i for the assigned order j.

Quality parameter can be measured as the proportion of good items produced by manufacturer i and is calculated as per Eq. (7);

$$Q_{ij} = \frac{g_{ij}}{a_{ij}} \tag{7}$$

Productivity P_{ij} is defined as the number of good items produced per unit of time and calculated as per Eq. (8);

$$P_{ij} = \frac{g_{ij}}{T_{now} - T_{ij}} \tag{8}$$

where T_{now} is the current time, and T_{ij} is the time at which manufacturer i starts production for the j^{th} assigned order.

The delivery parameter is associated with time required to produce the batch of M good items that will be shipped directly to the customer. This parameter is updated only when a batch is ready, not like the other parameters. It can be calculated after each batch by $D_{ijk} = TB_{ijk} - TB_{ij(k-1)}$, where TB_{ijk} is the time at which the manufacturer i produces the k^{th} batch of good items for the j^{th} assigned order with $TB_{ij0} = T_{ij}$. To be realistic and avoid biasness to a single batch delivery, the parameter used to calculate the performance after delivering the last batch should cover all batches delivered. Hence, D_{ij} is the average delivery time for all delivered batches is used and calculated by using Eq. (9);

$$D_{ij} = \frac{1}{K}\sum_{k=1}^{K} TB_{ijk} - TB_{ij(k-1)} \tag{9}$$

where K is the current delivered batch, and it has a maximum value of $\lceil R_{ij}/M \rceil$ if the manufacturer succeeds in delivering the ordered quantity without violating the thresholds. R_{ij} is the j^{th} ordered quantity from manufacturer i and M is the batch size.

Customers have different preferences for the four mentioned parameters. In order to reflect these preferences, AHP can be used to identify the weights for the different parameters [31, 32]. Importance factor is given to each attribute from 1 to 9, with 1 representing equal important and 9 as extreme important. a, b, c, and d represent the importance factor of cost, quality, delivery time, and productivity, respectively. A pairwise comparison matrix can be formed to compute the value of each attribute in decision making process. These normalized equations with weighted average of cost (w_c), quality (w_q), productivity (w_p), and delivery time (w_d) are given in Eqs. (10), (11), (12), and (13), respectively.

$$Weight\ of\ cost,\ w_c = \frac{\frac{1}{1+\frac{b}{a}+\frac{c}{a}+\frac{d}{a}} + \frac{a}{\frac{a}{b}+1+\frac{c}{b}+\frac{d}{b}} + \frac{a}{\frac{a}{c}+\frac{b}{c}+1+\frac{d}{c}} + \frac{a}{\frac{a}{d}+\frac{b}{d}+\frac{c}{d}+1}}{4} \tag{10}$$

$$Weight\ of\ quality,\ w_q = \frac{\frac{b}{1+\frac{b}{a}+\frac{c}{a}+\frac{d}{a}} + \frac{1}{\frac{a}{b}+1+\frac{c}{b}+\frac{d}{b}} + \frac{b}{\frac{a}{c}+\frac{b}{c}+1+\frac{d}{c}} + \frac{b}{\frac{a}{d}+\frac{b}{d}+\frac{c}{d}+1}}{4} \tag{11}$$

$$Weight\ of\ productivity,\ w_p = \frac{\frac{c}{1+\frac{b}{a}+\frac{c}{a}+\frac{d}{a}} + \frac{c}{\frac{a}{b}+1+\frac{c}{b}+\frac{d}{b}} + \frac{1}{\frac{a}{c}+\frac{b}{c}+1+\frac{d}{c}} + \frac{c}{\frac{a}{d}+\frac{b}{d}+\frac{c}{d}+1}}{4} \tag{12}$$

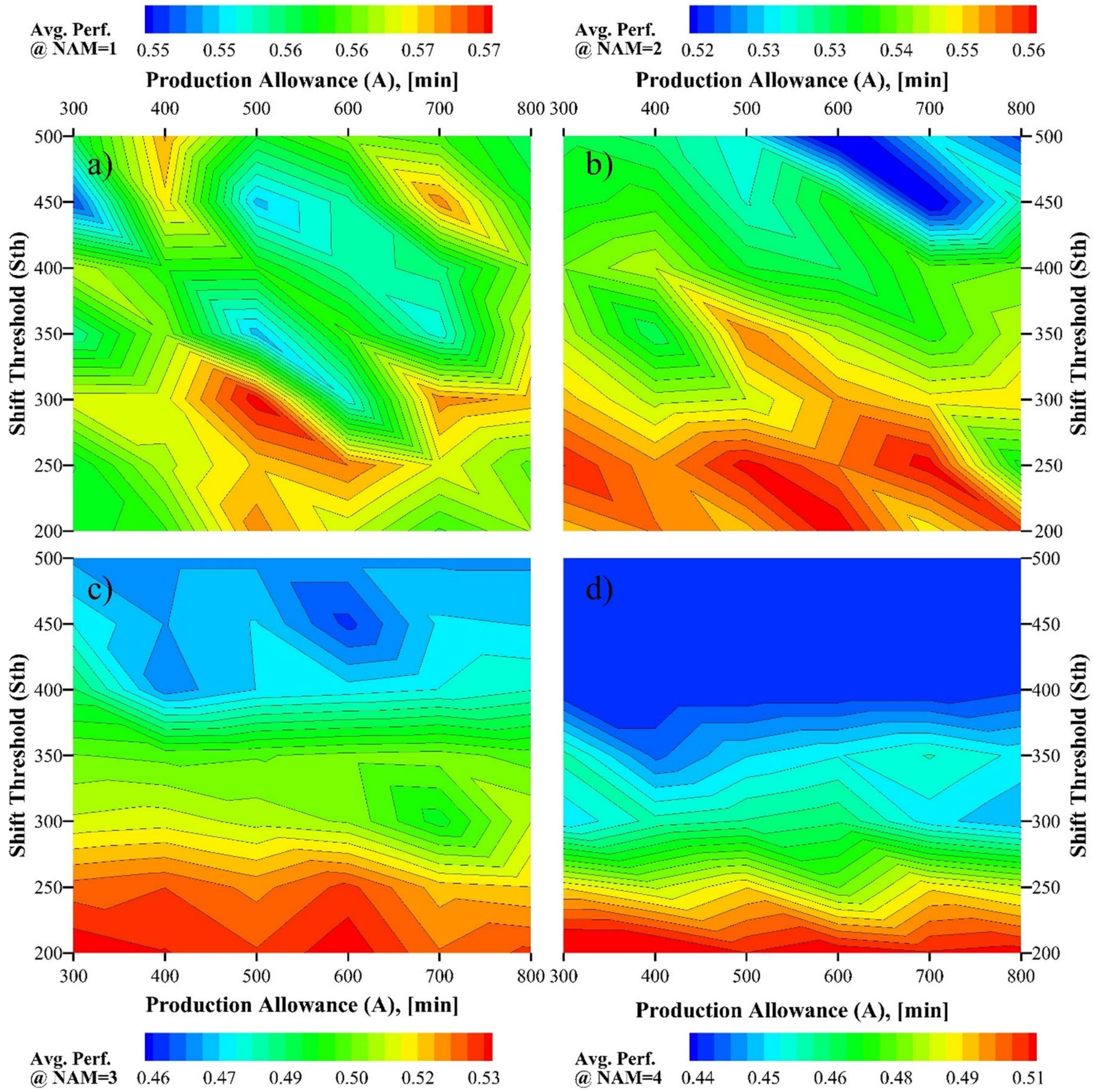


Fig. 9 Contour plots for average performance at (**a**) NAM = 1, (**b**) NAM = 2, (**c**) NAM = 3, and (**d**) NAM = 4 at varying values of the shift threshold (*Sth*) and production allowance (*A*)

$$Weight\ of\ delivery,\ w_d = \frac{\frac{d}{1+\frac{b}{a}+\frac{c}{a}+\frac{d}{a}} + \frac{d}{\frac{a}{b}+1+\frac{c}{b}+\frac{d}{b}} + \frac{d}{\frac{a}{c}+\frac{b}{c}+1+\frac{d}{c}} + \frac{1}{\frac{a}{d}+\frac{b}{d}+\frac{c}{d}+1}}{4} \quad (13)$$

The values obtained are the weights for the corresponding attributes, which will be used to select the manufacturer with the best criteria as per customer demand. Customer may be interested in one or more attributes compared to others so he/she can reflect this interest in his/her performance measure by using these weights and preferences.

Once a manufacturer i delivers the required quantity or if one of the thresholds is violated then the average performance measure, average cost, average quality, average productivity, and average delivery for the manufacturer should be updated using Eqs. (14), (15), (16), (17), and (18), respectively. These equations take into consideration that the updated average depends on the required quantity such that larger quantity will have more weight compared to smaller ones.

$$APM_i = \frac{\sum_{j=1}^{J_i} g_{ij}.PM_{ij}}{\sum_{j=1}^{J_i} g_{ij}} \quad (14)$$

$$AC_i = \frac{\sum_{j=1}^{J_i} g_{ij}.C_{ij}}{\sum_{j=1}^{J_i} g_{ij}} \quad (15)$$

$$AQ_i = \frac{\sum_{j=1}^{J_i} g_{ij}.Q_{ij}}{\sum_{j=1}^{J_i} g_{ij}} \quad (16)$$

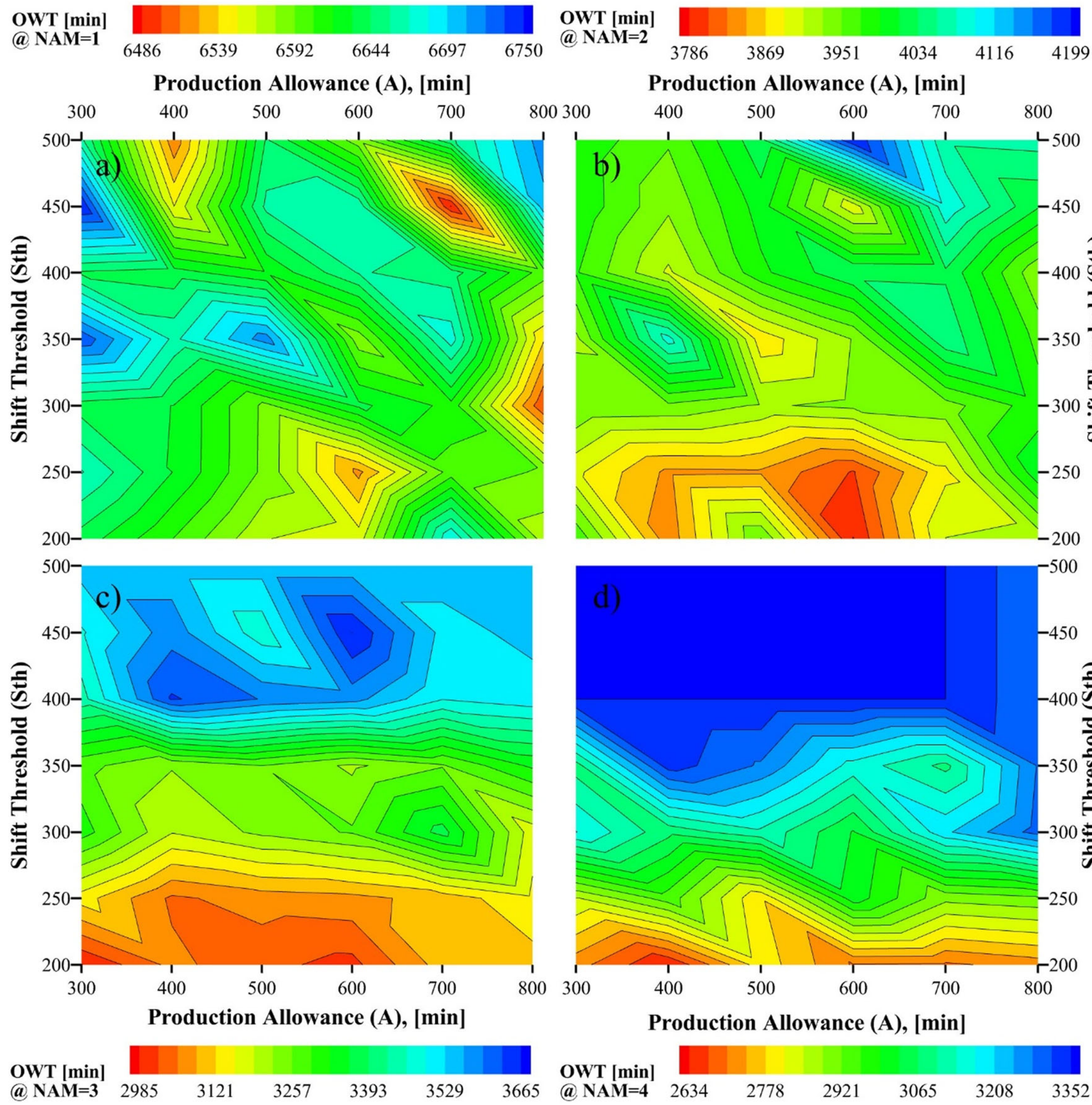


Fig. 10 Contour plots for optimal values of order waiting time at (**a**) NAM = 1, (**b**) NAM = 2, (**c**) NAM = 3, and (**d**) NAM = 4 at varying values of *Sth* and *A*

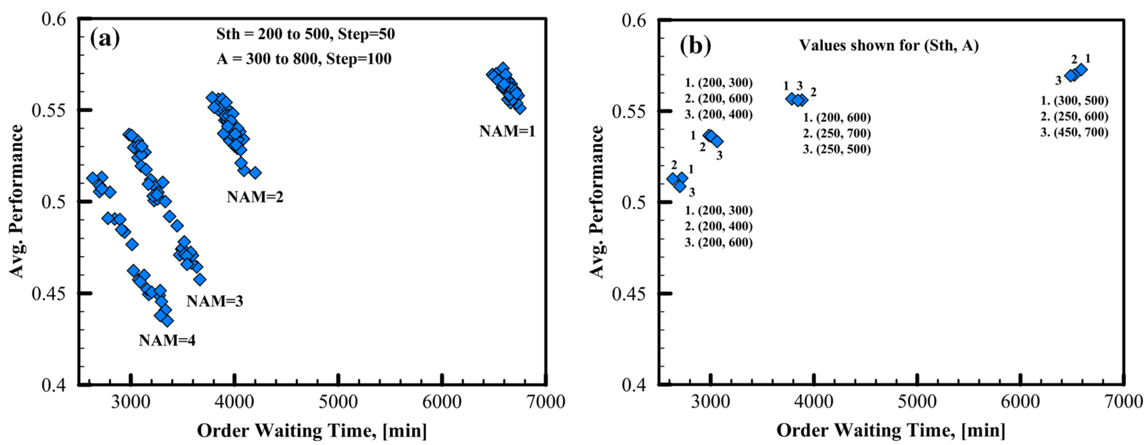


Fig. 11 Optimization results for case 1 by varying *Sth*, *A* and NAM (**a**) all solution points (**b**) pareto front solutions

Table 4 Maximum and minimum values of avg. performance and order waiting time, respectively, at different weights

Avg. performance	*cw*	*dw*	*pw*	*qw*	Order waiting time, (min)	*cw*	*dw*	*pw*	*qw*
0.859	0.125	0.25	0.5	0.125	6524	0.5	0.125	0.125	0.25
0.850	0.25	0.125	0.5	0.125	6524	0.25	0.25	0.125	0.375
0.817	0.125	0.125	0.5	0.25	6545	0.25	0.125	0.25	0.375
0.746	0.125	0.375	0.375	0.125	6555	0.125	0.375	0.375	0.125
0.716	0.25	0.25	0.375	0.125	6557	0.375	0.125	0.25	0.25
0.704	0.375	0.125	0.375	0.125	6573	0.125	0.375	0.125	0.375
0.697	0.125	0.25	0.375	0.25	6577	0.375	0.25	0.25	0.125
0.685	0.25	0.125	0.375	0.25	6580	0.125	0.125	0.25	0.5
0.658	0.125	0.125	0.375	0.375	6583	0.125	0.25	0.125	0.5
0.629	0.125	0.5	0.25	0.125	6588	0.25	0.25	0.25	0.25
0.598	0.25	0.375	0.25	0.125	6598	0.5	0.125	0.25	0.125
0.588	0.375	0.25	0.25	0.125	6602	0.375	0.125	0.375	0.125
0.579	0.125	0.375	0.25	0.25	6605	0.125	0.5	0.25	0.125
0.573	0.25	0.25	0.25	0.25	6606	0.125	0.5	0.125	0.25
0.560	0.5	0.125	0.25	0.125	6607	0.25	0.125	0.5	0.125

$$AP_i = \frac{\sum_{j=1}^{J_i} g_{ij}.P_{ij}}{\sum_{j=1}^{J_i} g_{ij}} \tag{17}$$

$$AD_i = \frac{\sum_{j=1}^{J_i} g_{ij}.D_{ij}}{\sum_{j=1}^{J_i} g_{ij}} \tag{18}$$

where J_i is the total number of assigned orders for manufacturer i at the current time, and g_{ij} is representing the number of good items produced and at the same time it is representing the quantity delivered by manufacturer i for the j^{th} assigned order. If the manufacturer does not violate any of the thresholds, then $g_{ij} = R_{ij}$, otherwise $g_{ij} < R_{ij}$.

The above averages are important to evaluate the whole system performance over time and the final performance of the system in case of comparing between different system setups. Since the system consists of N manufacturers, Eqs. (19), (20), (21), (22), and (23) are used to find the system average performance, average cost, average quality, average productivity, and average delivery, respectively.

$$SAPM = \frac{\sum_{i=1}^{N}\left(APM_i * \sum_{j=1}^{J_i} g_{ij}\right)}{\sum_{i=1}^{N}\sum_{j=1}^{J_i} g_{ij}} \tag{19}$$

$$SAC = \frac{\sum_{i=1}^{N}\left(AC_i * \sum_{j=1}^{J_i} g_{ij}\right)}{\sum_{i=1}^{N}\sum_{j=1}^{J_i} g_{ij}} \tag{20}$$

$$SAQ = \frac{\sum_{i=1}^{N}\left(AQ_i * \sum_{j=1}^{J_i} g_{ij}\right)}{\sum_{i=1}^{N}\sum_{j=1}^{J_i} g_{ij}} \tag{21}$$

$$SAP = \frac{\sum_{i=1}^{N}\left(AP_i * \sum_{j=1}^{J_i} g_{ij}\right)}{\sum_{i=1}^{N}\sum_{j=1}^{J_i} g_{ij}} \tag{22}$$

$$SAD = \frac{\sum_{i=1}^{N}\left(AD_i * \sum_{j=1}^{J_i} g_{ij}\right)}{\sum_{i=1}^{N}\sum_{j=1}^{J_i} g_{ij}} \tag{23}$$

For simulation, N manufacturers are considered for an online order size of Q. It is considered that order will be placed in a stochastic manner with a mean time between orders of TBO_{mean} and simulation model will run until Q_T orders are completed. T_{MTi}, T_{Mi}, T_{Ci}, T_{Ii}, T_{Fi}, and T_{MFi} represents material order time, machining time, cleaning time, inspection time, minor failure time, and major failure time for manufacturer i, respectively. The values assigned for machining, inspection, transportation, maintenance time (minor failures), and major failure are normally distributed for each manufacturer to observe stochastic behavior. The parametric values for simulations with standard deviations are defined in Table 1.

4 Simulation Model, Result, Optimization, and Sensitivity Analysis

4.1 Simulation model and results

The continuous supervised model is built in ARENA software and the results are compared to the model that follows the traditional manufacturing setup without shifting the assigned order. In the "continuous supervised model", orders

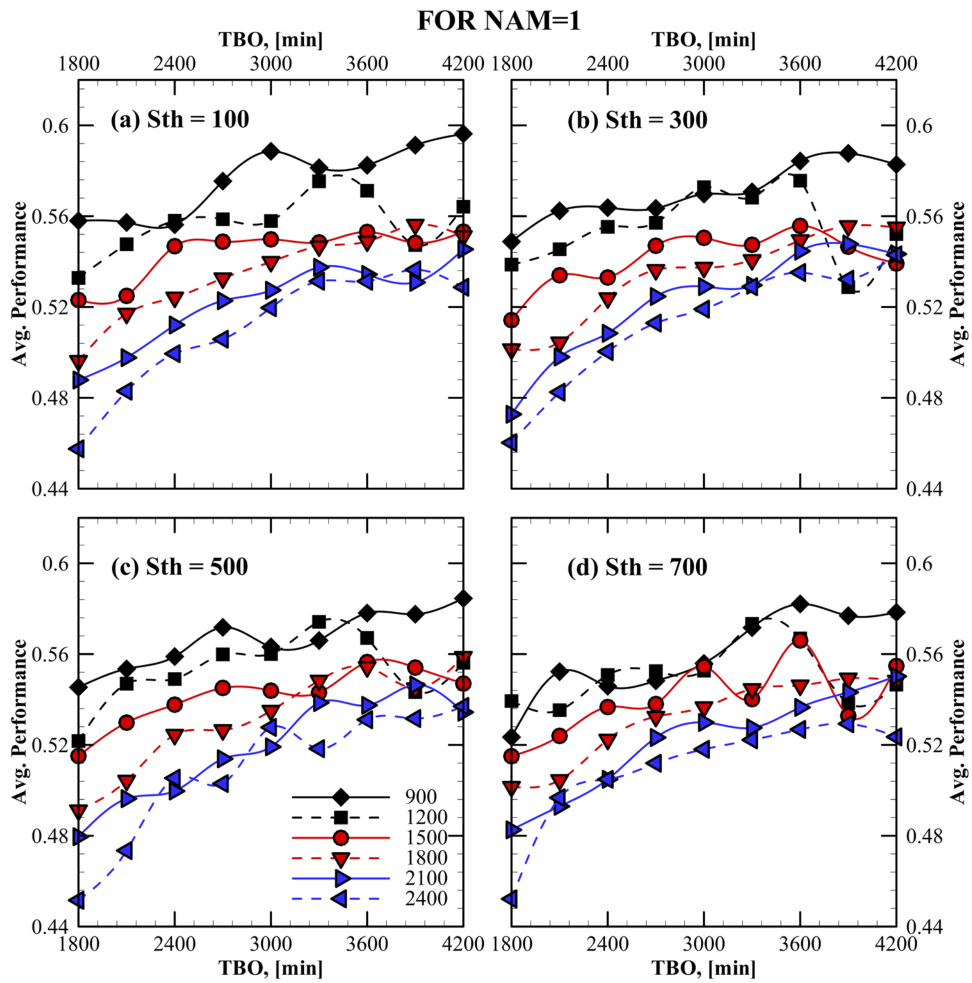


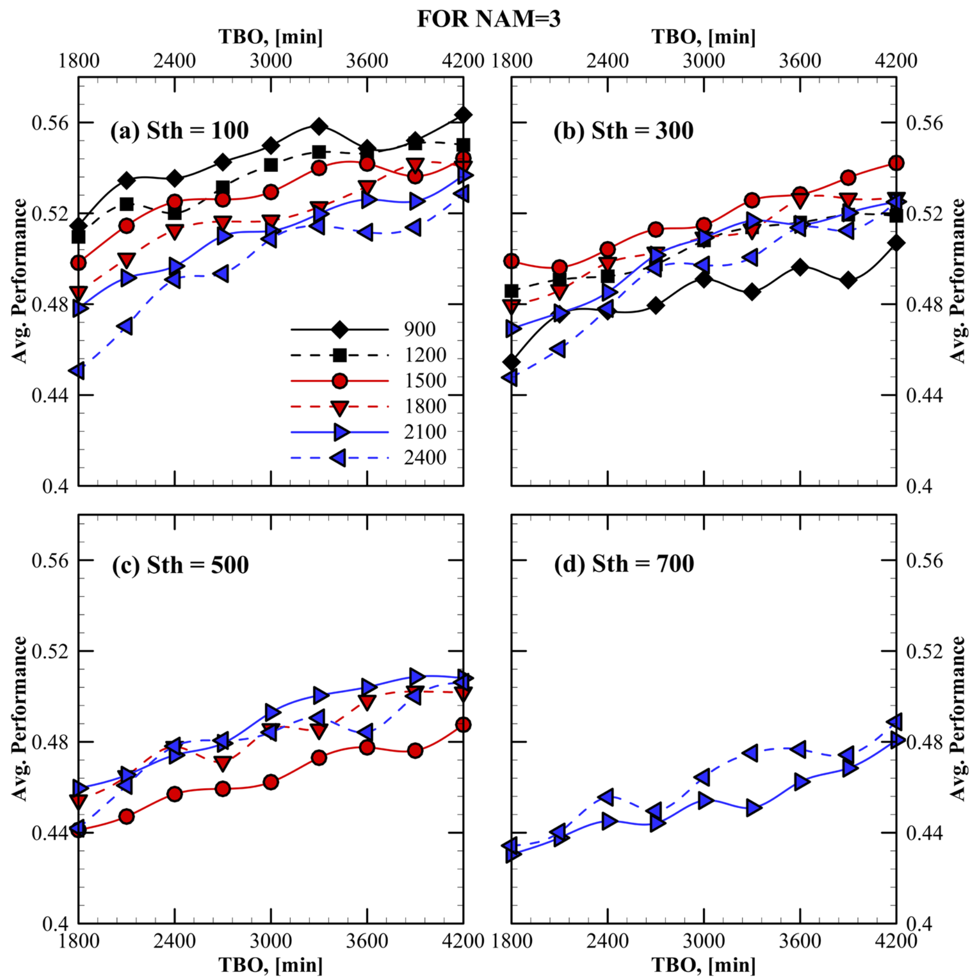
Fig. 12 Avg. performance plot against time between order (TBO) at NAM = 1 with varying thresholds at (**a**) $Sth = 100$, (**b**) $Sth = 300$, (**c**) $Sth = 500$, and (**d**) $Sth = 700$ and order size (Q) of 900 to 2400

arrival follows a Poisson process with a mean time between orders of $TBO_{mean} = 3000min$. The order size Q is random with three possible values 900, 1200, and 1500 items with probability 0.25, 0.5, 0.25, respectively. Once an order is placed on the enterprise, *NAM* manufacturers are assigned to fulfill the ordered quantity. The time required to supply the raw material to the manufacturer from the supplier T_{MTi} is normally distributed with $\mu = 1000min$ and $\sigma = 200min$. It is depending on the ordered quantity such that the early mentioned time is for supplying quantity of Q units and the time will differ as quantity differs from Q in case of shifting orders. The values assigned for machining time, cleaning time, inspection time, maintenance time for a minor failure, and recovery time from a major failure are normally distributed. Note the time between failures is exponentially distributed as shown in Table 1.

If a manufacturer fails to provide satisfactory results based on criteria, the order will be automatically shifted to a new manufacturer for the remaining quantity of the order. The order will only shift if the remaining parts are greater than$S_{th} > 300$. This condition will help in reducing the total waiting time for the orders plus taking into consideration the limitations of the minimum order size that can be accepted by a manufacturer. The eliminated manufacturer will be considered for the next order in case of availability. Similarly, if the new assigned manufacturer fails to deliver the required units with the required specifications, the order will be automatically sent to the next manufacturer in the waiting list. Produced units are shipped in batches to the customer and the batch size is$M = 50$. The thresholds values are chosen to be $C_{th} = \$3, Q_{th} = 0.85, P_{th} = 0.1unit/min$, and$D_{th} = 1000$. The values for w_c, w_q, w_p, and w_d are considered as 0.25 each. Sum of all weights shall be equal to 1.

A traditional production model (case 2) is considered in this paper, where the manufacturers are assigned randomly to allocate customer's order, with no shift of the order to other manufacturer in case of violating any of the performance thresholds. In practice, production data available in traditional manufacturing is noisy and unreliable. The real-time data collection in this setup is not possible without implementing I4.0 to ensure timely decisions to violations. In this

Fig. 13 Avg. performance plot against time between order (TBO) at NAM = 3 with varying thresholds at (**a**) $Sth = 100$, (**b**) $Sth = 300$, (**c**) $Sth = 500$, and (**d**) $Sth = 700$ with order size (Q) of 900 to 2400



model production will continue until the required quantity is produced and delivered to the customer. The performance measures of this model are also calculated and compared with the case 1, the continuous supervised model, to check the improvement in performance. All the parameters are taken same for both models except selection of manufacturer and shifting the order. The parameters that can affect and interrupt the production are unplanned downtime, machine failure, human error, political crises, and protest/strikes. The continuous supervised model is made to take timely action to handle the failures of machines and other situations by rerouting the order to other manufacturers to avoid any performance issues.

The model has been verified by extracting the simulation progress to an Excel sheet. The sheet is tracking the order time, selected manufacturer, updates of the performance indicators over time, violation of the thresholds and shifting time if any, and the update of the performance measure. The information that is extracted from simulation can be categorized in two layers. Layer 1 contains the information about the companies selected for the supplier's order, rejected manufacturers, performance of manufacturers (productivity, availability, quality, and cost), and delivered parts. Layer 2 consists of in-depth details and information during execution of production order. This contains the downtime for each manufacturer, number of rejected parts, increase/decrease in cost over the whole production time, delayed deliveries, and quality of manufacturing. Figure 5 represents the data collection in each layer for production activities.

The simulation results for individual manufacturers for case 1 and case 2 are presented in Fig. 6 and 7 ranging from manufacturer M1 to M10 by one-to-one comparison. It can be seen from the results that the average performance of all manufacturers to their corresponding manufacturers in case 1 is better than case 2. In case 1, maximum number of orders are assigned to M1 due to higher performance and M10 received least order due to lower performance when compared to other of manufacturers. The average performance for all manufacturers in case 2 plunges more than case 1 at many points due to major failure and retaining the order until the resumption of production. The improvement in the performance is the result of shifting the order at major failure and selecting the

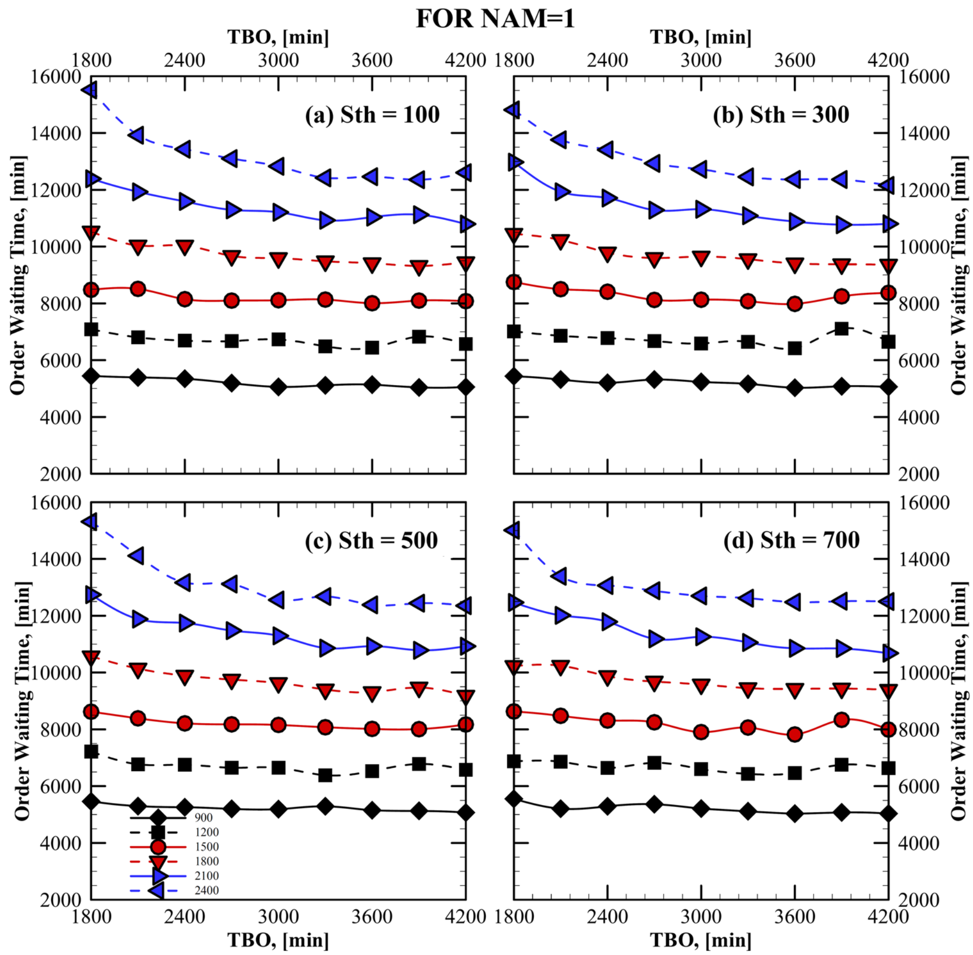


Fig. 14 Order waiting time plot against time between order (TBO) at NAM = 1 with varying thresholds at (**a**) *Sth* = 100, (**b**) *Sth* = 300, (**c**) *Sth* = 50, and (**d**) *Sth* = 700 and order size (Q) of 900 to 2400

manufacturer based on higher performance. Results from a single simulation are also presented in Fig. 8 to describe the improvement of each manufacturer against overall performance, overall productivity, and delivery time in case 1 with comparison to case 2. It is clear that difference is more in M8, M9, and M10, which is due to the low performance and higher failure rate in meeting the production order. Continuous monitoring enables case 1 to shift the order in case of major failure by selecting the manufacturers with higher performance to improve overall performance parameters including cost and delivery time.

To check the variation and stability of both cases, ten replications of simulation are performed, and results observed are close and statistical as presented in Table 2. The simulation is run for $Q_T = 1000$ with all other parameters as described above for single simulation. Table 2 shows the difference in average performance, average cost, average quality, average productivity, average delivery, and order waiting time after ten replications. Case 2 takes more time to finish the order and hence the order waiting time is close to 8000 min when compared to case 1 with 6500 min. The values of average performance reflect the overall behavior of productivity, cost, quality, and delivery. The higher values of performance and its indicators are subjected to the production performance of each manufacturer involved in the production. It can be observed that in all replications, results are favorable for the proposed model. This provides the proof of effectiveness of the monitoring and shifting the production in case the threshold values are violated.

As in case 2, the manufacturers are randomly selected to assign orders from customers and the order will not be shifted in case of any violation. This results in delayed production leading to late deliveries, poor quality, and increased cost. The parameters that can affect and interrupt production are unplanned downtime, machine failure, human error, political crises, and protests/strikes. Case 1 is made to take timely action to handle the failures of machines and other situations by rerouting the order to other manufacturers to avoid delay.

4.2 Optimization and Sensitivity Analysis

Case 1 is simulated in ARENA at different conditions as listed in Table 3 to obtain optimized values and investigating the effect of various parameters over a range of possible values.

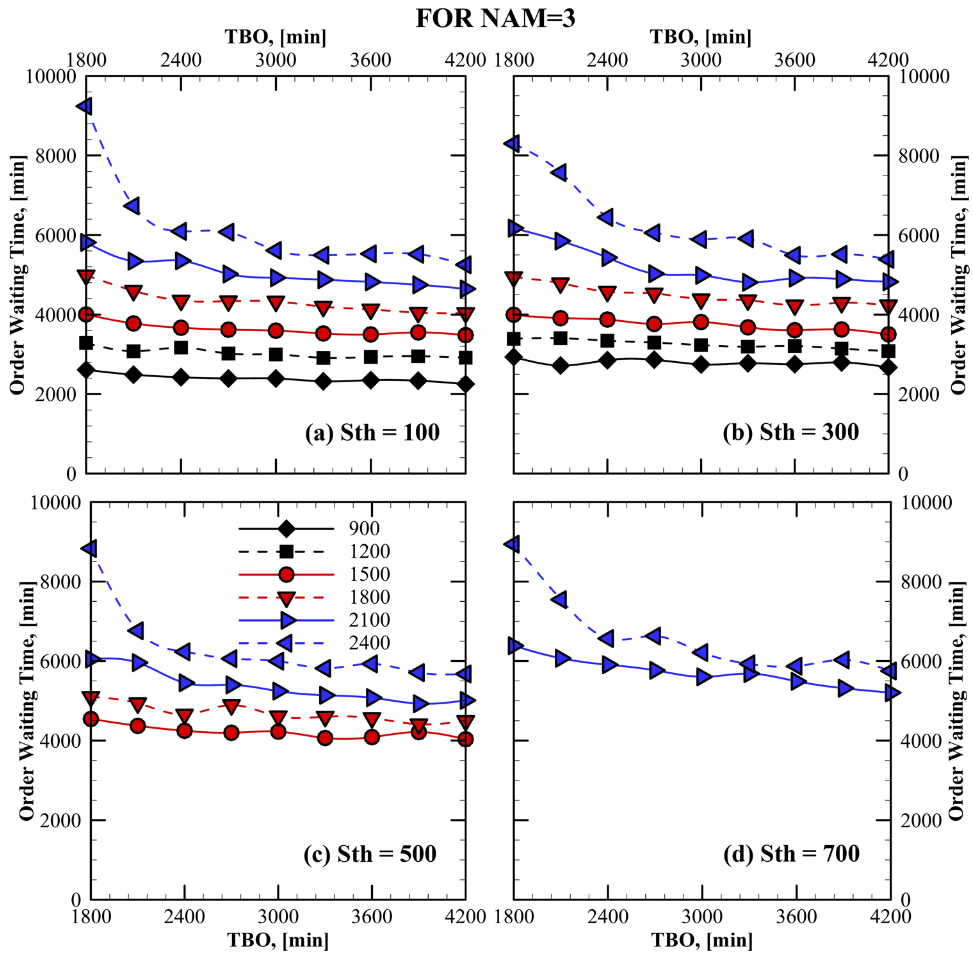


Fig. 15 Order waiting time plot against time between order (TBO) at NAM = 3 with varying thresholds at (**a**) $Sth = 100$, (**b**) $Sth = 300$, (**c**) $Sth = 50$, and (**d**) $Sth = 700$ and order size (Q) of 900 to 2400

All of this is done using OptQuest which is a "black box" optimization tool in ARENA. Three sets of values are simulated separately, and results are plotted and tabulated to visualize the effects on average performance and order waiting time. Parameters with initial values, incremental step size, final values, and constraints are given in Table 3. The objective of the simulation is to maximize the average performance (APM) and decreasing the order waiting time (OWT).

4.2.1 Optimization for Set No. 1

The results for values assigned as per set no. 1 are depicted in Fig. 9: Contour plots for average performance at (a)- NAM = 1, (b)- NAM = 2, (c)- NAM = 3, and (d)- NAM = 4 at varying values of the shift threshold (Sth) and production allowance (A). and Fig. 10. The maximum values of the avg. performance calculated is 0.527 at NAM = 1, $A = 500$ min, and Sth = 300 followed by 0.569 at NAM = 1, $A = 600$ min, and Sth = 250. Similarly, the minimum order waiting time is calculated as 2633 min at NAM = 4, $A = 400$ min, and Sth = 200 followed by 2699 min at NAM = 4, $A = 700$ min, and Sth = 200. From Fig. 9: Contour plots for average performance at (a)- NAM = 1, (b)- NAM = 2, (c)- NAM = 3, and (d)- NAM = 4 at varying values of the shift threshold (Sth) and production allowance (A)., it is observed that increasing value of Sth will reduce the avg. performance of the system and similarly increasing NAM with same Sth will also reduce the avg. performance. However, A will slightly decrease the avg. performance and increasing NAM will further reduce this value. As can be seen from Fig. 10, increasing NAM will sharply reduce the OWT, and the lower values of Sth will also reduce the OWT. Higher values of A will slightly reduce the OWT. Red color is used to designate the maximum value of performance in Fig. 9: Contour plots for average performance at (a)- $NAM = 1$, (b)- $NAM = 2$, (c)- $NAM = 3$, and (d)- $NAM = 4$ at varying values of the shift threshold (Sth) and production allowance (A).. However, the objective function of minimum order waiting time is highlighted in red in Fig. 10. Lower values of shift threshold resulted in improved and better-quality monitoring and increased performance. Order waiting time is inversely proportional to the number of assigned manufacturers. An order distributed to four manufacturers will result in quick delivery by decreasing the time between order assigned to manufacturers. Figure 11(a) represents the optimization against set no. 1 values, and Fig. 11(b) gives a pareto front solution of selected points to highlight the maximum performance and minimum order waiting time. These two objectives are conflicting.

4.2.2 Sensitivity Analysis for Set No. 2

For the values assigned as per set no. 2, the maximum value calculated for avg. performance is 0.859 at $c_w = 0.125$, $d_w = 0.25$, $q_w = 0.125$, and $p_w = 0.5$ followed by 0.851 at $c_w = 0.25$, $d_w = 0.125$, $q_w = 0.125$, and $p_w = 0.5$. Similarly, the minimum order waiting time is equal to 6523 min at $c_w = 0.5$, $d_w = 0.125$, $q_w = 0.25$, and $p_w = 0.125$ and at another combinatory values of $c_w = 0.25$, $d_w = 0.25$, $q_w = 0.375$, and $p_w = 0.125$ followed by 6544.87 min at $c_w = 0.25$, $d_w = 0.125$, $q_w = 0.375$, and $p_w = 0.25$. Some of the results of maximum performance and *OWT* against various values of weight are listed in Table 4. In this simulation, the weight of productivity governs for higher performance compared to others. Similarly, the weight of cost and weight of quality has more influence in decreasing the *OWT*. Parts made of good quality will be sent to WH; however, if parts are rejected, production time will be higher to complete the order.

4.2.3 Sensitivity Analysis for Set No. 3

Finally, the simulation is run for the values in set 3 to check the average performance over a wide range of *Sth*, *Q, TBO,* and *NAM*. The maximum value of *NAM* is set to 3 and minimum as 1. The *Sth* is varied from 100 to 700 with increasing the step of 100 parts. Similarly, the value of *Q* is considered as 900 with an increment of 300 and up to 2400. The values of *TBO* are taken in the range of 1800 to 4200 with step size 200. A total of 1134 combinations of calculations are simulated and due to the constraint of $\frac{Q-Q_{dev}}{NAM} > S_{th}$, some of the solutions were infeasible. The remaining values are plotted to get the avg. performance and *OWT* for varying values of *Q*, *TBO,* and *NAM*. The results are plotted in Figs. 12, 13, 14 and 15 It is clear from Figs. 12, 13 that an increase in *Sth* and *Q* will lower the average performance. Increasing *NAM* will decrease the average performance slightly. This is due to selection of multiple higher performing manufacturers for a single order. The remaining orders will be distributed among available manufacturers with slightly lower performance compared to the above assigned manufacturers. However, increasing the *TBO* will increase the performance effectively. Due to the increased time between orders, the frequency of selection and availability of high-performance manufacturers will increase also. As we increase *NAM* and S_{th}, the effect of *Q* on average performance becomes less significant and all lines approach near to each other (as can be seen in part c and part d of Fig. 13). This behavior can be explained as, higher threshold value of *Sth* allows the manufacturer to retain the order in large quantity without shifting it to another manufacturer. This accumulatively decrease the average performance and shifting of orders will reduce.

Figures 14 and 15 show the *OWT* plots with varying values of *Q*, *TBO* and *NAM*. For *NAM* = *1,* the order waiting time is increased tremendously for higher quantity and frequency of order. Increasing *NAM* will distribute the order to multiple manufacturers, resulting in smaller *OWT*. *Q*, *TBO,* and *Sth,* all have a significant impact on the *OWT.* A higher ordered quantity will demand higher production time and upcoming orders will have to wait for an extended time. Similarly, the higher time between order placement will give surplus time to manufacturers to finish the order, as can be seen from trends in Figs. 14 and 15

5 5. Conclusion

Distributed manufacturing (DM) was introduced and managed by an enterprise to maximize the utilization of production and manufacturing resources. A network of manufacturing companies registered to this enterprise will have access to the orders worldwide making them prone to secure manufacturing orders under specifications. This is facilitated by I4.0 allowing access to manufacturers behavioral data and supporting decision making for job dynamic allocation based on performance. A simulation is performed to calculate the maximum average performance of manufactures based on four attributes: cost, quality, productivity, and delivery. The proposed model in case 1 takes advantage of the performance monitoring under I4.0 to shift the order once a manufacturer has failed to satisfy the four attributes and the remaining quantity to be produced is greater than a specified shift threshold. This helps in improving the average performance with decreased delivery time. The effect of several independent input and design parameters are considered to obtain higher average performance and lower order waiting time. The proposed model outperforms the traditional model that is based on random order assignment with no synchronization. Our proposed model can be employed in different industries by implementing Industry 4.0 to take advantage of real-time monitoring, gathering, and analyzing data, and implementation of production strategies in case of failure to get better results than traditional manufacturing management.

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