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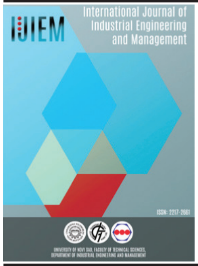


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# Complex Production-Inventory Replenishment Problem with Uncertainty in Customer Behaviour

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## ABSTRACT

A flow-shop production-inventory system can become very complex in terms of production planning and scheduling. One of the causes of complexity in such a system is the uncertainty of customer demand behaviour which disrupts production lines and inventory control. The uncertainty in customer demand behaviour that causes production disruptions can be in the form of order cancellation, change in order delivery sequence and due time. In general, such disruptions cause order shortages, late order delivery, and the underperformance of resources, amongst others. This paper considers the random combination of occurrences of these disruptions under different production scenario problems. An innovative framework that embeds agent-based simulation, heuristic algorithm, and inventory replenishment strategy is proposed to tackle these disruption problems. The integration of these methods formed a robust platform for adapting and accommodating disruptions with minimum impact on production operations. An experimental study is performed, and the results determine the impact of disruptions under different demand and inventory statuses. An inventory replenishment method is compared with sequential and instantaneous replenishment methods to establish the significance of the proposed method. The proposed method outperformed the sequential and instantaneous methods in terms of the total number of late or unsatisfied orders as well as the level of overall inventory sustainability as impacted by disruptions.

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## 1. Introduction

Although there has been a wide range of research related to flow-shop manufacturing operations, it is still regarded as a complex system consisting of various problems. The flow-shop manufacturing system has become increasingly complex due to the evolving manufacturing intelligence and continuously changing market behaviour [1]. New methodologies or techniques are then required to tackle the challenges faced by manufacturing operations. This suggestion brought about the smart manufacturing concept, where production and inventory control is placed at the centre of manufacturing performance improvement [2]. Production resources such as machines, operators and the inventory control policy are key elements of manufacturing sustainability and value creation [3]. In a flow process operation, the cause of complexity is governed by some unplanned but not unexpected occurrences. The occurrences, like disruptions, interrupt the planned production schedule and cause shortages that leave customer orders late or unsatisfied [4].



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Disruption in flow-shop production can be caused by internal and external factors [5],[6]. External factors include inadequate raw material supply, logistics, weather conditions or customer behaviour [7],[8]. Consumer behaviour in the automotive industry is uncertain and difficult to predict due to emerging technology, market and different factors, including economic, political, cultural, demographic and natural factors, as well as consumers characteristics which are reflected by attitude, motivation, perception, personality, knowledge and lifestyle [9]. Internal factors can be in the form of a machine breakdown, skilled operators' availability and other production resource shortages [8].

In this study, the Original Equipment Manufacturing problem is considered, where automotive parts and components (order demands) are requested by customers (automotive assembly line) from their supplier (OEM facility). It is a case where customer orders are requested in a specified sequence, quantity and time of delivery to satisfy automotive assembly line operations. However, this initial customers' order requirement changes due to uncertainties in customers' assembly line, referred to as uncertain customer behaviour occurrences. The uncertainties may result in the order being cancelled, sequences being altered, and delivery due time being updated.

Consequently, order cancellation increases the machines' idle time and leaves free time slots. Changes in the sequence increase the number of machine setups, and changes in delivery due time cause many late or unsatisfied orders. These changes affect production schedules and impact production performance. However, the disruption that affects the production schedule has no potential of stopping or blocking production but rather interrupts the production schedule or affects production performance, as stated in [10]. This is because this disruption has no direct impact on flow-shop resources such as machines which may breakdown and potentially stop production. The impact of the disruption on the production plan and schedule is the main consideration of this study.

For this reason, techniques to help adapt to and accommodate customer-imposed disruptions with minimum impact on OEM flow-shop production are highly required. A replenishment policy is then required to pay back any borrowed items if free slots result from disruptions. The purpose of this study is to understand and address three possible types of customer disruptions, along with their random combinations and their impact on production schedules. Therefore, the innovative contribution of this paper to the research field proposes a new inventory replenishment strategy for solving manufacturing disruption problems caused by uncertainty in customers' behaviour. This allows gradual replenishment rather than focusing on specific orders to prevent unnecessary inventory while other order inventory levels are at risk. In addition, this combination of agent-based modelling and heuristics optimisation for gradual replenishment of inventory has not been introduced before.

The rest of this paper is organised as follows. Section 2 reviews the literature on disruption modelling in the manufacturing environment. Section 3 presents the proposed methodology that was applied to the disruption problem. Section 4 provides experimentation and results analysis. Section 5 demonstrates the sensitivity analysis and comparison study. Finally, Section 6 provides a conclusion and recommendations for further study.

## 2. Review on Customer Behaviour and Disruption Modelling in Complex Manufacturing Environments

In the literature, researchers have investigated various disruptions associated with complex manufacturing environments constituting a series of challenges to productivity and performance [11].

In relation to disruptions faced in the manufacturing sector, authors in [12] investigated flow-shop disruption where customer changing demand behaviour is considered. The impact of random machine breakdowns disrupting a two-stage assembly flow shop was proposed in [13]. Production disruption caused by combined machine breakdowns and dynamic job arrivals was studied in [14]. Similarly, disruption problem caused by machine breakdowns in a flexible job shop was studied in [15]. The disruption caused by due date constraints in a dual-resource flexible job shop was discussed in [16]. Variation in job processing times as the cause of disruption impacting production schedules was considered in [17]. In a similar attempt, [18] researched product mix as disruption causing irregularity in job processing. Disruptions emanating from imperfect production processes under different regulations and uncertainties were discussed in [19]. Disruption associated with random capacities and times was studied in [20], for which an efficient heuristic was developed. Authors in [21] identified delivery delay and quantity loss as a cause of sudden transportation disruption in the production supply chain. Similarly, the production and ordering policies under capacity disruption were considered in [22] using Economic Order Quantity with Disruptions (EOQD) model.

In terms of approaches, [23] proposed a hybrid algorithm to solve scheduling problems in a make-to-stock and make-to-order production environment. In [24], a memetic algorithm was developed considering the due date for joint production and distribution schedules. In [25], bi-level non-linear programming was formulated for supply chain integrated scheduling. [26] presented a simulation-based FITradeoff method to select rules to resolve scheduling problems. [27] developed batch delivery schedules to determine efficient production. In [28], a serial-batch delivery scheduling was developed in relation to two agents and due date assignments competing for a single machine. Authors in [29] proposed a dynamic scheduling algorithm to manage manufacturing disruption. In [30], a robust scheduling optimisation with replenishment capability was developed to resolve uncertain machine failure disruptions.

Regarding other heuristic approaches and their applications in inventory replenishment, it focused on determining shortage orders, borrowing orders, and rescheduling borrowed orders for inventory replenishment. The replenishment process is done gradually using the extended replenishment strategy adopted from the works by [31], [32], and [33]. It is assumed that the heuristic will be applied when there is any type of disruption in the production flow shop. This is when orders need to be rescheduled for inventory replenishment. The agent-based model provides additional information for the heuristic implementation. Other works by [47], [48] and [49] assume that the heuristic will be applied when there is any type of randomly occurring disruption in the production flow shop. This is when orders need to be rescheduled for inventory replenishment. While this heuristic targets gradual non-instantaneous inventory replenishment, the heuristics in [34] target a sequential and instantaneous replenishment method. In [34], the production disruption problem caused by customer demand behaviour was considered. The study proposed a framework that associated agent-based modelling, embedded heuristic approach and inventory control strategy to tackle the disruption problem. However, the proposed method is limited in its resolution approach. The work lacked the sustainable control of inventory level to respond to the impact of disruption continuously, especially as it affects production schedules. It focuses on keeping inventory levels to the maximum and offers high priority for very low orders or at critical inventory levels to mitigate disruption effects, also in [12], which focused on customer behaviour but tackled the impact of the combination of three customer-imposed disruptions – changing quantity, changing delivery time and changing production sequence. The study introduced inventory sustainability as a means of accommodating the consequences of disruptions. This is different from the [34], which is mainly focused on investigating the disruption consequences and recovery strategy

Meanwhile, an agent-based modified heuristics model is proposed for providing an improved schedule in the presence of different occurrences of uncertain customer behaviour. It focuses on a different combination of the disruptions, the effect on three inventory level classifications, and a non-instantaneous replenishment strategy for production sustainability. The new method is associated with inventory control as a disruption recovery measure for sustainable responsiveness to disruptions. An extensive literature search established no record of the problematic nature in association with the uniqueness of this resolution method. For instance, [15] only considered machine breakdown as the factor disrupting, while [16] associated due date constraints as disrupting the shop floor. The nature of this disruption problem, which is a concern for the manufacturing industry, including Original Equipment Manufacturing (OEM), is to describe in the next section.

However, in the above studies, disruption problems and internal disruptions in production resources were tackled from the supplier side. None of the studies focused on disruptions caused by uncertain behaviour of customers of the nature presented in this paper, especially when considering the different combinations of disruptions caused by customers. Furthermore, it lacks specific and suitable resolution measures for the identified problem.

# 3. Research Methodology

## 3.1 Methodology, Justification and Reason

This paper adopted and further improved the Production-Disruption Inventory Replenishment (PDIR) framework proposed in [12]. The previous methodology framework (Figure 1) was presented as it comprised agent-based modelling, a heuristic algorithm, and the association of inventory control as a replenishment strategy to solve production disruption problems.

Although other approaches could solve production-inventory problems, they would not have direct comparison factors with the same problem situation or production settings suggested in this study. It is worth mentioning that the used framework characterised successfully production problem situations where customer assembly lines are on constant standby waiting for OEMs production delivery per time.

The developed methodology consisted of a number of techniques that have been carefully selected to deliver the aim of this paper. The methodology justification is presented in Table 1.

The agent-based approach models the flow-shop operations to understand the current situation and identify and establish other issues. The agent-based modelling approach is also designed to help capture 'available time' resulting from uncertain customer behaviour, including order cancellations. Also, a heuristic algorithm is proposed and integrated with an agent-based model to collectively capture the effect of the disruptions problem and solve it. This subsequently provides a solution that requires the flow shop to be adaptive and accommodate disruption while satisfying customer demands. A case study is used as a test bench to justify the agent-based model, including the proposed heuristics algorithm. A sensitivity analysis study is conducted to verify the performance of the developed system and justify its performance under changing variables in terms of the KPIs. Finally, standard deviation measurements are calculated to identify the effectiveness of the proposed heuristic algorithm.

In the next section, the methodology framework of this paper is discussed.

## 3.2 Improved Production Disruption-Inventory Replenishment (i-PDIR) Framework.

In most cases, the problem's nature and objective requirements contribute to developing a resolution framework. In the literature, various frameworks of a similar nature have been developed and applied to solve complex manufacturing problems of different magnitudes [12],[36],[10],[22]. For instance, the framework of [21] was designed for disruption recovery and post-disruption periods and to determine the influence of disruptions on production. Other studies, such as [37] and [8], have also developed integrated frameworks that associate key problem-solving components to achieve desirable outcomes. Since the key framework components of the i-PDIR framework form the baseline for the solution strategy envisaged for the problem discussed in this paper, it is considered an obvious option.

However, the significant difference is the additional capabilities of the framework and an improved and more adaptive heuristic algorithm which offers a more sustainable solution strategy for the production disruption problem. The proposed heuristics algorithm in this paper provides a policy that works in such a way as to gradually replenish inventory after the inventory has been used to support production shortages caused by disruptions. The previous heu-

**Table 1.** Methodology Justification

| Approach/Technique | Reason |
|---|---|
| **Agent-based modelling** (Approach) | To mimic the flow-shop operations in the form of collaborative agents to capture 'available time' resulting from uncertain customer behaviour occurrences. |
| **Heuristics Optimisation** (Technique) | To achieve the best practice of production-inventory control resulting in the best replenishment strategy of products. This technique was selected due to its flexibility in adjusting and adapting to the changing constraints, high uncertainties and complexities faced in the current problem. |
| **Case Study** (Technique) | To justify the performance of the proposed heuristics algorithm against the developed one in the improved Production-Disruption Inventory Replenishment (PDIR) framework used in [12]. This disruption problem's nature fits the original equipment manufacturers' case, so it was selected. |
| **Sensitivity Analysis** (Technique) | To explore the robustness and accuracy of the developed model outcomes under uncertain demand conditions. This was conducted because other methods mentioned in the literature would not have direct comparison factors with the same experimental setting and methods suggested in this study. |
| **Standard Deviation** (Statistic) | To statistically measure the dispersion or spread of each inventory level obtained by each scenario. The dispersion results theme reflects the effectiveness of the proposed heuristics. |

ristics algorithm proposed by [12] was designed only to accommodate and adapt to the three disruption types identified based on five different possible inventory cases described in the paper. Therefore, this is tagged as an improved PDIR (i-PDIR) framework (Figure 1).

The i-PDIR framework is presented to respond to a random combination of production disruption caused by uncertain customer behaviour. It operates in such a way as to accommodate and adapt to disruptions with minimal impact on production, where inventory control serves as a replenishment strategy. Unlike the previous PDIR framework proposed in [12], this improved PDIR framework aims to satisfy production shortages through inventory borrowing while maintaining sustainable inventory levels. This is made possible through the additional functionalities of the embedded heuristic algorithm (as discussed in section 3.2.3 below) within the agent-based modelling capabilities.

As depicted in Figure 1, the improved framework captures the production processes triggered by customer demands based on their assembly line requirements. In an 'ideal' disruption-less situation, the framework indicates no significant need for production support from inventory (borrowed orders); as a result, there is no need for the extended heuristic algorithm to aid the replenishment strategy. However, uncertain customer behaviour creates production disruption due to assembly line uncertainties. These disruptions in the production flow-shop are in the form of changes in production, quantities, and delivery due times. The changing demands satisfaction as required is not guaranteed because disruptions cause inevitable shortages and delays. This is because the original production schedule must be altered. According to the framework flow, the customer uncertain behaviour occurrences translate into customer orders. The customer order requirement forms production processes simulated within the agent-based environment. Since disruption causes shortages and delays, an adaptive heuristic algorithm is employed to reschedule and facilitate inventory borrowing and replenishment as enabled through agent-based modelling capabilities. Inventory control is introduced as a production support strategy through borrowing and replenishment.

In this strategy, shortage orders are borrowed from the inventory when disruptions occur and then replenished for continuous production support. The replenishment is made possible through the ability of the agent-based approach to reveal 'available time' created as a result of uncertain customer behaviour occurrences. A heuristic algorithm enables the rescheduling of borrowed orders by utilising the 'available time'. Rescheduling borrowed orders back to the inventory is done alongside customer demand. The completed customer orders and any borrowed quantities (to complete the order) reach the dispatching node where customer demand is successfully satisfied. The next production cycle commences if the production period has not been fully exhausted.

In the next section, the individual components of improved PDIR are explained.

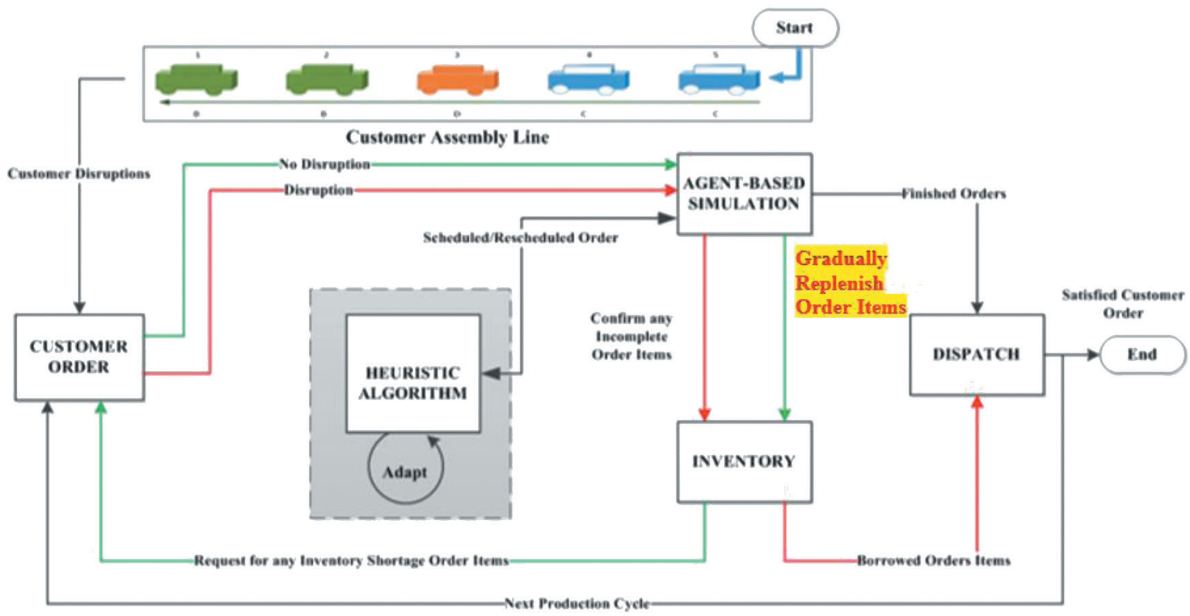



**Figure 1.** Improved Production Disruption-Inventory Replenishment (i-PDIR) Framework [12]

### 3.2.1 Agent-Based Module

This section presents the development and implementation of the ABM approach incorporated in the improved PDIR framework of manufacturing process scheduling for the system simulation.

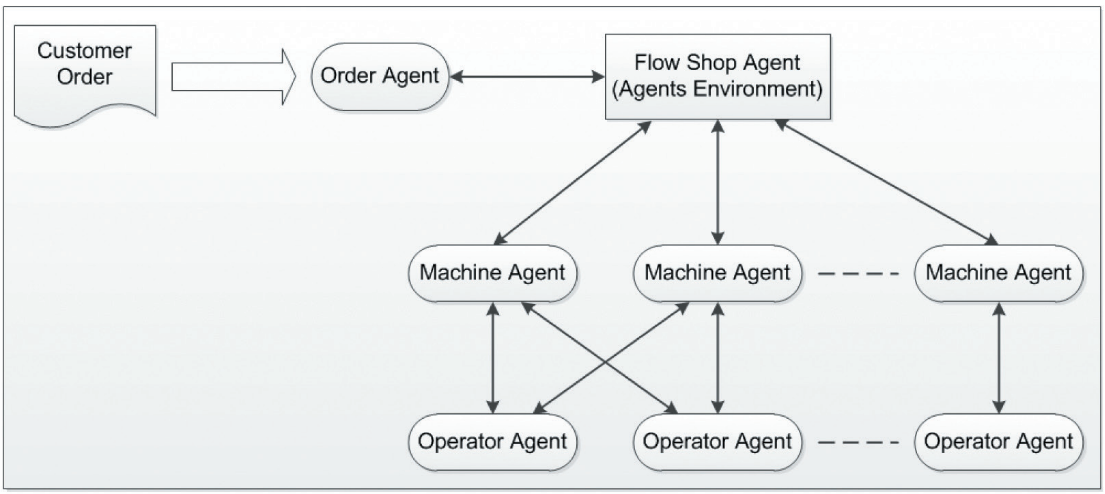
The choice of selecting the agent-based simulation approach as a suitable technique in this research was inspired by the investigation of related studies. [38] applied agent-based modelling to disruption problems in the transportation industry. Specifically, the investigation conducted in the manufacturing industry revealed the implementation of an agent-based simulation modelling approach in [39] and [40], amongst other related studies. In the past, production-inventory scheduling problems have been tackled using various well-known simulation modelling methodologies, but recently, agent-based modelling has gained popularity as another helpful technique to deal with simulation problems in several disciplines.

Agent-based modelling has been reviewed for this study to investigate its viability in handling the disruption problem. Based on the current trends in simulation methodology, the agent-based method is essential because it provides advanced opportunities to find solutions to the research problem and evolve with the current technology. This quality is found useful in the agent-based simulation modelling method. Agent-based modelling can be described through its architectural model, as shown in Figure 2.

Figure 2 shows that a customer order was received and translated into an order agent, then passed to the flow shop agent (agent environment). Several machine and operator agents worked collaboratively to order agents through the flow shop agent while the flow shop agent provided the information for order processing operations. The order production is started based on the process plan and schedule allied to the order agent through the flow shop agent. The details of each agent's information and connectivity in the ABM system will be discussed.

**Flow Shop Agent (Agent Environment):** The flow shop agent acts as a controller in the manufacturing system. It holds the process rules for order operations and allocates machine agents to order and operator agents to machine agents. The machine and operator allocation and order scheduling mechanism is conducted within the flow shop agent. According to the pre-defined sequence of operation of order processing, the system adaptation to any disruptions is based on the proposed heuristics algorithm.

**Order Agent:** The order agent receives customer orders in the form of part types and then splits these order types into a sequence of operations. Each split consists of units (quantity) of order types in the predetermined production sequence. Each order agent holds the information/attributes regarding its specific customer order, including order arrival time, order quantity, split, due date, due time, and order sequence. The order operation route is given to the flow shop agent controller to provide scheduled order processes generated by the interaction between machine agents and operator agents before being sent back to the order agent. According to the order requirement specifications, the order agent received the plan and schedule of order operation, including




Architectural Model of the Agent-Based System

**Figure 2.** Architectural Model of the Agent-Based System

allocated resources (machines and operators).

**Operator Agent:** Each operator agent represents an operator in the pool of operators in the manufacturing production cycle. Operators are allocated to machines based on their availability for the job and skillset.

**Machine Agent:** On the flow shop, individual machines are represented by a machine agent with information/attributes such as machine capacity, setup time for each order processing, type of order which can be processed, machining time for each order type, processed order information, and operator engagement information.

After receiving order information from the flowshop agent, the machine agent considers the information to determine whether it can process the order with the allocated operator. If there is a good match for both machine and operator on order, the order goes straight into processing or is placed in a queue if machines or operators are currently busy.

The development of agents includes identifying their collaborations; hence, a messaging sequence model is required to present how agents collaborate.

The idea of the proposed messaging sequence within the agent-based environment is obtained from [37], where the idea was implemented in the supply chain industry for the supply chain entities representing the interactive ability of individual agents.

The messaging system is useful because it allows informed interaction among agents. Agents' activities and information can be stored, exchanged and acted upon by another agent within the system. This enables order processing through messages such as order requests, resource allocation, order production, and dispatch information sent within the system. Therefore, the messaging sequence concept of the agent-based model is adopted in this paper (Figure 3) for the three agents (order, machine and operator) to interact when customer requests are sent to the production floor to be processed.

The customer sends order requests to the production manager, which are updated on the production floor. Upon receipt of a customer order request, the production schedule updates machines based on the order information. The order and machine schedule assign operators to the production job. As a result, a machine allocated to an operator engages the order for production processes. The production processes occur in a loop of operation until all assigned orders have been completed. According to the request, the completed order information is passed to the production floor to dispatch to the customer.

The concept of the knowledge about the ABM approach for the current problem can be visualised using Figure 4, adapted from [38], showing a simple conceptual map of ABM relationships.

Figure 4 shows what agents are and their relationships with each other within the agent-based model. It also shows the individual action agents perform, the goals they achieve, and the agent-based model composition.

### 3.2.2 Inventory Strategy Module

The concept implemented for the inventory control module was adapted based on the investigation of

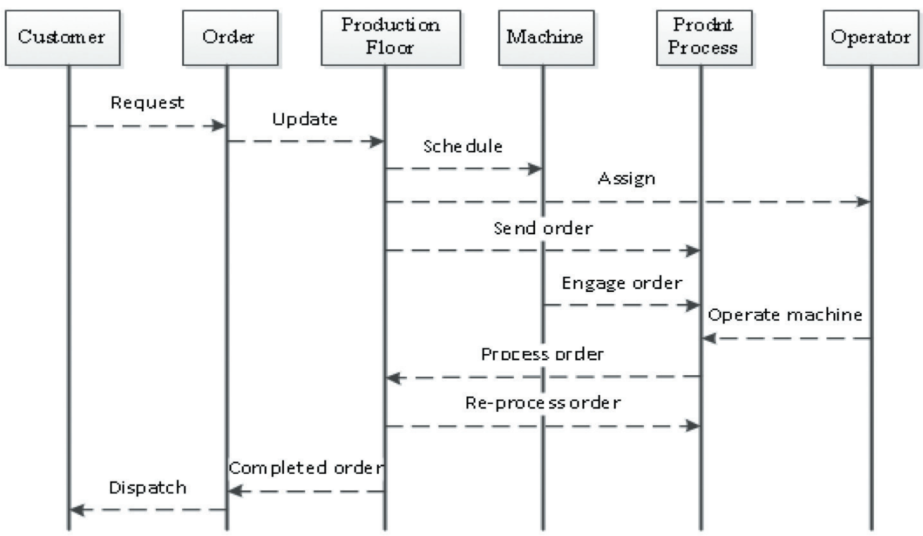



**Figure 3.** The System Message sequence diagram [31]

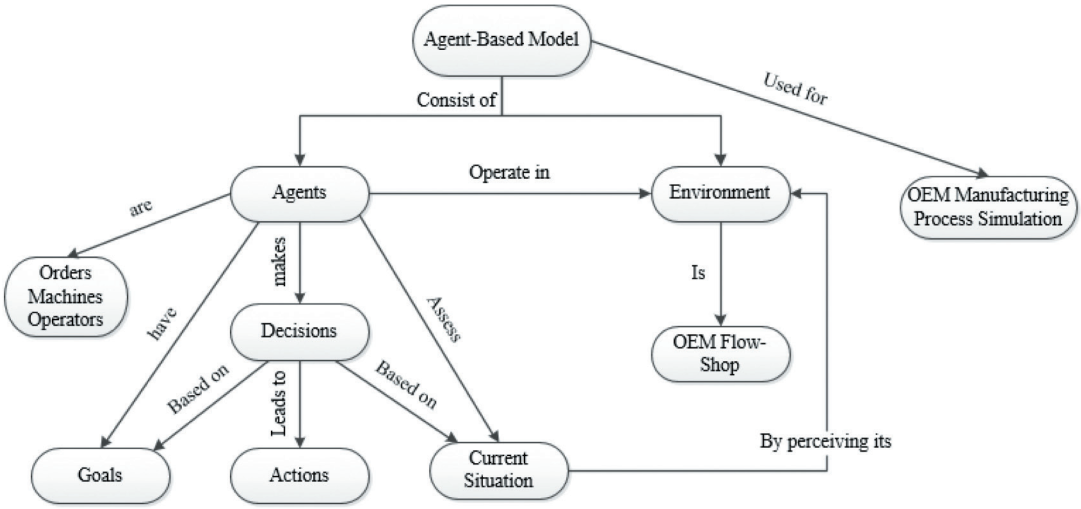



**Figure 4.** A simple ABM visualisation

related studies. The studies of [43] and [44] utilised an inventory replenishment strategy for deteriorating items in finding a solution to the problem of production disruption. The same idea has been used in the supply chain industry by [45] and [46], forming part of the integrated units for the disruption problem.

The inventory module is one of the proposed framework components through which the inventory replenishment strategy is applied. It focuses on satisfying customers' changing requirements in the face of disruption through inventory support and replenishment of the inventory through strategic replenishment scheduling on the flow shop. The idea relates to non-instantaneous replenishment referred to in [47], [48] and [49]. Non-instantaneous replenishment occurs when production is not instant, and inventory replenishment is gradual rather than in lots. The three papers discuss optimal replenishment policies for non-instantaneous deteriorating items. In [44], the focus is on deteriorating items with a quantity discount. In [47], stock-dependent demand is the focus where optimal replenishment policy was proposed, while [49] based their study on joint-pricing replenishment for non-instantaneous deteriorating items.

This study builds on these practical motivations concerning production-inventory systems from these authors. However, the objective is to provide a strategy that applies inventory as support for production to recover from disruption. This is based on a gradual sequential inventory replenishment policy.

The proposed policy works in such a way as to gradually replenish inventory after the inventory has been used to support production shortages caused by disruptions. The support from inventory is in the form of parts (order) 'borrowing' and needs to be replenished to maintain inventory levels of orders for continuous production support. Orders are borrowed from their corresponding part types when production shortages satisfy customer demand by completing customer order quantity in due time and right sequence. The replenishment of borrowed parts is done when there are free time slots (available time) and pre-defined rules (as detailed within the heuristic algorithm). The free slots or available times are utilised to replenish borrowed orders and are usually created by disruption types like order cancellations. The inventory levels of part types are classified as full, safe, and critical inventory levels. However, the number of parts to be replenished depends on the available time and the processing time of each unit of the selected part. For instance, the total number of parts per unit process time would be less or equal to the total available time. The replenishment attempt would continue to prioritise critical inventory until two or more inventory levels of parts are at safe levels. At this stage, the decision is made through agent-based autonomous capability using the knowledge of current inventory levels, the available time, process time of each part type, production rate and shortages, and demand rate to select part type and quantity to replenish. This is the idea of the proposed gradual inventory replenishment policy. In this manner, the proposed strategy is sustainable to adapt to disruptions and manage production processes.

The heuristic algorithm module, which incorporated the decision rules and formed a strategic part of the integrated framework, is discussed in the next section.

### 3.2.3 Heuristics Algorithm Module

Heuristic research is an approach that allows researchers to gain insights and discover methods that allow further investigation into the problem domain, particularly in manufacturing production problems [50]. According to [51], one of the methods of designing a heuristic is intensive study and observation of a target nature and feature of the selected problem. The use of heuristics can be regarded as an experiential guide to problem-solving [52].

For this reason, a more practical approach is adopted to develop heuristics by observing reality, using an OEM manufacturing context as a study case benchmark for related problems. This is similar to [53], where a metaheuristic algorithm was developed to compute a robust production sequence of a real-world case production system. The development of the heuristic algorithm considers actual demand, disruptions, productions and inventory levels scenarios. In addition, with an industrial expert view, it captures relevant possibilities for disruption occurrences and inventory level status. This particular heuristic approach is different from one applied in both [35] and [12] in that when developing the heuristic, the inventory level status was categorised into five scenario cases in response to disruption occurrences. The algorithm considered the replenishment approach for each case. Case 1 represents where all inventory levels are full, and no replenishment is required as no disruption causing shortages occurred. Case 2 represents all inventory levels at a critical stage where replenishment will be based on available and minimum setup time. Also, for case 3, which represents all inventory at a safe level, inventory replenishment is random. For case 4, where one inventory level is critical and others are safe with varying levels, the critical inventory level is prioritised. In case 5, where two or more inventory levels of the order are critical, the replenishment of critical inventory is based on available time, minimum setup time, and demand status. Based on these cases, the algorithm sets out steps for improving production performance during disruption occurrences. Ultimately, the algorithm helps to maintain the inventory levels of all order types involved in production. Inventory level maintenance is a process that establishes continuous support for production shortages to meet expected service levels to satisfy customer demand.

The proposed heuristic algorithm offers a technique for synchronising inventory and production decisions. The strategy is related to manufacturing system finished product inventory levels, which is the case of manufacturing systems receiving different order demand types from customers. Ideally, the manufacturing facility will process orders as they are received and schedule them based on the flow of shop resources. They are also expected to maintain corresponding inventory levels for all order types. A functional inventory policy is expected to guide against order stock-out and over-stocking.

The development of the heuristic algorithm focuses on gradually replenishing inventory based on individual order levels rather than focusing on a particular order type. In this way, order inventory order levels would not be at risk (critical level), which might prevent them from supporting production. It considers the order with the lowest inventory level as a priority and replenishes up to the next order inventory. It considers orders of the same level by applying replenishment based on the production schedule. When there is an order inventory of the same level, the heuristic considers orders before and after the available time provided by the ABM. Based on different conditions, the heuristic algorithm considers creating a new setup where a different order type is expected to be replenished.

The heuristic algorithm steps also considered different inventory level scenarios and flow-shop available processing time. The scenarios are a) all full inventory; b) all critical inventory; c) all safe inventory; d) one critical one average inventory; e) two or more critical and average inventory; e) two or more critical inventory; f) two or more average inventory.

This algorithm's overall objective is to apply a rule-of-thumb approach to provide the solution in a reasonable timeframe for tackling the disruption problems affecting the flow-shop production environment. In order to stratify the overall objective, the target of the algorithm is to track and account for the selected Key Performance Indicators (KPIs) and technical and operational aspects of production. This is for the performance measurement of the production and the applied algorithm against other comparison metrics.

The role of algorithm steps are as follows:

- Obtain demand requirements, input and production parameters (step 1).
- Use baseline modelling rules to sort demand in sequence to allow subsequent re-sequencing (step 2).
- For each production day, schedule demand in the sequence of their due time (step 3).
- Perform rescheduling when there is a change in demand sequence or/and change in due time (step 4).

- Prioritise order satisfaction by borrowing from inventory where necessary (steps 5 and 6).
- Obtain available time through ABM time-sharing to support production and/or ensure sustainable inventory levels (steps 7 and 8).
- Using available time for replenishment, schedule orders for inventory using the scenario cases to maintain reasonable inventory levels for each type and keep track of inventory levels per time (steps 9 and 10).
- Ensure inventory levels are maintained, and production is supported whenever possible whenever the time is available (step 11).
- Keep records of production, unsatisfied orders, shortages, borrowed orders, inventory levels, replenishment, due time and satisfying orders to measure performance and analysis (step 12).
- Perform all steps until production ends (step 13).

The scalability of the heuristic algorithm is evident as it works well for the varying production scenario experiments such as low, average and high demands under critical inventory levels (discussed in section 5 below). The notations used in the proposed heuristics algorithm are listed below:

**Heuristic notations**

- n = number of orders
- Q = Demand quantity
- ΔQ = Disrupted demand quantity
- t = Demand delivery due time
- Δt = Disrupted delivery due time
- Qs = Demand sequence
- ΔQs = Disrupted demand sequence
- Qi = Inventory quantity
- P = Production
- Qb = Borrow quantity from inventory
- Qu = Unsatisfied demand
- Qf = Satisfied demand (This includes type & quantity of order)
- S = Shortage
- Qr = Replenishment quantity
- $Qr_{min(max)}$ = The minimum of the maximum number of replenishment quantity
- N = current day
- $N_{+1}$ = Next day
- ABM = Agent-Based Model
- $AT_{time}$ = Total available time
- ACtime = Current available time being allocated
- $T_s$= Machine setup
- $T_p$ = Process time
- Pd = Production duration

The following steps represent how the heuristic algorithm is executed to improve production performance despite disruption and borrowing.

**The Heuristic Steps**

*1: Obtain Q, t, Qs, Qi, and Pd.*

*2: Sort Qs processing based on order modelling rules*

*3: Schedule Q in Qs of t for N*

*4: Re-schedule if ΔQ, ΔQs, and/or Δt for N*

*5: For P ≤ (Q or ΔQ)*

- *If P = (Q or ΔQ), then $Q_f$*
- *Else if P < (Q or ΔQ), then S end if.*

*6: For S, Borrow Qb from Qi, where Qb = (Q or ΔQ) - P*

- *If P+ Qb = (Q or ΔQ), then $Q_f$ ➔ S = 0 where Qi > 0*
- *Else if P+ Qb < (Q or ΔQ), then $Q_u$ ➔ S > 0 where Qi ≤ 0 end if.*

*7: Obtain $AC_{time}$ each of $AT_{time}$ (where $\sum AC_{time} = AT_{time}$) from the ABM time-sharing decision.*

*8: For Qi ≤ 100% and $AT_{time} \geq 0$*

- *If Qi ≤ 100% and $AT_{time}$ = 0 then do nothing, else*
- *If Qi < 100% and $AT_{time}$ > 0 then*

*9: Schedule $Qr_{min\ (max)}$, where $Qr > 0$; $Qr = \sum Qr_{min\ (max)}$*

*9.1 If critical or safe and different $(Qi - Qb)$ levels for given $AC_{time}$ then Replenish $Qr$ for the least $(Qi - Qb)$ level, until ≤ the nearest $(Qi - Qb)$ level(s) then goto step 9.2 if = to nearest $(Qi - Qb)$ level(s) else select next $AC_{time}$ and repeat step 9.1end if*

*9.2 If critical or safe and same $(Qi - Qb)$ levels for given $AC_{time,}$ then Calculate and select $(Qi - Qb)$ level with $Qr_{min\ (max)}$ obtained from ABM and Replenish $Qr_{min(max)}$*

*9.3 Repeat step 9.2 until no $(Qi - Qb)$ levels are the same, then goto step 9.1*

*9.4 If more than one $Qr_{min\ (max)}$ are equal for the same for $(Qi - Qb)$ levels then, Replenish $Qr_{min\ (max)}$ at random or for minimum $T_p$ and minimum $T_s$ until ≤ the nearest $(Qi - Qb)$ level(s) or $AC_{time} = 0$ or $Qi = 100\%$ (whichever comes first) end if, endif.*

*10: Update the new Qi level as $(Qi - Qb + Qr)$*

*11: Repeat Step 9 until all $Qi = 100\%$ or/and $AT_{time} = 0$ or end of N production cycle (whichever comes first)*

*12: Display P, $Q_u$, S, $Q_f$, Qb, t, Qs, Qr, and Qi*

*13: Repeat steps 1 – 12 for $(N_{+1})$ until Pd is completed.*

## 4. Experimental Results and Discussion

A case study based on one of the biggest Original Equipment Manufacturers of automotive parts and components, such as exhaust pipes, fuel filler neck, diesel particulate filters, etc., in the UK, was conducted to justify the performance of the proposed algorithm. Three issues were identified from the literature, including the manufacturing-assembly configuration layout [54], the make-to-order type of production [55], and just-in-time inventory characteristics, as such systems require careful inventory control because it represents a large percentage of the total usage inventory value [56]. These aspects suit the nature of the investigated problem, and hence, an OEM was used to assess the performance of the developed agent-based model along with the proposed heuristics optimisation algorithm.

The selected scenarios are directly based on the factory production settings. These scenarios were run with a random combination of the three types of disruptions. Different demand volumes and critical inventory statuses were considered for experimentation for each disruption combination. The critical inventory status is selected because it is the most challenging constraint when disruption occurs, based on expert consultation.

The three challenging scenarios and their combinations are listed as follows;

- High order volume vs Critical inventory level (HC)
- Average order volume vs Critical inventory level (AC)
- Low order volume vs Critical inventory level (LC)

The High, Average and Low order volumes scenario of order number ranges of

- High order volume: 80-100 orders
- Average order volume: 40-50 orders
- Low order volume: 20-25 orders

For High order volume scenarios, 3 shift patterns were set, 2 shift patterns for Average order volume while a single shift for Low order volume as follows:

- Shift 1: 00:01 - 08:00
- Shift 2: 08:01 - 16:00
- Shift 3: 16:01 - 23:58

Each scenario was considered under a Critical inventory level of 10 conditions to mimic a real-life production scenario. The range of order volume has been selected to replicate the real-life production order range. The order quantity range has been set as random distribution to maintain a controlled variation with the critical level inventory status considered in these experiments. The number of shifts is assigned corresponding to the order volumes. The Critical inventory levels are set to understand production behaviour under this limit. The inventory is one of the most influential constraints that impact the production-replenishment process. Therefore, it is crucial to study its behaviour during disruption occurrences. The selected shift patterns mimic the real-life system operation, corresponding to the demand volume.

The impact of the proposed framework on agent-based and heuristic algorithms is discussed based on the experimental results in terms of inventory behaviour and late/unsatisfied orders.

## 4.1 Inventory Level Behaviour

In Figures 5-7, the overall behaviour of the 'As-Is' (which is the current system situation) inventory and the proposed heuristic algorithm can be observed for the 100 order types over the 20 days production period. The inventory replenishment strategy, which demonstrates gradual and non-instantaneous replenishment, is shown. The graphical representations in 6-7 indicate Critical inventory levels of 10 orders under Average and Low order volume scenarios for the current state and at the point of replenishment when the production period is completed.

It can be observed in Figure 5 that as much as possible of the zero inventory levels were replenished. This is because order volume and disruption are high, while inventory support is critical. This implies persistent production shortages and a lack of inventory support. The situation requires as much replenishment as possible to minimise the number of late orders and sustain inventory levels.

However, there are conditions to be met before replenishment can take place. The conditions that govern the heuristic algorithm for replenishment are as follows:

- Machine and operator availability at available time slots used for replenishment.
- Available time slot sufficient for order quantity awaiting replenishment.
- The similarity of machine setup for the order types in between the available time slots

This explains why some orders were not replenished even though they were at zero levels. The situation is slightly different for average disrupted orders in Figure 6. There are fewer orders at zero inventory, and inventory levels are more sustained. This indicates a corresponding average impact of disruption on production in this scenario. Replenishment of orders is possible when other conditions are satisfied. These conditions include machine and operator availability at the time when it is available. The replenishment is possible when order quantities and their process times fit within the available timeslots. When all these conditions are not satisfied, replenishment might not occur, even when there is available time and inventory is at zero levels, in Figure 7, where virtually all inventory levels are seen at the maximum except order 4. This situation in Figure 7 means that random disruption of low

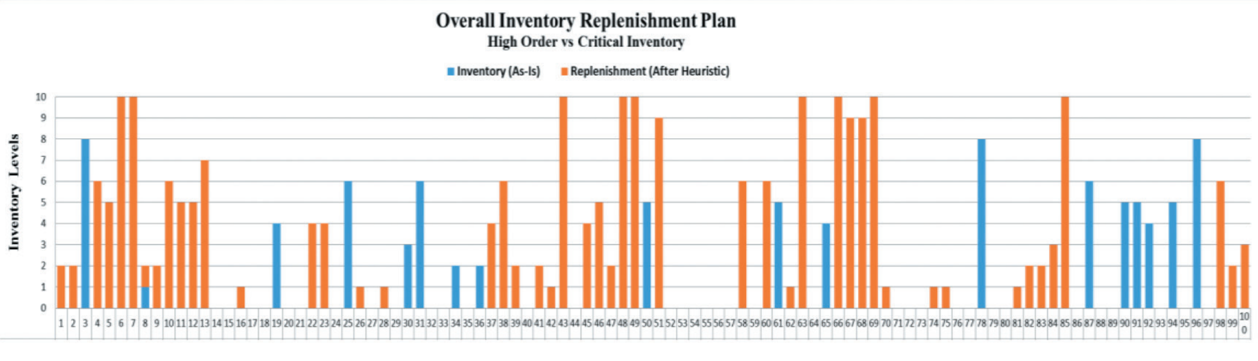



**Figure 5.** Replenishment strategy graph of High order vs Critical inventory

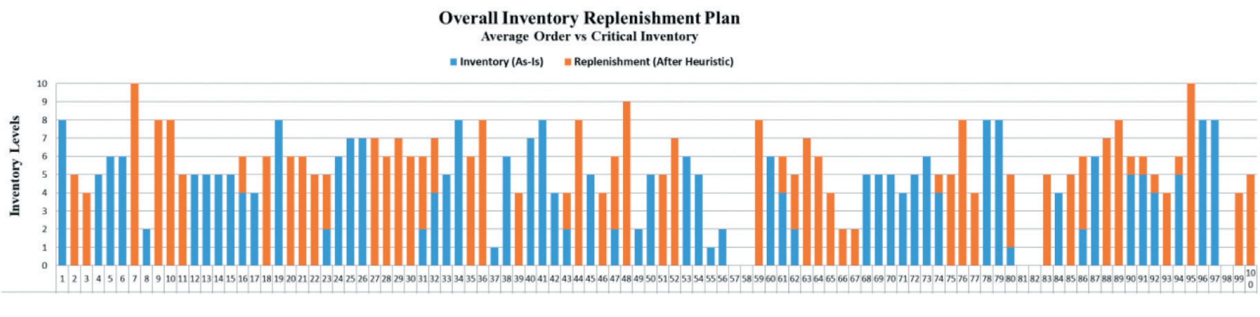



**Figure 6.** Replenishment strategy graph of Average order vs Critical inventory

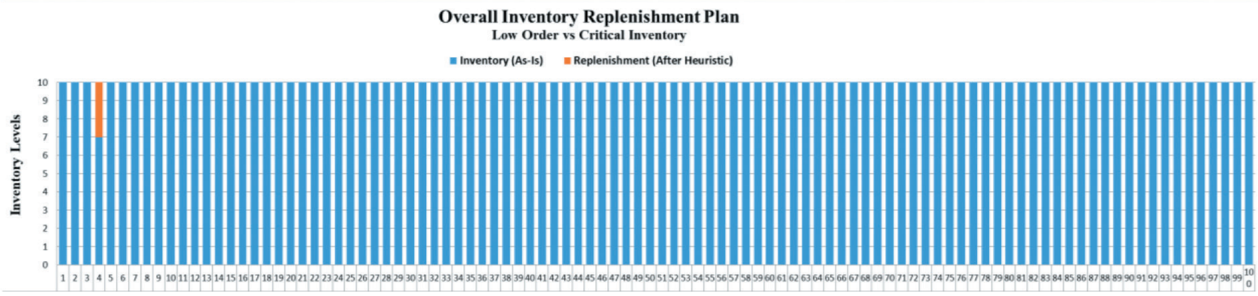



**Figure 7.** Replenishment strategy graph of Low order vs Critical inventory

order volume has little or no effect on flow-shop production.

To justify the proposed method's performance, its results are compared with the sequential replenishment method in the next section.

### 4.2 Total Number of Late/Unsatisfied Orders

One of the purposes of the proposed approach is to satisfy customer demand even in the face of disruptions continuously. Customer order satisfaction can be measured by the number of orders delivered. As KPIs, the number of late/unsatisfied orders is used to demonstrate the impact of the proposed heuristic on the flow-shop operation compared to the current operating state. Table 2 presents the results of the initially selected three order types for all experiment scenarios.

Table 2 highlights the total demand after disruptions for all scenarios and calculates the total number of late/unsatisfied orders for both 'As-Is' and when the proposed heuristic is applied. In the High order Critical inventory (HC) scenario, 1152 orders are late in the 'As-Is' situation. Compared with the proposed heuristic (675 late orders), there is a 41% improvement in the number of late/unsatisfied orders. Meanwhile, for the Average order Critical inventory (AC), 38% improvement was achieved when the proposed heuristic was applied. When the proposed heuristic was applied, the Low order Critical Inventory (LC) percentage improvement record was 100%. This means there is no late or unsatisfied order even when there are disruptions under this scenario. Even though the proposed heuristic method did not completely satisfy all customer orders for both HC and AC scenarios, it demonstrates a significant improvement that minimised the number of late or unsatisfied orders in all cases of critical inventory limit.

## 5. Sensitivity Analysis and Comparison Study

Other methods mentioned in the literature would not have direct comparison factors with the same experimental setting and methods suggested in this study, and hence, they might give a biased judgement. Therefore, a sensitivity analysis study and a comparison study with other suggested and proposed methods are carried out to verify the performance of the developed system and justify its performance under changing variables in terms of the KPIs.

### 5.1 Sensitivity Analysis

A sensitivity analysis study of changing model parameters is carried out to measure the parameters' impacts of fluctuations on the outputs and verify the developed system's performance. In this study, the behaviour of the developed system in response to different levels of demand, order numbers, and inventory is of utmost interest to test performance. The sensitivity analysis explores the robustness and accuracy of the developed model outcomes under

**Table 2.** Total demand vs unsatisfied orders

| Scenarios | Total Demand after Disruptions | As-Is | Proposed Heuristic |
|---|---|---|---|
| HC | 4820 | 1152 | 675 |
| AC | 2547 | 248 | 153 |
| LC | 1261 | 15 | 0 |

uncertain demand conditions. The uncertainty in demand caused by customers' disruption causes variations in order and inventory level parameters. Monitoring the relationship among these parameters and the impact of their variations in the model parameter setting is useful for identifying the inputs that cause significant uncertainty in the KPIs and for practical model analysis.

The proposed algorithm for replenishment is compared with the current state of "As-Is", a sequential replenishment method and instantaneous inventory replenishment proposed by [35]. The idea of non-instantaneous and gradual inventory replenishment of the proposed algorithm makes both the sequential and instantaneous methods comparable. This is related to the variable inventory levels at the time of replenishment. The proposed algorithm is developed to strategically replenish inventory based on each level, quantity and time availability. The sequential method replenishes inventory in order sequence by considering the required order number or each order inventory per time. On the other hand, the instantaneous method replenishes order inventory instantly. See Table 3 for variable parameters applied in the range: High Order Volume (100-120); High Demand Volume (80-100); Average Order Volume (40-60); Average Demand Volume (40-50); Low Order Volume (20-40); Low Demand Volume (20-25); Full Inventory=100; Safe Inventory Volume =50.

Table 3 shows the effect on late order KPI caused by changes in input parameters. A small change in high-order demand at the full inventory level significantly changes the number of late orders. As shown in Table 2 above, the highest number of late orders is recorded for high demand.

However, the lowest number of late orders at 383 reveals the better-performing method proposed in this study compared to other methods. The average level of order demand variation has a corresponding level of effect on late orders. However, the performance of the proposed method shows superiority with zero and 33 late orders at full and safe inventor levels, respectively, compared to other methods. The considerable variation in low-order demand at both full and safe inventory levels results in no late orders. This indicates that huge demand variation might not significantly affect KPI when high or safe inventory levels are maintained.

The robustness of the proposed method is more sensitive to high order demand at full or safe inventory levels, and the impact is insignificant for low order demand under the same inventory level parameters.

## 5.2 Comparison Study

A comparison study is also conducted to determine the effectiveness of the proposed approach for solving the disruption problem.

The standard deviation was used to statistically measure the dispersion or spread of each inventory level obtained by HC, AC, and LC scenarios. This is because the inventory fluctuates with changing demand, and the measure of dispersion is one of the ways to judge whether the fluctuations are smooth. However, the smoothness degree justifies the approach's effectiveness in performance [57]. The critical inventories for high (HC), average (AC) and low (LC) levels are selected as the lowest values of the data range and are more likely to diverge compared to full or average-level inventories with a wider range. Table 4 compares the three methods and the 'As-Is' current state by calculating the standard deviations from their mean-based inventory level behaviour.

The standard deviation measures the dispersion of the results of all the scenarios. The effectiveness of the proposed heuristics is shown by less dispersion of the results obtained. The proposed heuristic for replenishment for the HC scenario tends towards an average of 13.3, which indicates a more sustain-

**Table 3.** Comparison of Late Order KPI

| Data Set- Parameters | | "As-Is" | Sequential | Instantaneous Replenishment Method | Proposed Heuristic |
|---|---|---|---|---|---|
| High Order | Full Inventory | 785 | 521 | 455 | 383 |
| High Demand | Safe Inventory | 710 | 408 | 311 | 209 |
| Average Order | Full Inventory | 164 | 125 | 37 | 0 |
| Average Demand | Safe Inventory | 205 | 384 | 178 | 33 |
| Low Order | Full Inventory | 0 | 0 | 0 | 0 |
| Low Demand | Safe Inventory | 0 | 0 | 0 | 0 |

**Table 4.** Comparison of High Order Volumes

| Standard Deviation | | | | |
|---|---|---|---|---|
| **Scenarios** | **As-Is** | **Sequential** | **Instantaneous Replenishment Method** | **Proposed Algorithm** |
| HC | 16.4 | 14.3 | 18.2 | 13.3 |
| AC | 21.2 | 29.5 | 31.6 | 13.3 |
| LC | 4.22 | 4.11 | 4.40 | 1.28 |

able level for high-order inventory than the current state (As-Is) and other methods of replenishments. The standard deviation of the "As-Is" with the instantaneous method for AC is increased by 49%, which indicates the worse scenario as it provided a higher standard deviation value from 21.2 to 31.6. Likewise, the sequential method gives an increased standard deviation of 39%. The best improvement provided by the proposed heuristic for replenishment at the LC scenario is 70%, indicating a sustained inventory level capable of responding to disruption from the flow shop. Under the LC scenario, the 3% value for the sequential method indicates the lowest and relatively minor significance support for production disruption. Under the AC scenario for the proposed heuristic for replenishment, a 37% improvement is considered a significant sustainable inventory control. In general, comparing "As-Is" against the proposed heuristic for replenishment, the heuristics outperformed the "As-Is" against both the sequential and the instantaneous replenishment methods.

## 6. Conclusion and Future Work

The production disruption caused by uncertainty in customer behaviour, causing complex behaviour for the flow-shop system, has been successfully tackled through the improved PDIR framework. The improved framework was developed to assist production planners in a flow-shop system to manage disruptions, which is crucial to customer satisfaction. The innovative framework included the integration of agent-based simulation, heuristic algorithm and inventory replenishment. The technique as a whole took into consideration the agent-based messaging model of problem-solving, the adaptability of the heuristic to the changing disruption problems and the inventory replenishment to control and support shortages caused by disruptions. The improved heuristic for non-instantaneous replenishment makes it possible to achieve inventory smoothness. This assisted in accommodating and responding to disruption, with sustainable advantage from the inventory control.

The experimental study was conducted for high, average and low order demand under critical inventory levels, demonstrating the heuristic algorithm's effectiveness and scalability within the improved framework. Comparing the proposed method with the sequential method of replenishment showed a quantifiable improvement in terms of the number of late/unsatisfied orders. The best performance of the proposed heuristic for replenishment is achieved under the LC scenario with a percentage improvement of 70% compared with other "As-Is" situations for the LC scenario of other replenishment methods.

This study used a real-life case study to justify the proposed algorithm. The impact from the wider-industrial perspective is the provision of informed decision-making potentials to production managers, schedulers, and planners with related disruption problems similar to the one considered in this paper, especially within the OEM production environment.

Limitations arose since no solution approach or method fits all problems possibilities. As the study attempted to tackle customer-imposed production disruption in OEMs flow-shop, in flow-shop setting, the cost of holding inventory and unsatisfied orders are significant to performance estimation. Cost function has not been considered in the developed approach, but rather the inventory was utilised as strategic means of dealing with disruptions and satisfying customer orders.

Further study can consider the cost impact of the late/unsatisfied order to help with budgeting. Also, the impact of uncertain customer behaviour can be extended to open shop and job-shop systems. To further investigate disruption impact and production performance, other meta-heuristics techniques, such as Genetic Algorithms or Swarm Optimisation, could be used to explore more promising solutions. Likewise, other behavioural customer consequences would be a good area of research, including preferences, quality and attraction to other similar products demand. It is worth mentioning that the selection and use of appropriate statistical hypotheses tests could be further investigated from the statistical point of view to justify the significance of achieved inventory level results using the developed algorithms.

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