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Agent-Based Modelling and Heuristic Approach for Solving Complex OEM Flow-Shop Productions under Customer Disruptions

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Abstract

The application of the agent-based simulation approach in the flow-shop production environment has recently gained popularity among researchers. The concept of agent and agent functions can help to automate a variety of difficult tasks and assist decision-making in flow-shop production. This is especially so in the large-scale Original Equipment Manufacturing (OEM) industry, which is associated with many uncertainties. Among these are uncertainties in customer demand requirements that create disruptions that impact production planning and scheduling, hence, making it difficult to satisfy demand in due time, in the right order delivery sequence, and in the right item quantities. It is however important to devise means of adapting to these inevitable disruptive problems by accommodating them while minimising the impact on production performance and customer satisfaction.

In this paper, an innovative embedded agent-based Production Disruption Inventory-Replenishment (PDIR) framework, which includes a novel adaptive heuristic algorithm and inventory replenishment strategy which is proposed to tackle the disruption problems. The capabilities and functionalities of agents are utilised to simulate the flow-shop production environment and aid learning and decision making. In practice, the proposed approach is implemented through a set of experiments conducted as a case study of an automobile parts facility for a real-life large-scale OEM. The results are presented in term of Key Performance Indicators (KPIs), such as the number of late/unsatisfied orders, to determine the effectiveness of the proposed approach. The results reveal a minimum number of late/unsatisfied orders, when compared with other approaches.

Keywords: Agent-based modelling, Heuristic algorithm, Production disruption, OEM flow-shop.

1. Introduction

In today's era of global market competition, product quantities, sequence of operations and time to market form some of the challenging factors which manufacturers deal with daily (Mulky, 2013). The increasing changes in demand requirements (Lim and Zhang 2004) for manufacturing products and the volatility of the supply chain network have become overwhelming for production decision makers (Christopher & Holweg, 2011). For OEMs of automobile parts and components, where production relies on customer demands, satisfying these demands becomes a priority to remain in business. In this context, the OEMs are part of a car manufacturing supply chain network that processes raw materials and/or assemblies. They supply semi-finished products as parts and components for the assembly lines of the main automobile manufacturing customers. Thus, OEMs seek to explore measures and adopt a strategy to respond to the ever-changing customer environment which causes disruptions to demand quantities, due dates and sequence of orders in the flow-shop environment. The nature of these disruptions in OEMs has made it impractical to use traditional production planning and scheduling packages for decision making, because existing techniques are no longer suitable. Thus, a more adaptive approach is required.

For this reason, the embedded agent-based technique is explored in this study which, despite disruptions, ensures that the customer demand requirement is met by timely delivery in the correct quantities. The applicability of the agent-based technique for disruptions of the type being studied are documented in Fung & Chen (2005); Wojtusiak et al., (2012); Monostori et al., (2006); Sekala and Dobrzanska-Danikiewicz (2015); Shen et al., (2006); Gomez-Cruz et al., (2017). The problem of disruption in the OEM industry discussed in this study is associated with customer demand, order sequence, quantity and delivery due time, and are classified under production disruption (Paul et al., 2015).

The replenishment of inventory has often been linked with production in the manufacturing industry. It is an important contributor in manufacturing production as it relates to raw materials, work-in-progress, and finished products storage (Luikkonen, 2015) as discussed in related supply chain problems (Wang et al., 2015; William & Tokar, 2008; Hammami et al., 2017). Therefore, the inventory replenishment concept is utilised for disruption problems in OEMs to give ‘strategic’ production support to facilitate the effectiveness of the proposed approach.

The performance of OEMs in the manufacturing sector is vital, as they can influence business revenue which is a measure of economic performance. For these reasons, this study will be of interest to manufacturing stakeholders, researchers, government agencies and members of the general public with direct interest in the manufacturing performance of OEMs.

This study aims to develop and apply a simulation-based integrated decision support system, for solving flow-shop disruption problems of OEMs, to provide an adaptive production system which will improve productivity.

The novelty of this paper is that it proposes a new inventory replenishment strategy for solving manufacturing disruption problems caused by customers. It is necessary to replenish gradually rather than focusing on specific orders to prevent keeping 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 the paper is structured as follows: section 2 presents the review of related literatures. Section 3 describes the real-life OEM problem that has been investigated. Section 4 detailed the breakdown of the framework with its entities. In section 5, the experiments, results and analysis of a real-life case study are presented. This includes a comparison between the results of the proposed method and other methods. Section 6 concludes with the summary of the findings together with recommendations for further research.

2. *Literature Review on related disruption problems*

Over the years, many researchers have investigated the problem of disruptions in different industries, most especially in industries such as supply chain and manufacturing (Paul et al., 2015).

In the supply chain industry, Qi et al. (2004) investigated demand disruption in one-supplier-one-retailer supply chain. The goal of the work was to analyse the costs incurred due to changes that occurred as a result of disruption. Tang (2006) investigated supply chain disruptions which causes breakdown and longer recovery time. Erandi and Peter (2018) developed a framework using a modified version of the Risk Numeric Analysis model to manage disruption in supply chains. Rasti-Barzoki and Hejazi (2013) addressed the problem of an integrated due date assignment and production batch scheduling delivery causing disruption in a make-to-order system with multiple customers. Xanthopoulos et al. (2012) proposed a generic single period (news vendor-type) inventory model for capturing the trade-off between inventory policies and disruption risks in a dual-sourcing supply chain network. Synder at el. (2016) researched supply chain disruptions with the need for strategy decision and inventory control and discussed related modelling approaches. Chopra and Sodhi (2014) discussed management approaches towards reducing the risks of supply chain disruptions. In Paul et al. (2017) a supply chain mitigation planning approach using an effective heuristic to deal with sudden disruption was developed. Hasani and Khosrojerdi (2016) proposed an efficient parallel Taguchi-based memetic algorithm with a hybrid Adaptive Large Neighbourhood Search (ALNS) to tackle a robust global supply chain network affected by disruption and uncertainty. In Chen et al. (2017), the risk of production disruption and stochastic demand for a production-retail system was addresses by proposing two contracts (known as Advance Payment Contract (APC) and Buyback and Minimum supply quantity Contract (BMC)) to coordinate the system.

In the manufacturing sector, Lin and Gong (2006) investigated production line disruption caused by machine breakdown. Chen et al. (2012) proposes a model for a periodic-review inventory system with disruption involving two suppliers. In Steiner and Zhang (2011) disruptions caused by change in due-dates causing delays of orders was investigated. Paul et al. (2014) developed a real time disruption recovery model for a two-stage production-inventory system. Lin et al. (2016) considered disruption problems through the influence of customer disruption on specific quality levels in a Thin-Film Transistor Liquid Crystal Display (TFT-LCD) manufacturing. In Dastidar and Nagi (2007), two mathematical models and two heuristic algorithms were proposed for production scheduling due to assembly operations batch splitting disruption problems. Lozano and Medaglia (2014) investigated disruption problems caused by sequence-dependent batch and product incompatibilities in an automotive glass facility. Surjandari et al. (2015) based their study on disruption related to scheduling in an assembly job shop with parallel machines that produce multi-item multi-level product. Wang et al. (2012) studied disruption impacting the quality of product sequencing. Hazir and Kedad-Sidhoum

(2014) addressed integrated for batch sizing and just-in-time scheduling disruption problems where upper and lower bounds for batch sizes were imposed. Rolon and Martinez (2012) adopt agent-based modelling for production systems problems of unplanned disruptive events such as arrivals of rush orders, shortages and delays of raw material as well as equipment breakdowns. In Herrmann (2013) disruption problems relating to more restrictive retractions in flow shop scheduling were investigated. Bilyk et al. (2014) tackled the disruption problem of unequal ready times and precedence constraints for jobs in an identical parallel machines setting.

In Adediran and Al-Bazi (2018), disruption problems caused by customers' changing requirements were considered. A simulation-heuristic model was proposed using an inventory replenishment strategy to mitigate impact of disruptions. The limitation of this proposed approach is that it did not consider sustaining the inventory levels after items in the inventory have been used to minimise the impact of disruption.

Among the above related studies, very few papers focused on the disruption directly caused by customer disruption on flow-shop production. Disruption caused by customers through continuously changing requirements makes production planning and scheduling a more complex task. Also, very little attention has been given to disruptions in flow-shop production, especially within OEM industry. Some of the previous works have shown serious attempts at solving various types of disruption problems in different industries using different methods. The focus of these works was only based on disruptions that can be considered internal to the system, not necessarily those imposed by customers that occur unexpectedly.

However, this work presents an innovative dynamic and adaptive heuristic algorithm that minimises the impact of disruptions imposed by customers, taking into consideration random occurrences of these types of disruption. The work extends that of Adediran and Al-Bazi (2018) by presenting an agent based system which includes a new replenishment strategy that encourages a more sustainable inventory level as a measure for disruption recovery. The description of this disruption problem situation is presented in section 3 below.

3. Problem description

The description of the research problem relates to an OEM flow-shop facility. It represents cases of three customer-imposed disruptions on OEM flow-shop production, in which customers alter original demand quantity, the time required for delivery, and inevitably change the original sequence. All of these alterations affect planned production processes, overstretch resources and create shortages, and hence the need for adequate recovery measures.

In an OEM flow-shop facility, the goal is to continuously satisfy customer demand in a competitive market environment. The problem starts when customer orders are received with a specific quantity, due time and sequence of delivery, any of which could subsequently be subject to change. For quantity, all or part of the initial quantity can be cancelled. For due time, the initially agreed due time can be brought forward. For sequence, the sequence of delivery of order numbers can be altered. These changes occur due to uncertainties on the assembly line for the customer. The changes that occur cause disruptions to the production schedule on the OEM flow-shop. Cancellation disruption caused by changes in quantity increases the idle time for resources (e.g. operators and machines), which results in a low utilisation of production resources. Changes in the sequence of delivery might affect the number of machine setups, which consequently increases idle time, if orders of the same type now follow each other in the production queue. Alternatively, these sequence changes might increase the number of setups, if orders of a different type then follow each other, thereby, increasing the total demand on the resources. Disruption in due time in all cases create more late/unsatisfied order deliveries. Both changes in due time and sequence of delivery cause production shortages, which means that the required customer order quantities are late or not fully satisfied. This is because the flow-shop capacity for the OEM is unable to accommodate emergency changes by the customer in due time or sequence of delivery. From a different perspective, this means that the parallel and concurrent production-assembly lines of both the OEM and the customer are truncated. With the main objective being to fully, or partly satisfy the customer order, the OEM flow-shop needs to adapt itself to accommodate disruptions to achieve this goal. To meet this objective, the inventory (I) of finished orders is introduced to provide order support in terms of borrow (B) to satisfy customer orders. When customer order quantities are not met in due time or in the right sequence, items are taken from inventory (borrow) to complete production. As this is a daily and continuous process, the inventory needs a replenishment plan to continue to support production. The production idle time created by cancellations translates into ‘available time’ for this replenishment. The longer the idle time, the more orders that can be replenished. In a given period of production, disruptions occur causing shortages or creating available time. In turn, the inventory tries to support production, and needs to be subsequently replenished using the ‘available time’ for higher productivity of the flow-shop. The proposed resolution framework was developed in response to this problem and is discussed in section 4 below.

4. Research Methodology

4.1 Production Disruption-Inventory Replenishment (PDIR) Framework

The nature of the problem and its objective requirements constitute a significant consideration for the development of a resolution framework. In the past, different frameworks have been developed and applied to complex manufacturing problems (Ivanov, 2010; Gunasekaran and Ngai, 2005; and Guillen Badell and Puigjaner, 2007). Researchers have also integrated various framework components based on solution criteria involving key elements in the decision-making process (Dumetz et al., 2015; Jasti and Kodali 2015; Hedenstierna et al., 2009). For these reasons, the PDIR framework (Figure 1), proposed in Adediran and Al-Bazi (2018) is recalled as it incorporates the three components: a solution algorithm, agent-based modelling and an inventory module. The framework makes a significant contribution and presents a resolution platform to handle disruption problems that are peculiar to OEMs. In a characteristic make-to-order and make-to-stock production setting, an inventory link with the production environment is necessary.

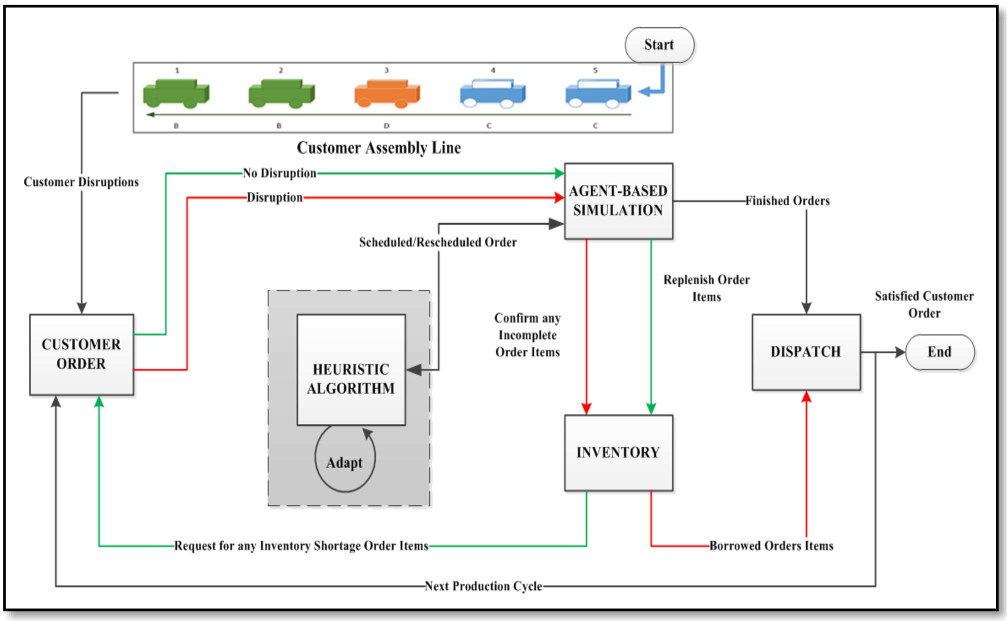


Figure 1: Production Disruption-Inventory Replenishment framework (Adediran and Al-Bazi 2018).

The framework captures production processes initiated by customer assembly line requirements. The sequential and timely assembly operations are the basis for order demand. However, assembly line uncertainties force changes in demand requirements. The changes mean some order demands might not be satisfied in due time, causing shortages and delay, as they disrupted the original planned production schedule. As disruptions such as cancellation create gaps in production, changes in the sequence of order delivery and due time put stress on production and create backlogs. In order to respond to the disruption, an adaptive heuristic algorithm is suggested to reschedule production processes. The heuristic algorithm not only reschedules the process but helps the system to adapt through the agent-based modelling capabilities of handling system complexities (Lee et al., 2015). Unsatisfied order items can be borrowed from inventory, which represents a rescue plan for maintaining customer satisfaction. When there is disruption, the order demand for the customer can be satisfied from inventory (i.e. borrowed), then the inventory must be replenished for the borrowed order. The heuristic algorithm schedules a replenishment order within the ‘available time’ to maintain inventory levels. The ‘available time’ is the time saved on the production line because of the disruption. For example, random cancellation which creates a time gap in between processes or changes in the sequence of delivery. This can cause orders of the same type to follow each other on the production line, meaning the setup time can be saved. This repetitive process continues in a daily production cycle. Each of the framework modules are discussed further in the next section, which starts with agent-based simulation, followed by inventory replenishment and then heuristic optimisation which captures the implementation for all these components.

4.1.1 Agent-based simulation

The agent-based simulation incorporates the other two resolution entities discussed earlier. It also deals with scheduling and resource allocation within the flow shop.

The agent-based simulation process is carried out through negotiation, collaboration and communication between different agent types identified in the system. Based on the research problem requirements, the developed simulation is expected to achieve the following functions highlighted below:

- To accept input parameters such as the order information (i.e. type, quantity, and due date), machine information (i.e. number, process, setup time, and processing time), operator information (i.e. skills, number, and availability) that are required for processing orders in the flow shop manufacturing system setting to achieve minimal idle time, and high utilisation, and which satisfies all constraints including the delivery due times of product orders;
- To assign and schedule the required order operation according to the specified system resources (i.e. machine and operator), based on the pre-defined assignment plans.
- To improve the utilisation of each of the manufacturing system resources;

The different functions identified with agent-based simulation are due to the autonomous capability of individual agents, as represented in the agent framework shown in Figure 2.

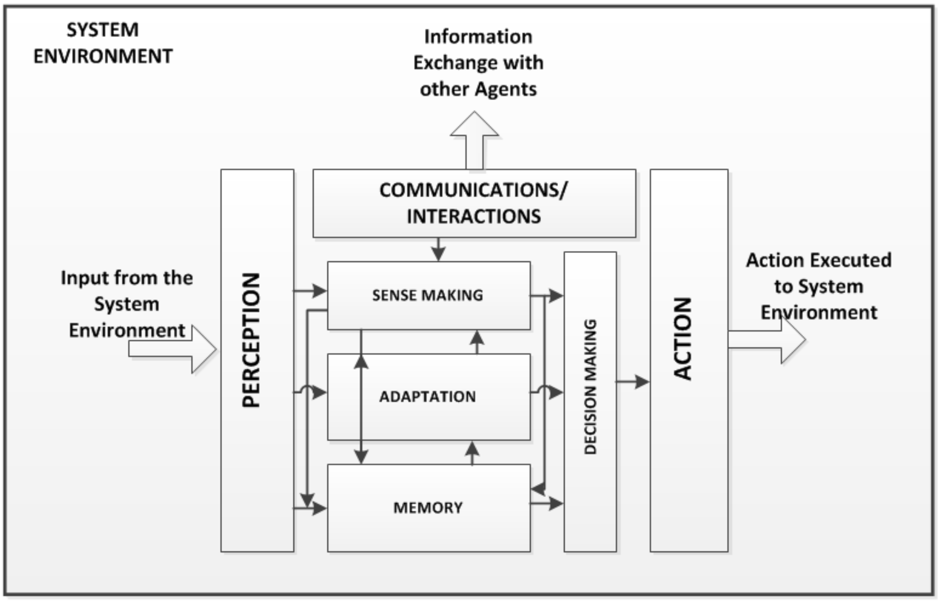
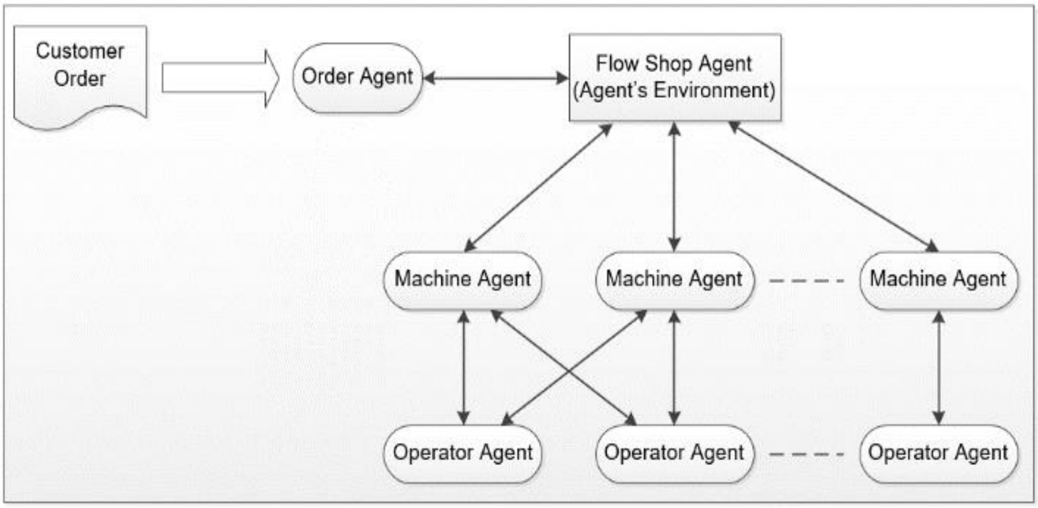


Figure 2: Individual agent framework.

According to figure 2, individual agents possess qualities which allow them to perceive the environment, adapt to changes, make sense of events around them, save events in memory, and make decisions which allow them to take action that can be communicated to other agents within the system environment (Wang et al., 2008). These qualities form the basis of the agent-based application in this study, which make it possible for production resources such as machines and operators to be adequately assigned to processes for order production.

The agent-based simulation environment is modelled in Microsoft Excel using VBA codes. The general industrial acceptability of this MS software package and its easy accessibility for users make the Excel environment a reasonable modelling choice. In this study, there are four system agents identified and considered, where the customer is the initiator. They are: *machine, order, operator*, and the *flow shop agent*, which all interact within the system environment shown in figure 3, the architectural model of the agent-based system.



Architectural Model of the Agent-Based System

Figure 3: Architectural model of the agent-based system.

The model architecture in figure 3 shows that the customer order is received, translated and transferred to an order agent, which is then passed on to the flow shop agent (agent environment) (Baptista et al., 2014). Through the flow shop agent, several machine and operator agents work collaboratively, to serve order agents, while the flow shop agent also provides the information for order processing operations. Order production is started based on the process plan and schedule, which is allied to an order agent through the flow shop agent (Cupek et al., 2016). The interaction of individual agents within the agent-base system is made possible through the agent-based messaging system (Rolon and Martinez, 2012).

(i) Agent-Based Messaging System

The idea for the messaging sequence within the agent-based environment in this study was obtained from Pan et al. (2009), where it was implemented in the Supply Chain industry for the SC entities which represent the interactive ability of individual agents. In figure 4, the system message sequence-diagram shows the communications between the three agents including the customer, production floor, processes and inventory.

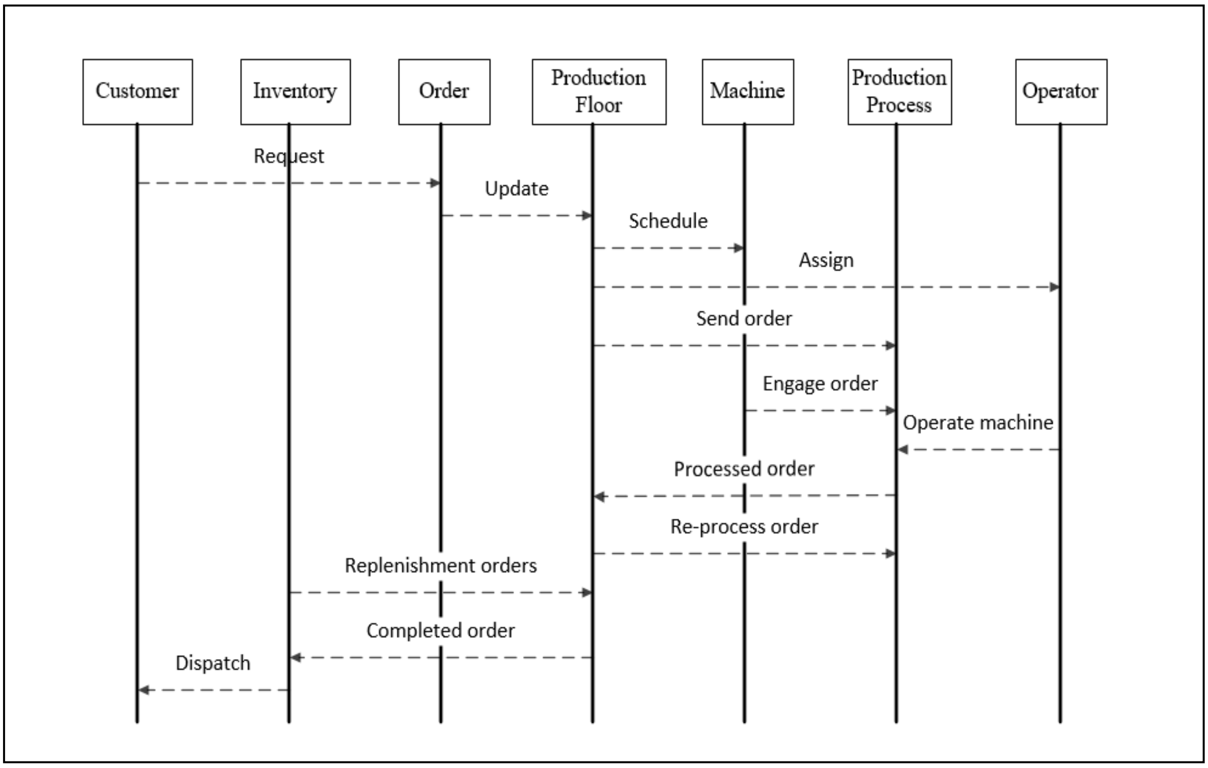


Figure 4: The System Message Sequence-Diagram (Adediran and Al-Bazi 2018).

It reveals the type of messages being sent and received by individual entities which enable order processing through messages such as order requests, resources allocation, order production, inventory and dispatch information that are being sent within the system.

The customer sends an order request, which is updated on the production floor. Upon receipt of the customer order request, the production floor schedules machines based on the order information. The order and machine schedule are used to assign operators to the production job. As a result of the machine being allocated to an operator, the order is engaged for the production process. The production process proceeds in a loop of operations until all the assigned orders have been completed. At which point, the completed order information is passed on to the production floor for order dispatch from the inventory to the customer according to the request. When disruption occurs an inventory-support production replenishment order is sent to the production floor to maintain the inventory level.

The agent-based messaging sequence imitates the flow-shop operation and helps achieve the best interaction between agents and the inventory-replenishment strategy to reduce production shortages. This is because the solution components are embedded in the heuristic as the third component of the

PDIR system framework. Most importantly, the messaging system makes agent-based decision making possible. Ultimately, the agent-based messaging system serves as an influential linkage among agents and supports the execution of the heuristic algorithm commands through messaging sequences of production activities.

4.1.2 The Non-Instantaneous Non-Deteriorating Inventory replenishment strategy

The proposed inventory replenishment strategy focuses on satisfying the changing requirements of the customer. This is achieved through inventory support and then replenishing the inventory by strategic replenishment scheduling on the flow shop. The idea relates to non-instantaneous replenishment referred to in Chang et al. (2010), Soni (2013), and Wu et al. (2006). Non-instantaneous replenishment occurs when production is not instantaneous, and inventory is replenished gradually, rather than in lots. The three studies discussed optimal replenishment policies for non-instantaneous deteriorating items. In Chang et al. (2010), the focus is on stock-dependent demand. In Soni (2013), price and stock sensitive demand, under permissible delay in payment, is emphasised, while Wu et al. (2006) based their study on stock-dependent demand and partial backlogging.

In this study, the optimal inventory replenishment strategy is presented for non-instantaneous non-deteriorating items where the demand is changing requirements in terms of sequence of delivery, due date and order cancellation. The graph below in figure 5 cites an example of ($O_1 \ldots O_n$) order inventory levels. In production planning, these different levels of inventory illustrate the extra stock needed to be maintained in order to lessen the risk of stock shortages caused by the disruptions. The maximum inventory level is achieved when the inventory is 100% full. The inventory level is safe when it is not below average (50%), and is critical when below average, close to zero or at zero percent. Each order in inventory is expected to support the satisfaction of customer demand in case the actual production is insufficient. The proposed inventory replenishment strategy aims for the best utilisation of 'available time' with minimum setup and processing time, which leads to a maximum number of order items (quantity) to be replenished per order, within a given production cycle, over a period.

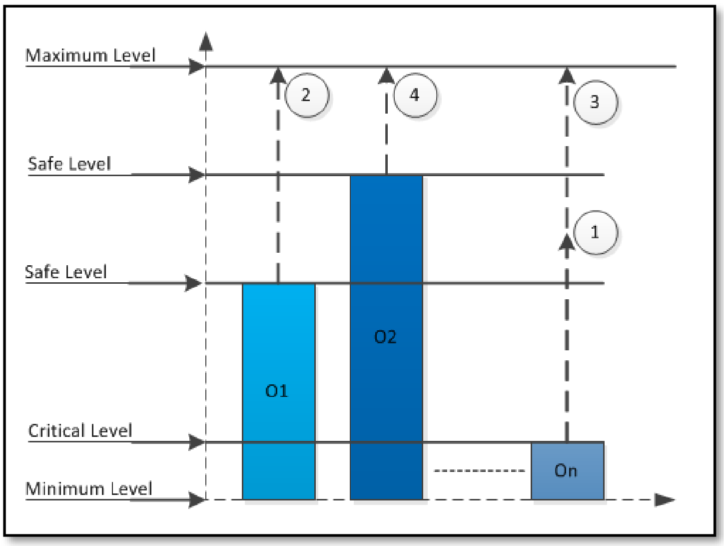


Figure 5: The proposed replenishment strategy.

According to the proposed replenishment strategy, which aims to support production and maintain inventory which falls below the maximum level, figure 5 shows how order replenishment is achieved using ($O_1 \ldots O_n$) orders to maintain inventory levels. The number denotation (1), (2), (3), (4) in the diagram indicates the suggested sequence of replenishment and the heuristic decision. Order O_n at the critical level is the priority (1), while order O_1 at a safe inventory level but lower than order O_2 is the second replenishment priority (2) and so on. The details of the proposed heuristic optimisation to establish the system behaviour using a disruption and replenishment plan is discussed in section 4.1.3 below.

4.1.3 The Heuristic Algorithm

The heuristic algorithm developed in this study is adopted as an extension of the heuristic algorithm proposed in Adediran and Al-Bazi (2017). This extended version is designed to accommodate and adapt to the three types of disruptions in five different possible cases where inventory is applied for production support, as it is in Adediran and Al-Bazi (2018). However, the heuristic algorithm presented in this paper has been applied not only to help adapt to disruption, but to also help maintain sustainable inventory levels. This is described as inventory level behaviour.

Case 1: This is when the inventory levels for all order types are at a maximum, suggesting that all required orders can be satisfied, and no replenishment is required.

Case 2: Is when the inventory of only one order type is at a critical level while others are at maximum (i.e. full) level. In this case, only this order type will be replenished until the available time is exhausted.

Case 3: This is the situation where the inventory of two or more order types is below the maximum level (i.e. either critical or safe). In this case, the order types will be replenished until the available time is exhausted. The priority will be determined by dealing with the orders with the most critical level of inventory first.

Case 4: This is the situation where the inventory levels of two or more order types are below their maximum and at the same level. In this case, the setup and processing time are considered to determine replenishment.

To avoid creating unnecessary setups, order types with the same setup are replenished based on setup and processing time. In terms of processing time, the number of order items to produce depends on the processing time of the individual order.

Case 5: In this scenario, the inventory levels of two or more order types are a combination of the same and different inventory levels. The order which was most critical is considered for replenishment. If two or more orders are at the same critical level, setup and processing time is considered for their gradual replenishment. When two or more orders are critical and at the same level with the same setup and processing time one order is selected at random for replenishment.

In addition to the above possible cases, the algorithm also considers machine processing time, resources availability, setup before and after each order process and the specific order type that requires replenishment. This is done to minimise the number of setups, idle time and consequently to achieve maximum resource utilisation.

The five cases above form the basis for the heuristic steps for the replenishment design to capture all possible instances of disruption effects that might occur.

The notation used in the proposed heuristic algorithm

- *D = Order demand quantity*
- *ΔD = Disrupted demand quantity*
- *DT = Due time*
- *ΔDT = Disrupted due time*
- *S = Sequence of demand*
- *ΔS = Disrupted sequence of demand*
- *I = Inventory*
- *P = Production*
- *n = number of orders*
- *B = Borrow quantity from inventory*
- *U = Unsatisfied order demand*
- *SD = Satisfied order demand (This includes type & quantity of an order)*
- *SO = Shortage*
- *R = Replenishment quantity*
- *N = current day*
- *N+1 = Next day*
- *ABM = Agent-Based Model*
- AT_{time} *= Total available time*
- AC_{time} *= Current available time being allocated*
- M_{setup}*= Machine setup*
- P_{time} *= Processing time*
- *PP = Production period*

The Heuristic Algorithm

1: Obtain D, DT, S, I, and PP.
2: Sort S processing based on order modelling rules
3: Schedule D in S of DT for N
4: Re-schedule if ΔD, ΔS, and/or ΔDT for N
5: For P ≤ (D or ΔD)
- *If P = (D or ΔD), then SD.*
- *Else if P < (D or ΔD), then SO end if.*

6: For SO, Borrow B from I, where B = (D or ΔD) - P
- *If P+B = (D or ΔD), then SD ➔ SO = 0 where I > 0*
- *Else if P+B < (D or ΔD), then U ➔ SO > 0 where I ≤ 0 end if.*

7: Obtain AT_{time} *(where* $AT_{time} = \sum AC_{time}$*) from the ABM*
8: For I ≤ 100% and $AT_{time} \geq 0$
- *If I ≤ 100% and* $AT_{time} = 0$ *then do nothing, else*
- *If I < 100% and* $AT_{time} > 0$ *then*

9: Schedule R, where R > 0
- *If critical or safe and different (I - B) levels for* AC_{time} *then Replenish R for the least (I - B) level, until* $AC_{time} = 0$ *or I = 100% (whichever comes first) else*
- *If critical or safe and same (I - B) levels for* AC_{time} *then Replenish R for the least levels of (I - B) with minimum* P_{time} *and minimum* M_{setup} *until* $AC_{time} = 0$ *or I = 100% (whichever comes first), else*

- If minimum P_{time} and minimum $M_{setup\ are}$ equal for same (I - B) levels then, Replenish R at random until AC_{time} = 0 or I = 100% (whichever comes first) end if, end if.

10: Update the new I level as (I-B+R)

11: Skip to next AC_{time} if AT_{time} > 0 and Repeat Step 9 until all I = 100% or/and AT_{time} = 0 or end of N production cycle (whichever comes first)

12: Display P, U, SO, SD, B, DT, S, R, and I

13: Repeat steps 1-12 for (N+1) until PP is completed.

The heuristic algorithm obtains the customer demand information such as the demand quantities (D), types in sequence (S), and due time (DT) as input, where full inventory (I) levels are assumed initially for order types. The demand type (S) is sorted for processing based on predefined order modelling rules such as the earliest due time. The demand is then scheduled daily (N) in the sequence of due times. Disruption can occur in terms of cancellation, which is disrupted demand quantities (ΔD), sequence change (ΔS) and/or change in the delivery due time (ΔDT). Customer demand satisfaction is determined under either disruption or no disruption. If the production quantities (P) are equal to demand or disrupted demand, then customer demand is satisfied (SD). However, in the case where the production quantities are less than demand, then there are shortages (SO). When shortages occur due to disruption, orders are borrowed (B) from inventory (I) to support production, where borrowed order quantities are production shortages from demand or disrupted demand quantities ($B = (D \text{ or } \Delta D) - P$). Customer demand becomes fully satisfied if the addition of the borrowed quantities with the production quantities is equal to the demand or disruption demand quantities. In this case, shortage is nullified to zero. However, if the addition of production and borrowed quantities are still less than the demand or disrupted demand quantities, there would be unsatisfied customer demand (U). This case would occur when inventory is less than or equal to zero and insufficient to cover the shortages. When order quantities are borrowed from inventory, replenishment quantities (R) are needed to manage all order inventory levels to avoid any future shortages. The inventory replenishment quantities are based on current inventory levels (I-B) of all orders. If inventory level of any order is full or less than 100% where there is no available time, then no replenishment is done. However, when inventory level is less than 100% and there is available time, the system searches for and utilises the available processing time, if the total available time (AT_{time}) is at least one. For each replenishment operation, the system utilises current available time (AC_{time}) until it is exhausted, where total available time is the sum of all the possible current available time. For schedule replenishment quantities (R), the current available time is allocated when the replenishment is less or equal to inventory borrowed quantities.

However, replenishing borrowed inventory quantities is considered for three different conditions for either critical or safe inventory levels; if inventory levels are different, the item with the lowest inventory level is considered for replenishment until either the current available time is zero or the inventory level is at maximum (i.e. full), whichever comes first. In the case where inventory levels are the same, process and setup times are considered, in which case items with the lowest times are selected.

The replenishment quantities are scheduled at random when items with the same inventory levels have the same minimum process and setup times. In all cases, the inventory is updated with replenishment quantities, giving the inventory new quantity values of (I-B+R).

To utilise all available total times at each replenishment attempt, the system searches for the next current available time and repeats all replenishments steps until all order inventory levels are full (100%), all available total time is exhausted or the daily production cycle (N) is completed, whichever comes first. The system generates and displays output in terms of number of production (P), unsatisfied orders (U), shortages (SO), satisfied demand (SD), borrowed orders (B), due time (DT), sequence (S), replenishment quantities (R), and inventory levels (I). The entire process is repeated for the next production day and continues until the production period is completed.

The implementation of the framework components, including the heuristic approach is the basis for the real-life case study considering combinations of change relating to sequence of delivery, due time and cancellation scenarios for high order demand while maintaining a full inventory level as detailed in section 5 below.

5. Computational Results and Discussions

Computational experimentation of a real-life OEM flow-shop is conducted to investigate the effect of the three disruptions. The OEM flow-shop is an automotive parts production facility selected for two reasons. Firstly, the continuously changing order requirement, particularly in a simultaneous production-assembly operation, was peculiar to automotive parts producers and their customers, thus creating a unique and ideal environment to study the disruption problems. Secondly, order cancellation, delivery sequence and specific time of delivery in this sector are critical. This is due to the storage limitation for the holding of excess stocks and the sequence-dependent customer assembly line. The actual customer demand and production data of the case study were fed into the developed system to study the emerging behaviour under different experimental scenarios. The developed agent-based simulation model was set up to represent the number of machine process lines in operation in the factory, for the selected number of products. Also, the system replicated the individual cycle time, processing time, and machine setup time as random range fittings. An experiment was designed to test the behaviour of the proposed solution under different order disruption scenarios. It was also to demonstrate the impact on inventory levels of the proposed order borrow and replenishment concept. The scenarios are presented and analysed in the section below.

5.1 Production Disruption Scenarios

The simulation model which is developed in Excel-VBA is the environment where the production disruption scenarios experiments were conducted. The experiment data was generated based on a real-life OEM flow-shop as a primary data source. As presented in Table 1, the experiment parameters are based on the production schedule for the weekly production demand plan, and are represented in days as provided by the OEM flow-shop facility. The parameters settings for the simulation are as follows:

Table 1: Experiment Parameters

System run time	24 hours
Number of shifts	3 of 8 hours each
Shift 1	09:00 – 17:00
Shift 2	17:00 – 01:00
Shift 3	01:00 – 09:00
Number of weeks/ production days	4 weeks/ 20 days
Number of operators	8 per shift
Number of machines	7 per shift
Number of processes	7 per shift
Number of order types	100
Number of orders volume	80-100
Inventory levels	100 for HF 50 for HS 10 for HC

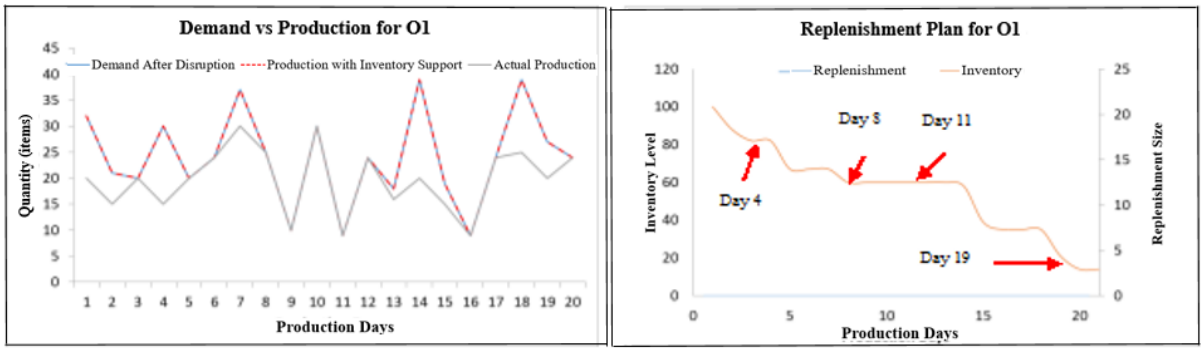
The experiment considered random combinations of the three types of disruption for:

- High order volume and Full inventory levels (HF).
- High order volume and Safe inventory levels (HS).
- High order volume and Critical inventory levels (HC).

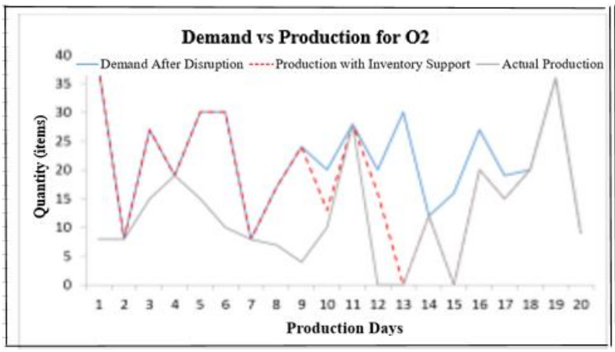
These were selected to imitate a real-life large-scale production environment. The impact of disruptions for High order volume is investigated for the three inventory levels category. This is because generally in such a complex production environment, high demand has varying effects on inventory levels. Although the system was tested for high order demand (volumes range 80 to 100), in this paper, three of the orders have been selected for discussion. This is to demonstrate the impact of the proposed approach and to illustrate the behaviour of production and inventory under random occurrences of disruptions.

5.2 Discussion of the key outcomes

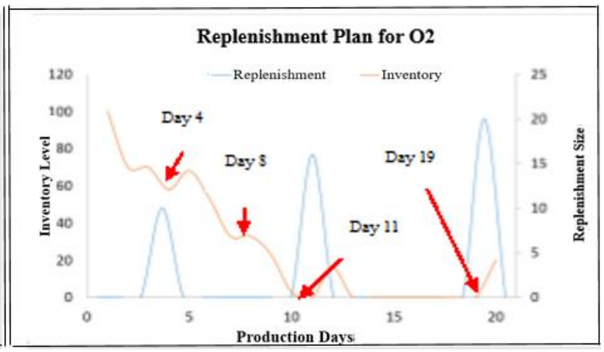
The discussion focuses on the key outcomes of interest, the demand on production and the implication for the inventory as shown in Figures 6-8 below. The impact of disruptions, which can be significant, can be measured by the behaviour of these two key outcomes. These figures show the system behaviour based on the demand after disruption, the actual production, and the production with inventory support. Likewise, it shows the inventory behaviour due to disruption and the replenishment decision for different inventory scenarios as suggested in the proposed heuristic.



(a) (b)



(c)



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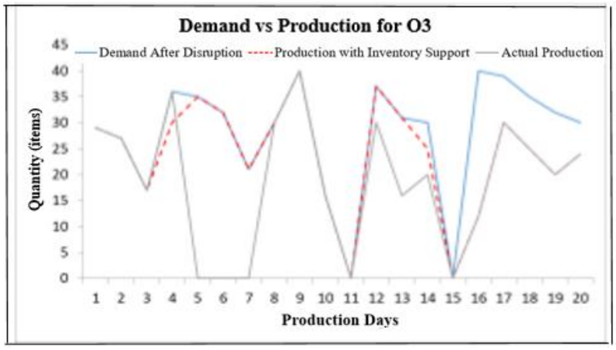
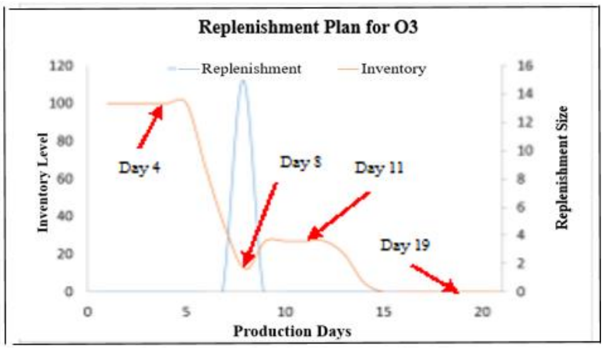


(e)



(f)

Figure 6: HF Experiment results: (a) The demand against production for O1, (b) The replenishment plan for O1, (c) The demand against production for O2, (d) The replenishment plan for O2, (e) The demand against production for O3, (f) The replenishment plan for O3.

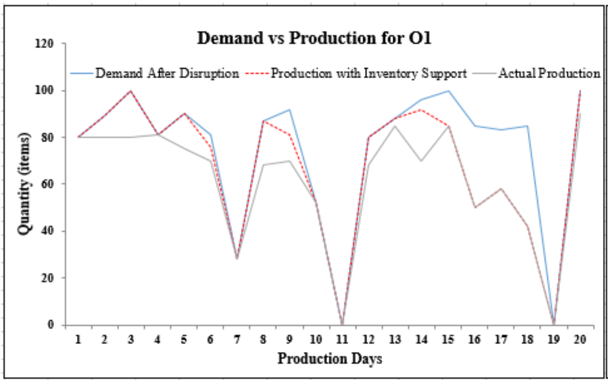
The order type O1, in Figure 6a has no replenishment because the inventory level throughout the entire production period was higher when compared with other order types O2 and O3. This was in conformity with the proposed heuristic algorithm which gave priority to order inventory with a critical level.

The first replenishment opportunity with available time occurred on day 4 as indicated in Figures 6b, 6d and 6f, where orders 1, 2 and 3 had current inventory levels from the previous day of 82, 58 and 100 respectively. Since the O2 inventory level was the least amongst them, it was replenished with 10 order units which took its inventory level up to 68. Likewise, on day 11, O2 in Figure 6d was the most critical at inventory level 0 and so was replenished with 16 order units using the available time.

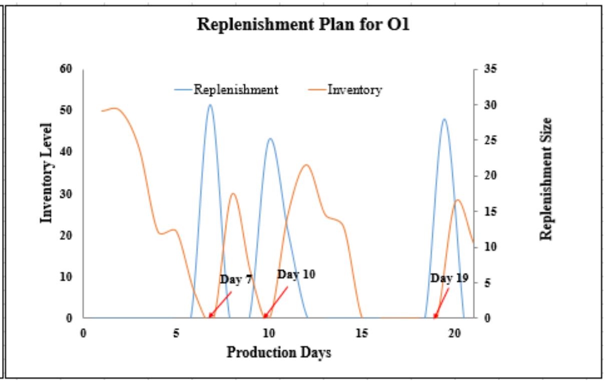
However, on days 12 to 18, Figure 6d shows that where the O2 inventory level was at 0, and Figure 6f shows that on days 14 to 20 where O3 was at 0, no replenishment occurred as there was no available time or resources for replenishment. However, O2 in Figure 6d was chosen for replenishment on day

19, despite having the same 0 inventory level as O3 shown in Figure 6f. This was decided based on the setup and processing times of each, which determined that the available time and resource was suitable to process more of O2 than O3. Again, in Figure 6a, although production was less than the demand, the inventory was able to support production without reaching a critical level. The slightly steady trend of the inventory reflects this consistent support. There was no replenishment of O1; the state of its inventory gives priority to orders O2 and O3 which were on zero level. In Figure 6c and 6e, the impact of disruptions reduced the order production which in turn created a drastic fall of inventory levels for both O2 in Figure 6d and O3 in Figure 6f respectively. The continuous fall in the inventory levels of these orders meant that there was no room for production support until replenishment happened. Although orders O2 and O3 recorded some number of unsatisfied orders as a result, the implementation of the proposed agent-based heuristic reduced the unsatisfied orders to the minimum.

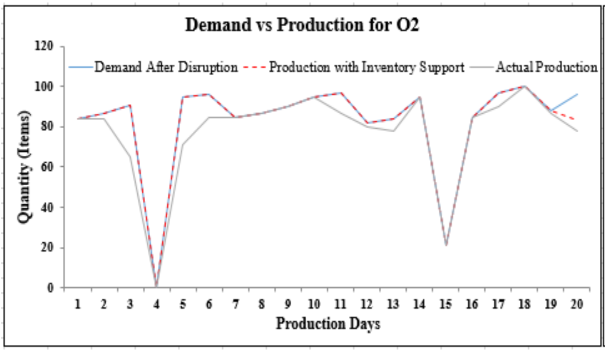
In Figure 7a and b below, the demand production and inventory replenishment plan of the first selected order (O1) is represented.



(a)



(b)



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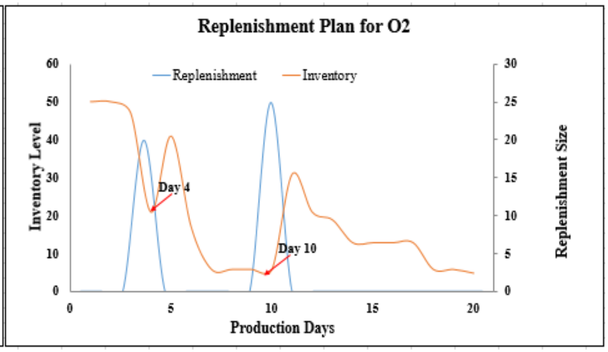
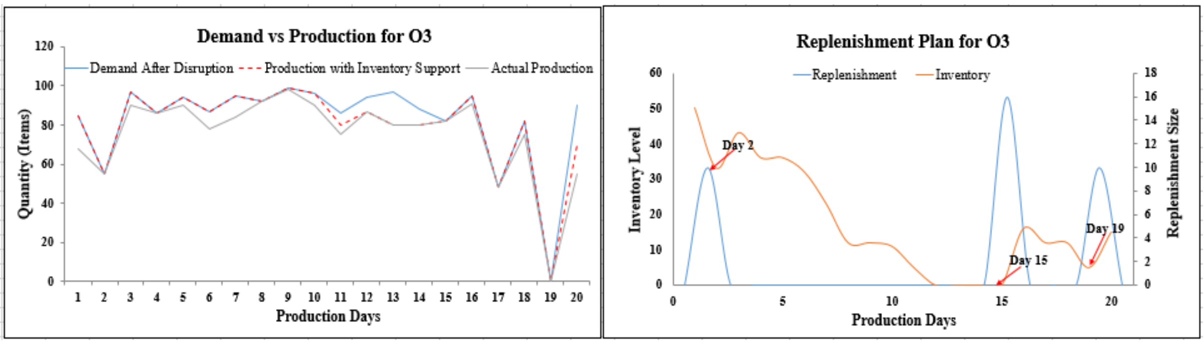


(d)



(e) (f)

Figure 7: HS Experiment results: (a) The demand against production for O1, (b) The replenishment plan for O1, (c) The demand against production for O2, (d) The replenishment plan for O2, (e) The demand against production for O3, (f) The replenishment plan for O3.

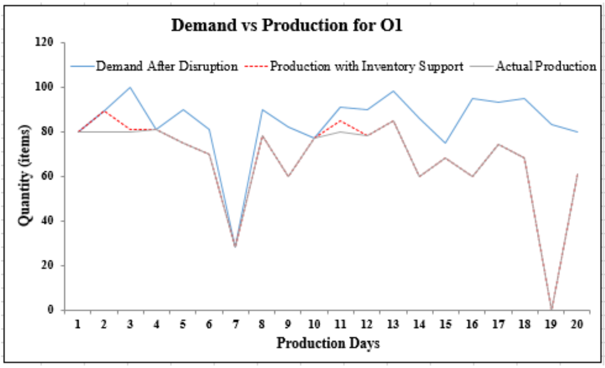
In Figure 7 (high order volume and safe inventory levels), the support for production shortage to prevent late/unsatisfied orders is evident from day 2 until day 5 when inventory level became zero. However, on days 7, 10 and 11, there were replenishments and continuous inventory support which eradicates late/unsatisfied orders before inventory went back to zero level on day 14. The production period where shortage and lack of support was experienced on the production flow-shop is shown by the demand after disruption trend which is clearly higher than production. In figure 7b, there are three instances of replenishment which explain why inventory was increased to further reduce production shortages. The level of inventory in this scenario is not always sufficient to support production, especially when production continually drops over a longer period of days as it is the case on days 14 to 18. In figure 7c and d, the demand production and inventory replenishment plan is shown for the second order (O2). The support from the inventory is evident from the trend throughout the production period until day 20. Figure 7e and f represent the demand production trend with the inventory replenishment plan for the third selected order (O3).

The consequences of disruption on production have more effect with safe inventory levels when the demand volumes are high. This is because inventory support was exhausted within the first 4 days. However, the situation is continually alleviated with replenishment implementation and effective resource utilisation. For instance, production drops due to disruptions from day 2 to day 5. For this reason, inventory levels drop in response to supporting production against order shortages. However, there was replenishment on days 7, 10 and 11 where inventory was topped up, which helped reduce the number of unsatisfied orders.

It can be deduced that the more disruptions causing replenishment, the less the number of unsatisfied orders as there would be support for production even when demand after disruptions is higher than actual productions. The situation in Figure 7d is different from Fig. b and f, because amount of actual production is almost equal to the demand after disruption and so the inventory level was sustainable until day 20 when 13 unsatisfied orders were recorded.

The interesting feature of the impact of disruptions for the three selected orders production is the drastic drop in the inventory levels. This happens in such a way that inventory levels tend towards zero. However, an intermittent rise of the inventory level, as the case of Figure 7b and d, came due to replenishment occurrences. The interesting part is that it is the effect of disruption such as the cancellation that created a time gap, which is referred to as ‘available time slots’ in this study, which are then utilised for inventory replenishment. This is an example of the system demonstrating an adaptive response to disruptions by taking advantage of its consequences as one of the key strategic solutions.

As shown in Figure 8a-f the level of inventories for the three order types were zero for most of the production period. This is because there are more demands after disruptions than the system can produce and for inventory to support. Although in Figure 8f there are two instances of replenishment, but the inventory level limits are critical and the choice for replenishment makes little difference considering the high demand volumes.



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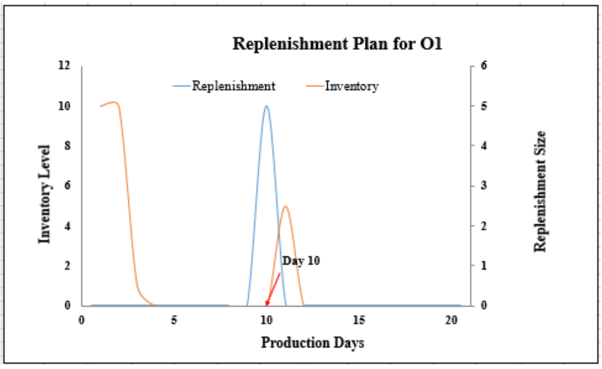

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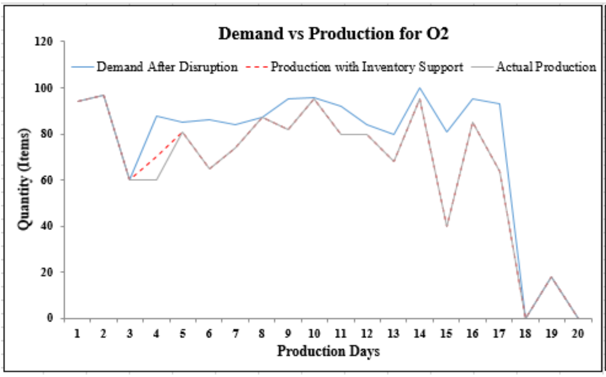

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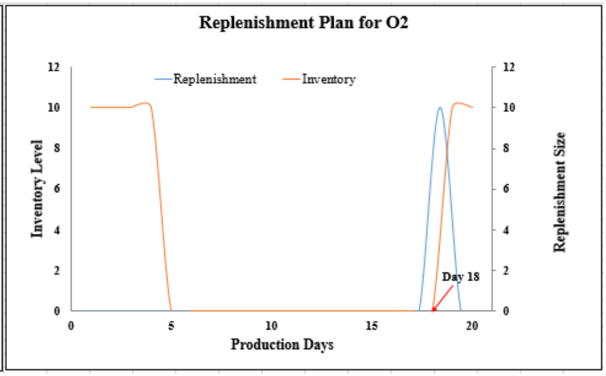

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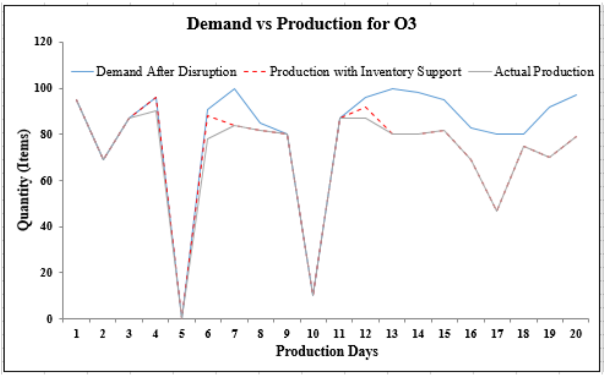

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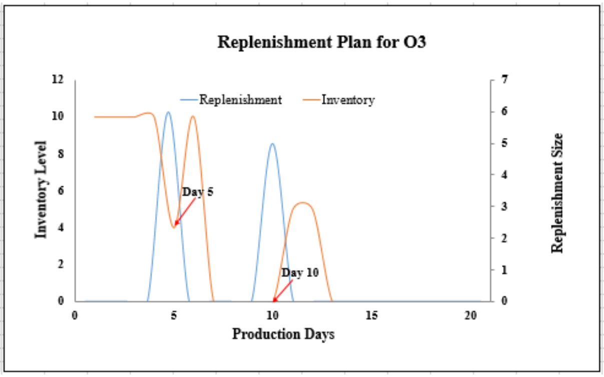

(f)

Figure 8: HC Experiment results: (a) The demand against production for O1, (b) The replenishment plan for O1, (c) The demand against production for O2, (d) The replenishment plan for O2, (e) The demand against production for O3, (f) The replenishment plan for O3.

As seen in figure 8, the consequences of disruption under the high order critical inventory status reveals a large number of unsatisfied orders. This is due to lack of inventory buffers for the production shortages. Even in the instances of replenishment from the inventory, the wider margin of disparity between the order volumes and the inventory level implies that support is not sustainable for disruptions to be managed as expected. It is however not realistic to hold critical inventory levels when higher order volumes are involved. The variation of inventory levels with high order volumes demonstrates the impact of combined disruptions on the flow-shop. Based on high order volume simulation results of the three inventory levels, full inventory levels demonstrate a much more sustainable selection to achieve the goal of accommodating disruptions while customer orders are being satisfied.

The results and the production and inventory behaviour revealed the applicability of the proposed heuristic algorithm for both disruption recovery and inventory replenishment. The algorithm demonstrated continuous support for production shortages and persistent maintenance for critical inventory level where possible. This impact revealed the effectiveness of the proposed heuristic embedded within the agent-based model.

5.3 Comparison with other production-inventory approaches

In this section, the proposed production-replenishment approach discussed in section 4.1.2 was compared with the sequential replenishment method and the Instantaneous Replenishment method proposed by Adediran and Al-Bazi (2018). Sequential replenishment was selected as one of the approaches for replenishing the inventory, particularly given the nature of the current replenishment. Also, the Instantaneous Replenishment method was selected as it considered the problem with a similar situation but replenished the inventory in an instantaneous manner. These two were selected because they are related to the current problem specifics and can be used to justify the sustainability assessment of the proposed approach in this study. It would be unrealistic for any other approach outside this domain to fully satisfy the problem requirements. Also, the random combination of disruptions that happens during the production operation and non-instantaneous replenishment makes it challenging for the system to be compared with any unrelated approach. However, for a fair evaluation, the sequential approach was compared with the proposed approach. The reason behind this comparison was to justify the superiority of the proposed approach over other approaches. The measurement criterion used for the comparison was the key performance indicator of the number of late/unsatisfied orders. The total number of late/unsatisfied orders for both approaches would define their corresponding impact.

Figure 9 below shows the result of this comparison which reveals the effectiveness of the proposed strategy over the sequential method using the scenario of low order volume and full inventory in terms of the number of late/unsatisfied orders over the 20-day production period.

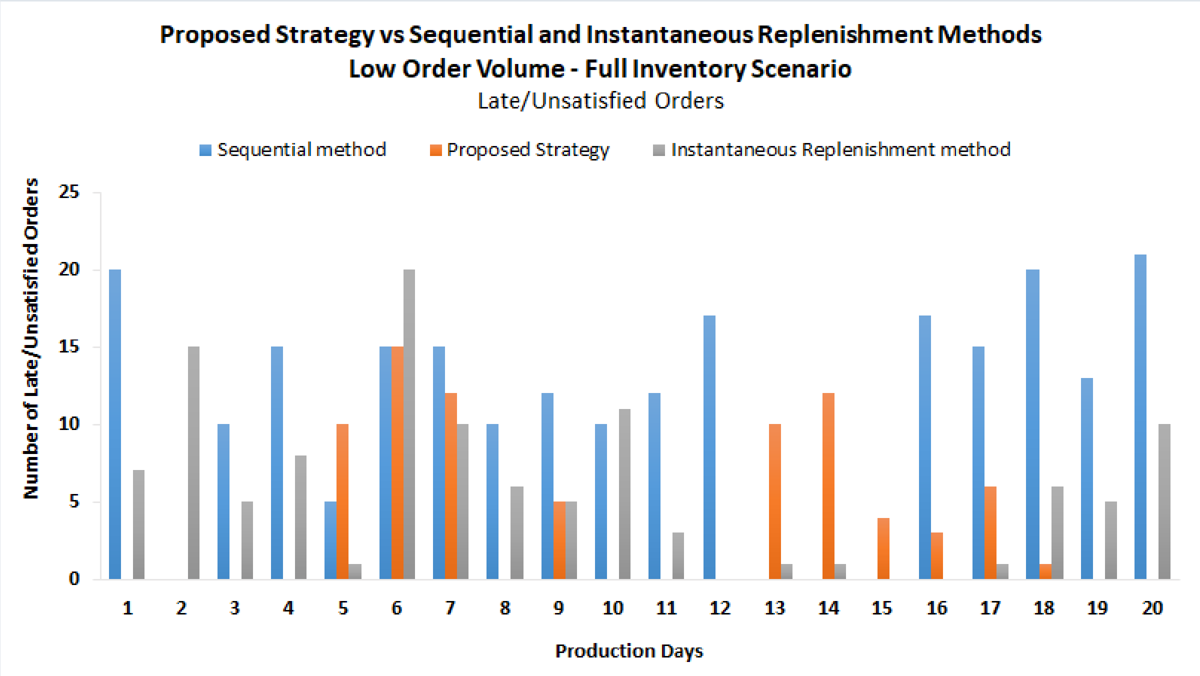

Figure 9: Proposed strategy vs Sequential vs Instantaneous methods

From the result of the comparison, there was an improvement in production in terms of the number of late orders to the customer due to disruptions. Over the period of 20 days, there were 483 orders requested in total where 78 orders were recorded late when the proposed approach was applied, as against the sequential replenishment approach which recorded 227 late orders and 115 late orders for the Instantaneous Replenishment method. The result of using the proposed approach showed a 66% improvement over the sequential method and 32% improvement over the Instantaneous Replenishment method.

In the Proposed approach, the available time slot (i.e. production time slot) was systematically utilised to control the number of late orders, limit the machine setup time and make the order due time and quantity a priority, without unnecessarily holding up orders in inventory, as directed by the proposed heuristic steps. Meanwhile, the alternative approaches tried to support production while sequentially replenishing the inventory. The focus of the sequential and Instantaneous methods was to keep inventory to the maximum. However, this increased the number of setups which reduced the production time and subsequently increased the number of unsatisfied orders.

Although the Proposed approach did not completely eliminate order lateness, it reduced it to the minimum even under a combination of disruptions and a limited number of production orders. The

Sequential method required higher numbers of unplanned replenishment orders while the Instantaneous Replenishment method required fewer but made the system maintain an unnecessarily high inventory level for orders that were not urgent (i.e. had an immediate due time), while urgent orders remained unsatisfied.

6. Conclusion and future work

The proposed new inventory replenishment strategy to accommodate the effect of disruptions was proven by the reduction of OEM flow-shop disruptions. The proposed innovative PDIR framework implementation minimised the number of late/unsatisfied orders and increased the quantity demanded for customer satisfaction in an OEM flow-shop. A different combination of production disruptions such as changes in the sequence of delivery, changes in delivery due time and order cancellations was considered. The framework approach also assigned resources effectively for order processes which increased productivity. This was evident in the outcome of the scenario experiments. The new heuristic algorithm made it possible not only to support production when there was disruption, but to continuously maintain sustainable inventory levels as when possible.

The results of the comparison showed that by applying the proposed approach, only 16.14 % of the total order demand was late over a 20-day production period, while 46.99 % of total orders were recorded as late by the sequential approach over the same period. The proposed approach presented a minimum number of late or unsatisfied orders which meant that disruption was kept to the minimum.

This study is expected to impact a wider audience in the academic environment as well as the supply chain for manufacturing in industry. The outcome is aimed to inform decision-making for relevant professionals such as schedulers, planners, and production managers. In academia, it is expected to provide an insight into unexplored problems, and this study's approach is applicable to other related problems. The details of this paper are expected to offer a deeper understanding of the problem domain for interested scholars in the relevant field of study and to help industry tackle disruptions of a similar magnitude for better performance. This study can be further progressed by implementing this meta-heuristic approach that could be used to provide optimal replenishment type and quantity in other situations. It can be tested for more combinations of high and low order volumes; with different initial levels of inventory (i.e. high, medium, and low); using different agent rules; or by comparison with other approaches.

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