Agent-Based Heuristics Model for Measuring Customer Disruption Impact on Production and Inventory Replenishment

Al Bazi, A. & Adediran, T. V.

Original citation & hyperlink:
Al Bazi, A & Adediran, TV 2022, 'Agent-Based Heuristics Model for Measuring Customer Disruption Impact on Production and Inventory Replenishment', International Journal of Industrial and Systems Engineering, vol. 40, no. 3, pp. 370-398. https://doi.org/10.1504/IJISE.2020.10031323

DOI 10.1504/IJISE.2020.10031323
ISSN 1748-5037
ESSN 1748-5045

Publisher: Inderscience

Agent-Based Heuristics Model for Measuring Customer Disruption Impact on Production and Inventory Replenishment

Ammar Al-Bazi[a], Tunde V. Adediran[a]

aa8535@coventry.ac.uk , ad2450@coventry.ac.uk

[a] *Faculty of Engineering, Environment and Computing, Coventry University, Coventry, West Midlands, CV1 5FB, UK*

Abstract

Agent-based simulation approach in production and inventory environment is capable of responding and adapting to disruptions caused by customers' changing requirements. The impacts of disruptions in production and inventory systems can be measured through learning and decision-making ability of system agents. In this paper, agent-based modelling integrated with heuristic optimisation approach is presented as embedded within a scheduling and rescheduling framework. The proposed approach is implemented in a disrupted OEMs parts manufacturing system. The integration of the framework modules in connection with inventory control helped production planners to manage disruptions by tracking order processing times and quantities and for performance measurement. The proposed approach is compared with the few existing related methods like the sequential method. The proposed approach not only revealed the impact of disruptions in terms of process times and order quantities but offered 'available times' which were applied for production support and inventory replenishment. This demonstrates a valuable and viable resolution strategy responding and adapting to disruptions caused by customers.

Keywords: Customer Disruption Impact, OEM Environment, Production scheduling, Inventory Replenishment, Agent-Based Simulation, Heuristics Optimisation

Biographical notes:

Ammar Al-Bazi is Senior Lecturer in Business Information Systems in the Faculty of Engineering, Environment and Computing and an associate member of the Manufacturing and Materials Engineering Research Centre at Coventry University, UK. He holds a Ph.D. in computer simulation and optimisation from Teesside University, UK. His research interests include hybrid simulation modelling, manufacturing and logistics simulation, metaheuristic optimisation algorithms and hybrid intelligent systems.

Tunde Adediran is currently a Manufacturing Simulation Leader (KTP Associate) at GKN Aerospace Limited. He holds a Ph.D. in simulation of manufacturing systems from Coventry University, UK. He graduated with M.Sc. in Engineering Management from the same University, UK. His research interests include agent-based modelling, production scheduling and optimisation algorithms.

1. Introduction

In today's production environment, the influence of customers has a strong impact not only on production schedules but also on inventory control. From the production point of view, customers have the power to alter demands and requirement at any possible time. This power makes it possible for customers to change demand details such as quantity, time of delivery and sequence of delivery. These kinds of changes made by customers have a direct impact on production schedules, especially when production has already been scheduled based on initial customer demands. The negative impacts on production result in high idle times, order shortages, low utilisation of both operators and machines, and late or unsatisfied delivery. This subsequently affects inventory holding quantities as they are relied on for support when there are production disruptions.

In an Original Equipment Manufacturing (OEM) environment, where demands need to be satisfied irrespective of customer changes, production schedules become extremely challenging to manage. When production is disrupted due to customer changes, the inventory can also be affected (Adediran and Al-Bazi 2017). Production and inventory are controlled by customer behaviour, while measuring the impact of customer disruption increases the awareness of the level of damage on production and inventory as well as quantifying the consequences of disruption. Therefore, the ability to measure these impacts to understand production and inventory behaviour in terms of time, units and cost is a welcome development. Knowing the amount of time and quantity impacted because of disruption is crucial in dealing with the problem.

The framework of an agent-based model and heuristic algorithm adopted in this paper is an extension of the one proposed by Adediran and Al-Bazi (2018), which was applied for adapting and accommodating disruptions in OEMs flow shop. However, the focus in this paper is to apply the extended version to measure and quantify the impact of disruptions on production and the consequences in terms of process time and quantity, through the advantages of agent-based modelling (ABM). The idea of measuring and quantifying the impact of disruptions on production has received little or no attention through any technique in literature.

This study proposes an integrated framework which includes an agent-based simulation model, the proposed heuristic optimisation algorithm and an inventory replenishment plan. The developed framework aims at adapting and accommodating inevitable disruptions in order to minimise the number of production shortages, increase the number of order deliveries and sustainably maintain safe inventory levels.

The novelty of this paper lies in the development of an innovative and adaptive heuristic algorithm, embedded within agent-based simulation to measure and quantify the impact of disruptions caused by demand requirements which are changed by customers on OEMs production flow-shop. This model will assist production planners and managers of various manufacturing systems-based inventory control practices including OEMs to produce efficient production schedules that guarantee gradual replenishment of inventory despite customer disruptions rather than focusing on specific orders to reduce unnecessary inventory while other order inventory levels are at risk.

The rest of this paper is organised as follow. In section 2, the related literature on agent-based modelling in manufacturing environments is analysed from different perspectives. Section 3 describes the problem statement. Section 4 introduces the developed Production Disruption-Inventory Replenishment (PDIR) Framework. In section 5, the design of the experiments and the results are discussed. The paper concludes in section 6 by summarising the key findings as well as suggestions for future research.

2. Literature Review on Impact of Disruption in Manufacturing Industry

In the literature, some studies have been conducted in a quest for identifying disruption in the manufacturing industry and modelling its impacts. The study by Darmoul et al. (2013) identified unexpected disruptions like resource failures, material unavailability, and rush orders operators' unavailability in manufacturing systems. It also investigated this potential for the monitoring and control of the manufacturing systems at the occurrence of these disruptions. The study proposed a framework, developed using a multi-agent approach, to help design software tools with the ability to assist with decision-making in dealing with various types of disruptions happening in manufacturing system. The work of Omega et al. (2016) proposed a supply-driven Inoperability Input-Output Model to analyse the impact of supply disruptions caused by natural and man-made disasters, economic shifts and government policies in a manufacturing system. The manufacturing supply chain such as facility breakdowns, transportation mishaps, intentional attack and natural disasters was the focus in Schmitt et al. (2017). To respond and recover from these disruptions, the study investigated adjustments in order activity across four echelons. Simulation experiments of the study show that the impact of a disruption depends on its location, with costlier and longer lasting impacts occurring from disruptions at echelons close to ultimate consumption. The manufacturing supply chain study of Lam and Yip (2012) identified that any disruptions at a port can have direct impact on the port's ability to continue operations, therefore affecting the supply chains and the parties served by the port. The study proposed the application of a Petri Net approach to analyse the impact of port disruptions. Ocampo et al. (2016) proposed a methodological approach to quantify the impact of supply disruptions in a manufacturing system in terms of increased cost-price of production output as a result of high price of value-added input. The study of Bhat and Yadav (2017) identify substantial indicators for performance measurement of factors causing disruptions in manufacturing industry. In Li et al. (2017) a multi-industry interdependence model is developed to quantify the short-term economic impacts of electric power disruption due to cascading failures within power system. In Adediran and Al-Bazi (2017), disruption problems caused by customers' changing requirements were considered. A simulation heuristic model was proposed using an inventory replenishment strategy to mitigate the impact of disruptions. The limitation of this proposed approach is that it does not measure the consequence of disruptions on production schedules and inventory plans. Contrary to Adediran and Al-Bazi (2018), this study measures the impact of disruptions in production times and demand quantities' consequences in addition to generating production schedules and inventory replenishment plans.

Having discussed related studies focusing on modelling and analysing disruption and its impact within the manufacturing environment, the limitations in the existing studies are very clear. Quantifiable measures of the consequences and the resulting impact of disruptions are lacking in literature. As a result, this study aims to fill this gap in knowledge by proposing an agent-based heuristic algorithm to measure the impact on process times, setup time, etc. and order quantities in the event of concurrent and unanticipated disruptions caused by customers' changing demand behaviours. The impact measurement helps obtaining 'Available Time' (AC_{time}) that is significant in resolving disruption problems. This specific valuable information has been overlooked in previous studies. In the next section, the problem description for which the proposed method is developed is presented.

3. Production Schedule Disruptions in the OEM Environment (Problem Statement)

In a typical OEM environment, customer disruption could be in form of cancellation of orders, change in order sequence or change in delivery time. These three types of disruptions can occur in different variations, as individual or combined. Any type of disruption, irrespective of their combination, affects production schedule and inventory control. Likewise, the resources' (such as machines and operators) utilisation rates are affected. Changes in sequence and delivery time can cause production shortages and late orders, whereas, order cancellations can create idle time for the resources. As a result, the first two disruptions have a drastic impact of reducing the inventory in a quest to satisfy demand through ‘borrowing’ from inventory. On the other hand, cancellation disruption can be used to minimise the impact and replenish the inventory while satisfying demand. This is possible by utilising the idle time (available time) to resolve order shortages and replenish the inventory as much as possible. Therefore, to improve the productivity of both machines and operators in OEMs and maintain an optimum inventory level, the consequence of such disruptions made by customers should be eliminated. If the impact of disruption can be identified in advance, it is expected to help production planners to generate contingency plans for rescheduling and inventory control whenever disruptions occur. The described problem statement is tackled through the developed method in this study as discussed in the next section.

4. Production Disruption- Inventory Replenishment (PDIR) Framework

As discussed in section 1, the framework proposed in Adediran and Al-Bazi (2017) which integrates the agent-based simulation, heuristic algorithm and replenishment strategy, is extended further and applied in this paper. This is because the previously proposed heuristic algorithm within the framework was too basic in terms of inventory replenishment and not sustainable for the current problem specification, which is complex in nature. Also, the collective capability of the previous framework is unable to measure the impacts of disruption, which is the focus of this paper. The previous framework is dubbed Production Disruption-Inventory Replenishment (PDIR) (Figure 1). The three modules of the PDIR framework are strategically linked in collaboration to solve the problem described in the previous section and to help measure the impact of disruption in terms of production times and order quantities.

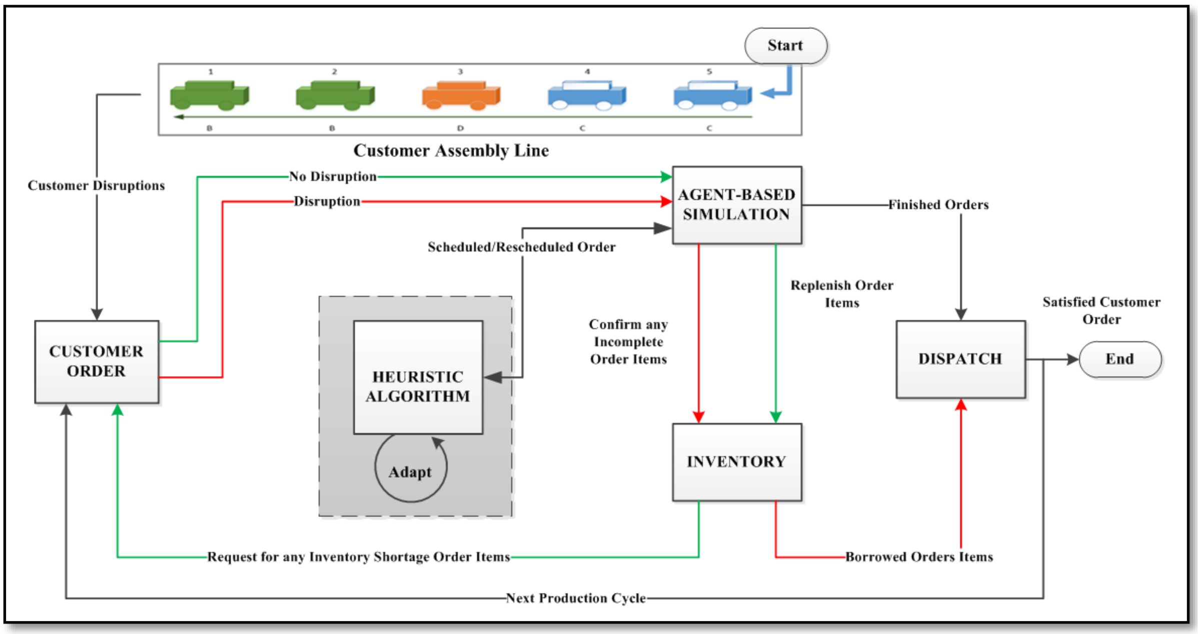

Figure 1 Production Disruption-Inventory Replenishment framework Adediran and Al-Bazi (2017)

In this study, the most significant working mechanism of the PDIR framework is the ability of the embedded ABM module to identify disruption types and measure their impact in terms of time and quantity. The discussion of the three main components of the PDIR framework is presented in turn in the next sections.

The heuristic algorithm adopted in this paper is an extension of the one proposed by Adediran and Al-Bazi (2018), which was applied for adapting and accommodating disruption in OEMs flow-shop. However, the extended algorithm in this paper focuses on measuring the effect of disruption through ABM detective mechanism and the impact of disruption on production and its consequences in terms of time and quantity. The description of the extended version is discussed in the next section.

4.1. Agent-Based Module

This section presents the development and implementation of the Agent-Based Modelling (ABM) method as incorporated in the PDIR framework. The choice of ABM method in this study was inspired by the investigation of the related studies. In the transportation industry, Rolon and Martınez (2012) applied the use of agent-based modelling in disruption problems. Specifically, the investigation conducted in the manufacturing industry revealed the implementation of agent-based simulation modelling approach in the work of Li et al. (2011) and Pan et al. (2009) amongst others related studies.

In the past, production and inventory scheduling problems have been tackled using various well-known simulation modelling methodologies but recently, the ABM method has gained popularity as another useful technique to deal with problems in several disciplines. The ABM method has been selected to investigate its viability to handle this type of problem. Based on the current trends in simulation methodology, it is important to select a method that provides advanced opportunities that are beneficial to finding a solution to the research problem and evolves with the current technology. This is a quality which has been found useful in the ABM method.

The manufacturing systems are comprised of agents that exist within this system environment. ABM is a suitable approach to model the behaviours of these individual agents within the ABM environment. It is an environment where agents engage in strategic behaviour and anticipate other agents' reactions when making decisions. ABM is also applicable to this problem because the past (previous customer orders) is not a predictor of future (next customer orders) requirements.

In this study, the ABM model enhances the goal of this study by scheduling and allocating orders and rescheduling orders under disruption, and ultimately measures the impact of customer disruptions. The ABM development process is carried out through negotiation, collaboration and communication among different agent types identified in the system. In the agent environment, there are three agent types identified; they are: order agent, machine agent, and operator agent.

Based on the problem requirements in this study, the ABM model is developed to achieve the following functions:

- To improve the utilisation of each of the manufacturing system resources.
- To identify disruption and create support for shortages. This is possible with ABM through learning production behaviour as disruption occurs.
- To identify available processing gaps created by disruption
- To share information within the integrated system units
- To accept input parameters such as the order information (type, sequence, quantity, due date), machine information (number, process, setup time, process time), operator information (skills, number, availability) that are required for processing orders in the flow shop manufacturing system setting with minimal idle or waiting time, high

utilisation and which satisfies all constraints including the delivery due times of product orders.

- To assign and schedule required order operations to specified system resources, i.e., machine and operator based on the pre-defined assignment plans.

The main advantage of using ABM is that its function of keeping track of time and sharing it with other agents and the use of the messaging sequence within the ABM environment. This idea was implemented by Pan et al. (2009) in their paper where supply chain entities were represented to be interactive among themselves. The messaging sequence diagram in Figure 2 represents message interaction involving the customer, production floor, order, machine, operator and process. This type of inter-relationship and message exchange among the system agents allows accountability of events and actions within the process. It also enables order processing through messages such as: order request, resources allocation, order production and dispatch information that are being sent within the system.

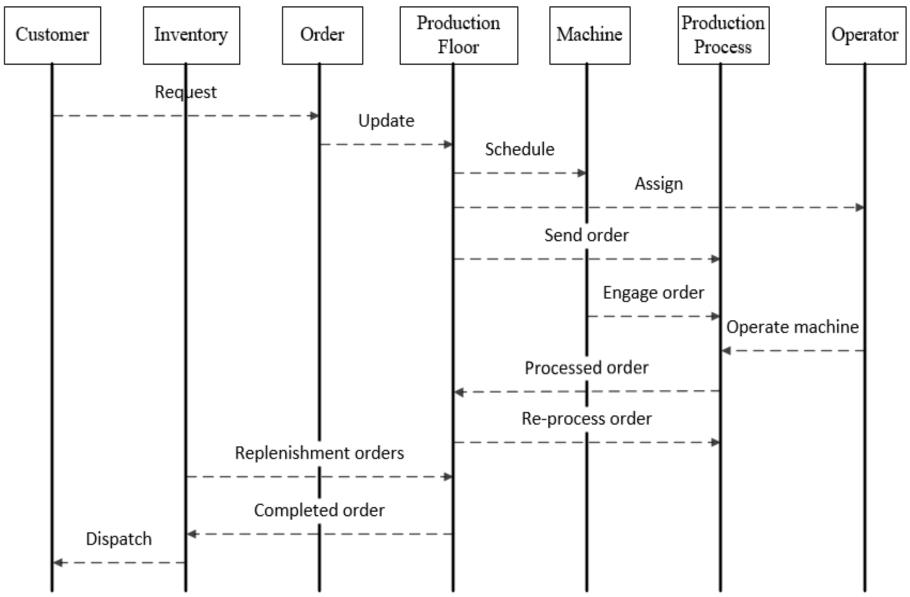

Figure 2 The System Message Sequence diagram (Adediran and Al-Bazi 2017)

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 jobs. As a result, the machine that has been 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, in which case, the completed order information is passed on to production floor for order dispatch to the customer according to request. This activity is crucial for measuring the time and quantity of an order. Within the ABM module, an occurrence of disruption is detected when there is a change in the original production schedules affecting both production times and order quantities. These changes in terms of production times and order quantities are communicated to quantify the impact of disruption within the ABM interactive entities for collective decision-making within the framework.

4.2. Inventory Replenishment Module

The inventory replenishment of six possible cases (Figure 3) in a flow-shop manufacturing system is discussed. The occurrence of disruptions means production shortages, hereby requiring support from the inventory. When the inventory gives support to satisfy production demand, inventory control level becomes low or critical without a swift replenishment plan.

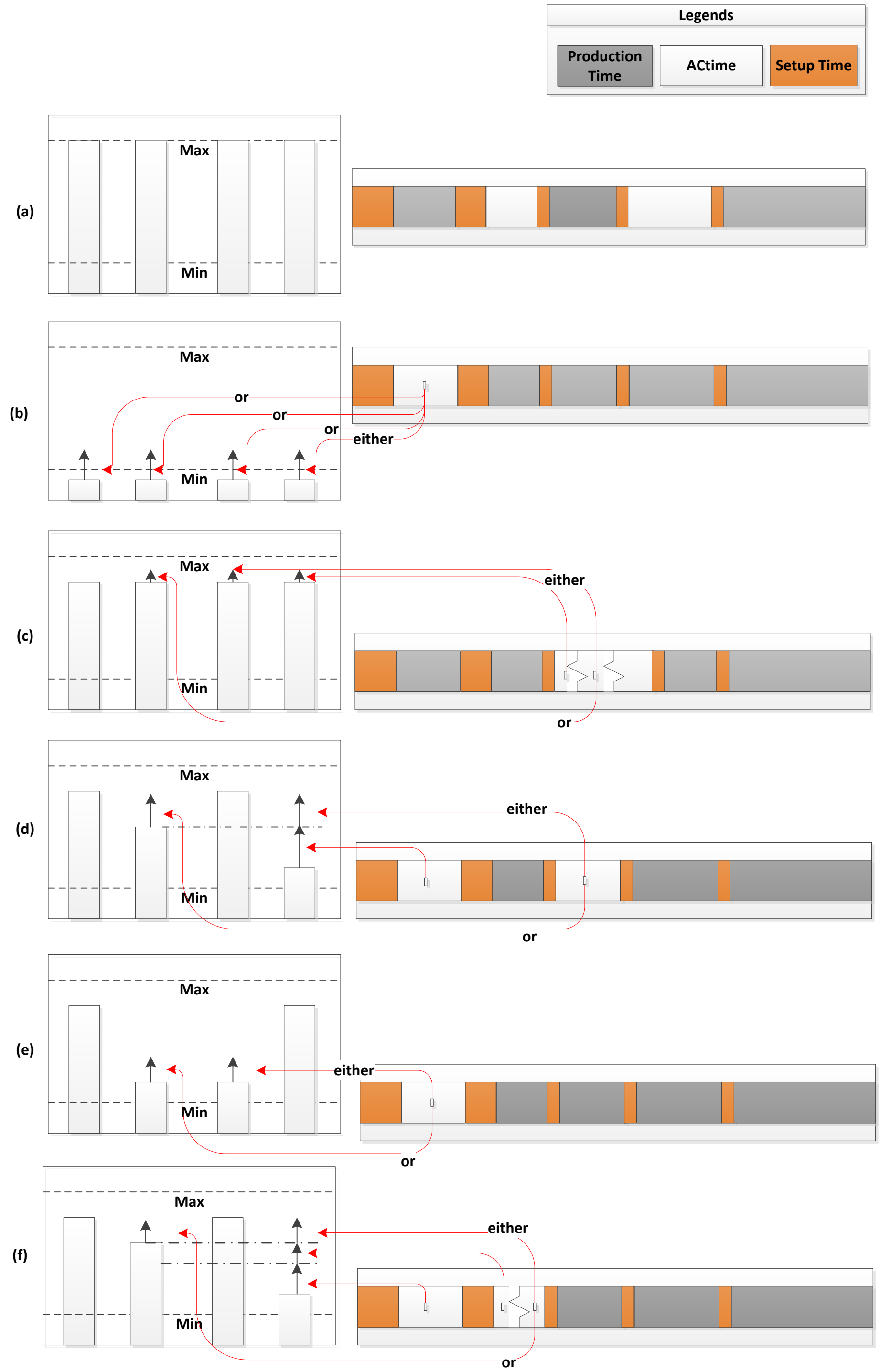

Figure 3 Inventory Replenishment Cases

In each of the cases, for each inventory level, maximum and minimum inventory levels are shown and the corresponding charts for 'Current Available Time' (AC_{time}) alongside the process and setup times. The AC_{time} is identified through ABM time tracking and it is determined through the total busy and idle times within a given production cycle. The AC_{time} presents the time created by the cancellation disruption described in section 3 above. This means the AC_{time} is the consequence of disruption measured in time. The AC_{time} is utilised through production rescheduling of replenishment orders. Each case shows different inventory levels and how the inventory replenishment is carried out.

In case (a), all order inventory levels are full. This means there is no order borrow or/and no replenishment is required even when there is available time. In this case, the available time is considered idle resulting in low utilisation of production resources. Case (b) shows a situation where all order inventory levels are at critical levels and at high risk of customer order demand shortages. Using the arrows to represent the levels of each replenishment attempt through the current available time, it shows the gradual replenishment of each level based on the proposed strategy. The strategy used is called the Min-Max strategy whereby the minimum order production quantity is selected from all maximum production quantities that can fit within the current available time for processing. This means the selected inventory is replenished to the level where others can level up within any given available time. The process continues to select minimum quantities from maximum where two or more order inventory levels are the same. The current available time in case (b) can be utilised for any of the order inventory levels that is selected through min-max strategy. The same situation occurs in case (c) where all order inventory levels are equal but at safe levels. The current available time can be utilised for any of the order inventory levels to hit its maximum level. Also, a situation can occur where the same available time can be shared for more than one order replenishment. This is dependent on the order quantity decided through the min-max strategy. In case (d), one of the order inventory levels is the least. In this situation, the least order inventory level is selected for the given available time for replenishment to be less or equal to the next order inventory level, as indicated by the arrow. After the first replenishment attempt, the situation becomes the case of two orders having the same inventory levels. This is the case where the min-max strategy is applied to select the minimum quantity of the maximum possible to replenish with the next available time, as it is the case in case (b) and (c). In case (e), two orders are on the same inventory levels. Using the min-max strategy, it can be decided either one or the other order inventory level will utilise the AC_{time}.

The situation in case (f) is where one order is least and below the level with the next least inventory level. Considering a limited current available time for the least inventory level replenishment, the available time is exhausted and not enough for the selected least inventory to level up to the next inventory level, and so, part of the next available time is utilised to bring the same order inventory to level up with the next order inventory. At the same levels, the remaining shared current available time can be utilised by any of the two-order inventory as decided using the min-max strategy. The min-max strategy and the time-sharing ability is made possible through the agent-based capability of making decision and information sharing.

The proposed strategy attempts to utilise all current available times resulting from disruptions to remedy the disruptions. In so doing, it helps to maximise the number of order quantities, and maximise resource utilisation while inventory levels are gradually replenished to avoid unnecessary order inventory. Order inventory replenishment continues using the time-sharing and the min-max strategy until all inventory levels are full or all available time is exhausted, whichever comes first.

The timing relationship in the production process in the event of disruptions is crucial to measuring the impact of time and quantities. For this reason, the production time analysis is developed as discussed in the next sub-section.

Production time analysis diagram

The Figure 4 below presents the production time analysis which demonstrates how times are measured, tracked and calculated within the production processes, especially when disruption happens to order number or type. It reveals the entire flow of process time, setup time, start and end time of individual order numbers within the production.

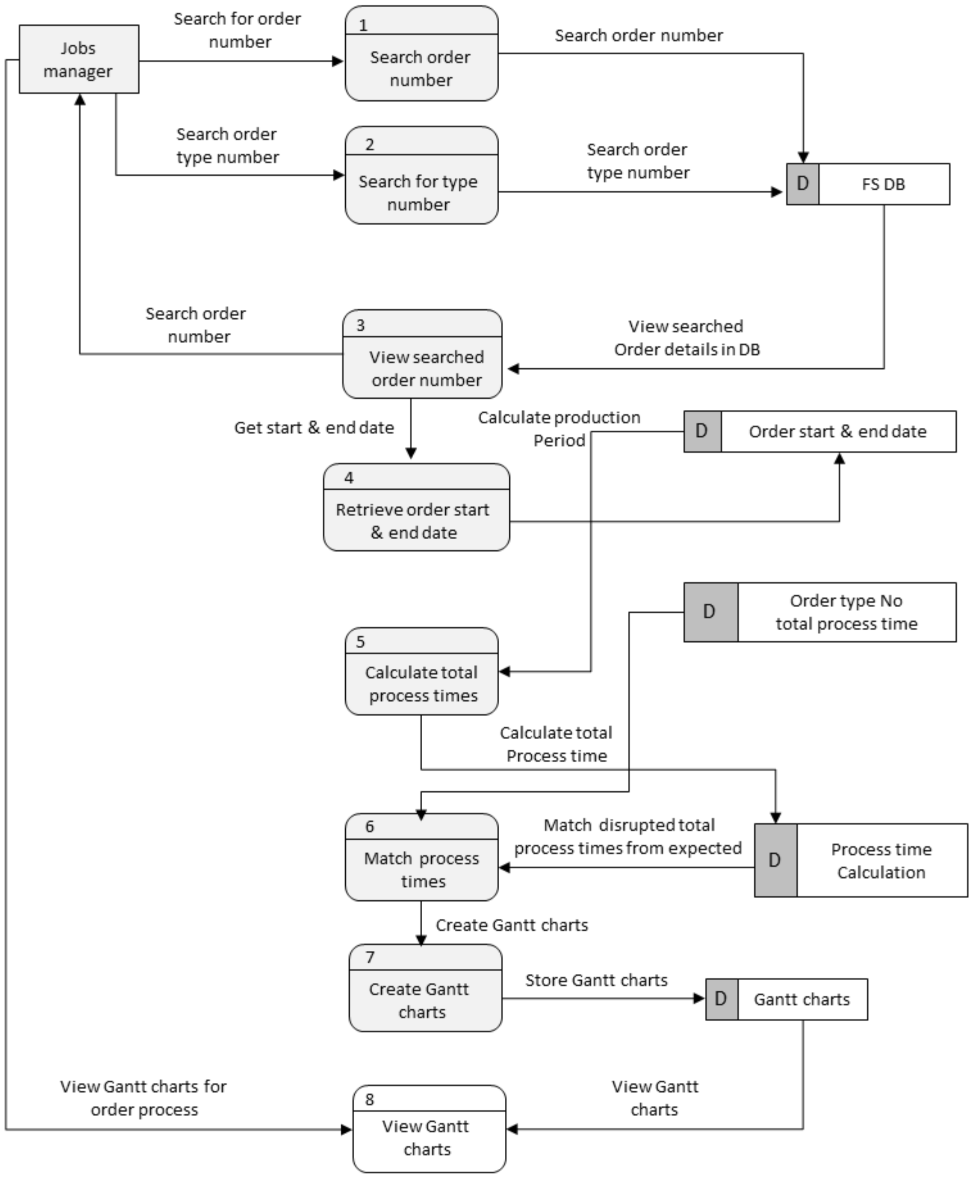

Figure 4 Production times analysis flow diagram.

The total process and setup times are calculated based on original and disrupted order start and end time to derive the available time, which is used for replenishment purpose, after inventory borrow, in case of disruption. The job manager in Figure 4 searches for order number and type through the flow shop database system. The details are sent to view to obtain the start and end date of orders from the retrieved order data. From the retrieved details, the total process time for each order is calculated as well as the setup times during the defined production days and the entire period. When disruption occurs by matching the disruption total process times with the originally expected process time and setup times, the available time is obtained. The system creates a visual representation of the process, setup and available times in the form of a Gantt chart. The Gantt chart is stored and can be view for production time analysis purpose. The analysis of time is made possible through the application of the extended heuristic algorithm. The function and application of the heuristic algorithm is discussed in the next section.

4.3. Heuristic Algorithm Module

The heuristic 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 is sorted in Sequence (S) for processing based on predefined order modelling rules of the system such as the earliest due time. The demand is then scheduled daily (N) in sequence of due times. Disruption can occur in terms of cancellation, which is Disrupted Demand quantities (ΔD), Sequence change (ΔS) or/and 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 quantities, then customer demand is satisfied (SD). However, in case the production quantities are less, 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 borrow quantities with the production quantities are equal to the demand or disruption demand quantities. In this case, shortage is nullified to zero. Meanwhile, 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 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 the 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 available process time, if the total available time ($AT_{time},$), which is a consequence of disruption, is at least one. For each replenishment operation, the system uses the Min-Max strategy by scheduling the minimum of the maximum possible replenishment quantity ($R_{min\ (max)}$) within the given or current available time (AC_{time}) until they are all exhausted, where total available time is the addition of all possible current available time. For schedule replenishment quantities ($R_{min\ (max)}$), current available time is allocated, where replenishment is less or equal to inventory borrowed quantities.

However, replenishing inventory borrowed quantities are considered for three different conditions for either critical or safe inventory levels; if inventory levels are different, the least inventory level is considered for replenishment using the current available time until it is zero or inventory is full, whichever comes first. When inventory levels are the same, the least with the same levels are considered based on ($R_{min\ (max)}$) strategy, where ($R_{min\ (max)}$) order inventory is selected. When the current available time is exhausted and not enough for the ($R_{min\ (max)}$) quantity to level to the next order inventory, part of the next available time is utilised through ABM time sharing ability. The replenishment quantities are scheduled at random when similar inventory levels have the same ($R_{min\ (max)}$) quantities. In all cases, the inventory is updated with replenishment quantities, giving the inventory new quantities 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%), 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 numbers 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). Each time disruption occurs, the heuristic is activated to identify shortages, determine borrowed orders from inventory and re-schedule borrowed orders to replenish the inventory.

5. System Verification and Validation

This study was conducted in the Unipart Eberspächer Exhaust Systems Ltd (UEES), one of the biggest Original Equipment Manufacturers of automotive products in the UK. This work is part of a collaborative research project between Coventry University and the UEES. For verification of the developed system, the experts, production and operation managers at UEES, reviewed and confirmed the appropriateness of the presented designs and specifications for the proposed system. Also, different operational time calculations were checked for acceptability with the existing real system. As part of the validation process, the simulation results were checked with the real-life system under the same parameters. The validation procedure was used to follow through a specific order production of an order with order quantity of 45 with 100% inventory level on a single shift. The order production flows through all 5 process stations until completion using 9 operators. The average total process time is 432 mins with the average resource performance rate at 90.1% for machines, 80.6% for operators and the total idle time 45 mins. The production time, setup time, process time, resource utilisation, idleness and waiting time were all checked for their closeness to reality. In some cases, time variations occurred which was as result of simulation time randomness. However, as this does not deviate significantly from the real-life results, they were accepted by the company experts as valid results.

6. Computational Results and Discussions

Three possible types of customer disruptions along with their random combinations and quantifying their impacts in terms of time and quantity on production schedules were investigated to understand their impacts on production schedule. For each disruption combination, different demand volumes and critical inventory status were considered for experimentation based on the following scenarios;

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

These are real life scenarios being conducted in the Unipart Eberspächer Exhaust Systems Ltd (UEES). The High, Average and Low order volumes scenarios of order type ranges of (100-120), (40-60), and (10-20) orders respectively. The order quantity ranges (80-100) for High, (40-50) for Average and (20-25) for Low order volumes and the Critical inventory level is (10). For High order volume scenarios, three shifts pattern were set, two shifts pattern 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

The range of order volume has been selected to replicate the real-life production order range. The order quantity range has been set to maintain a controlled variation with the three levels of inventory status considered in the experiments. The number of shifts is assigned corresponding to the order volumes. The High, Safe and Critical inventory levels are set to understand production behaviour under the three inventory categories. The selected shift patterns mimic the real-life system operation and correspond to the demand volume.

The impact of customer disruption on production and inventory replenishment as well as a number of relevant key performance indicators are discussed as follows.

6.1 Impact of Customer Disruption on Production and Inventory Replenishment

The impact that customer disruptions have made on production and inventory replenishment plans is determined by the consequences of time and quantity. Tables 1, 2, and 3 present the results for these impacts for High Order, Average Order and Low Order demand under Critical Inventory levels respectively. The critical inventory status is considered here as the most sensitive situation where the most measurable impact of disruptions can be obtained. The Order number are the orders that were affected by disruptions.

Table 1 Disruption Impact Measurement for High Order vs Critical Inventory Scenario

Order No	Disruption Type	Time Consequences (Mins)	Quantity Consequences (Units)	Impact on Production
1	All Disruptions	+1124-240(+884)	1248 of 1754	Available time & Borrow
2	All Disruptions	+1248-240(+1008)	1261 of 1785	Available time & Borrow
12	Cancellation	+1248	900 of 17400	Available time
15	Sequence and Due date change	-240	-	Borrow
16	Sequence and Due date change	+560-300(+260)	-	Available time & Borrow
17	Cancellation & Sequence change	+858	1210 of 1784	Available time & Borrow
24	All Disruptions	+1005-300(+705)	1245 of 1744	Available time & Borrow
26	Cancellation	+900	1200 of 1754	Available time
41	Cancellation & Due date change	+1142-300(+842)	1348 of 1785	Available time & Borrow
56	Cancellation	+788	1225 of 1770	Available time
59	Cancellation & Due date change	+1268-420(+848)	1250 of 1750	Available time & Borrow
60	Cancellation & Sequence change	+1240	1120 of 1774	Available time
75	All Disruptions	+1200-300(+900)	850 of 1725	Available time & Borrow
89	Cancellation & Due date change	+905-240(+665)	1241 of 1780	Available time & Borrow
90	Cancellation	+217	1452 of 1710	Available time
91	Cancellation & Due date change	+448-360(+88)	1348 of 1749	Available time & Borrow
92	All Disruptions	+1248-240(+1008)	1245 of 1741	Available time & Borrow
99	Sequence and Due date change	-300	-	Available time & Borrow

Table 2 Disruption Impact Measurement for Average Order vs Critical Inventory Scenario

Order No	Disruption Type	Time Consequences (Mins)	Quantity Consequences (Units)	Impact on Production
4	Sequence and Due date change	-560	-	Borrow
6	Cancellation	+562-120(+442)	451 of 750	Available time
10	All Disruptions	+541-240(+301)	520 of 748	Available time & Borrow
11	Sequence and Due date change	-240	-	Available time & Borrow
12	Cancellation & Due date change	+520-240(+280)	480 of 712	Available time & Borrow
16	Sequence and Due date change	-240	-	Borrow
19	Sequence and Due date change	-120	-	Borrow
38	Cancellation & Due date change	+540-120(+420)	523 of 740	Available time & Borrow
55	Cancellation & Sequence change	+560	621 of 784	Available time
64	Due date change	-120	-	Borrow
75	Sequence and Due date change	-120	-	Borrow
95	Due date change	-420	-	Borrow
99	Sequence and Due date change	-120	-	Borrow
100	Cancellation	+485-120(+365)	710 of 785	Available time

Table 3 Disruption Impact Measurement for Low Order vs Critical Inventory Scenario

Order No	Disruption Type	Time Consequences (Mins)	Quantity Consequences (Units)	Impact on Production
12	Cancellation	+480	420 of 450	Available time
13	Sequence and Due date change	-120	-	Borrow
36	Sequence and Due date change	0	-	Borrow
40	Cancellation & Sequence change	+240	356 of 459	Available time
41	Cancellation	+480	405 of 450	Available time
62	Cancellation & Due date change	+560-120 (+440)	400 of 480	Available time & Borrow
78	All Disruptions	+480-120(+360)	129 of 408	Available time & Borrow
88	All Disruptions	+480-120(+360)	120 of 448	Available time & Borrow
89	Cancellation	+480	255 of 438	Available time
91	Cancellation	+256	251 of 450	Available time

The results presented in the above tables show the order numbers that have been affected and the type of disruptions they are affected by. It is noticeable from all three tables that not all orders are affected by all disruption types and some orders are affected by two or just one type of disruption.

In Table 1, cancellation disruption on order 12 added +1248 minutes as available time to the process, likewise order 26 with +900 minutes of available time. This would give an opportunity for investing this time to produce items in case replenishment is required. In Table 2, in many occasions there are many borrows due to lack of time (-) and no improvement in the quantity of orders. For example, orders 64 and 95 are affected by change in due date delayed production by -120 minutes and -420 minutes respectively, and therefore replenishment is not possible after borrowing as there was no cancellation. When there is more time gained (+), the number of possible inventory replenishment opportunities is increased. This is the case in Table 3, where 420 units were replenished out of 450 units borrowed using available +480 minutes gained from cancellation.

In general, it is important to note that while cancellation is the only cause or among the causes of disruption, the impact on production is the available time which represents the added time (+) consequence.

6.2 Impact of Customer Disruption on Inventory Level and Replenishment Plan

In each of the presented scenarios, three order samples were selected randomly for analysis and discussion. This is to present a representative, clearer and better understanding of the inventory replenishment concept explained in Sections 4.2. and 4.3, through discussion. Most importantly, it is essential to prevent inconsistency in explanation which might create confusion while bringing the theoretical perception to life through real experimentation.

For the high order, critical inventory scenario, Tables 4.a, 4.b and 4.c display results of three selected orders to present the impact of disruption on the inventory behaviour including the best possible replenishment plan.

Table 4.a First selected order results (high order volume vs critical inventory level)

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		80	89	100	81	90	81	96	90	82	87	91	90	98	86	80	95	93	95	83	80
Demand After Disruption		80	89	100	81	90	81	28	90	82	77	91	90	98	86	75	95	93	95	83	80
Actual Production		80	80	80	81	75	70	28	78	60	77	80	78	85	60	68	60	74	68	0	61
Production PLUS Replenishment		80	80	80	81	75	70	28	78	60	82	80	78	85	60	68	60	74	68	0	61
Borrow		0	9	1	0	0	0	0	0	0	0	5	12	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0
Inventory	10	10	1	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0
Cancellation		0	0	0	0	0	0	0	0	0	10	0	0	0	0	5	0	0	0	0	0
Production with Inventory Support		80	89	81	81	75	70	28	78	60	77	85	78	85	60	68	60	74	68	0	61
Late/Unsatisfied orders		0	0	19	0	15	11	0	12	22	0	6	12	13	26	7	35	19	27	83	19

Table 4.b Second selected order results (high order volume vs critical inventory level)

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		94	97	81	88	85	86	84	87	95	96	92	84	80	100	81	95	93	100	98	92
Demand After Disruption		94	97	60	88	85	86	84	87	95	96	92	84	80	100	81	95	93	0	18	0
Actual Production		94	97	60	60	81	65	74	87	82	95	80	80	68	95	40	85	64	0	18	0
Production PLUS Replenishment		94	97	60	60	81	65	74	87	82	95	80	80	68	95	40	85	64	10	18	0
Borrow		0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0
Inventory	10	10	10	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	10	10
Cancellation		0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	80	92
Production with Inventory Support		94	97	60	70	81	65	74	87	82	95	80	80	68	95	40	85	64	0	18	0
Late/Unsatisfied orders		0	0	0	18	4	21	10	0	13	1	12	4	12	5	41	10	29	0	0	0

Table 4.c Third selected order results (high order volume vs critical inventory level)

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		95	89	87	96	84	91	100	85	80	94	87	96	100	98	95	83	80	80	92	97
Demand After Disruption		95	69	87	96	0	91	100	85	80	10	87	96	100	98	95	83	80	80	92	97
Actual Production		95	69	87	90	0	78	84	82	80	10	87	87	80	80	82	69	47	75	70	79
Production PLUS Replenishment		95	69	87	90	6	78	84	82	80	15	87	87	80	80	82	69	47	75	70	79
Borrow		0	0	0	6	0	10	0	0	0	0	0	5	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	6	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0
Inventory	10	10	10	10	4	10	0	0	0	0	5	5	0	0	0	0	0	0	0	0	0
Cancellation		0	20	0	0	84	0	0	0	0	84	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		95	69	87	96	0	88	84	82	80	10	87	92	80	80	82	69	47	75	70	79
Late/Unsatisfied orders		0	0	0	0	0	3	16	3	0	0	0	4	20	18	13	14	33	5	22	18

As shown in Tables 4.a-4.c, 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 there are two instances of replenishment, the inventory level limit is critical and makes little difference considering the high demand volumes.

The consequences of disruption under the high order critical inventory reveals a remarkable number of unsatisfied orders. This is due to lack of support for the production shortages. Even in the instances of replenishment of the inventory, the wider margin of quantity 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 demonstrate the impact of each with disruptions combining on the flow-shop. Based on high order volume simulation results of the three inventory levels, full inventory level demonstrates a much more sustainable selection to achieve the goal of accommodating disruptions while customer orders are being satisfied.

For the average order, critical inventory scenario, Tables 5.a, 5.b and 5.c display results of three selected orders to present the impact of disruption on the inventory behaviour including the best possible replenishment plan.

Table 5.a First selected order results (average order volume vs critical inventory level)

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		43	41	42	46	47	42	45	49	44	48	43	41	47	42	44	43	42	41	40	49
Demand After Disruption		43	41	42	0	47	42	45	49	44	48	43	41	47	42	44	43	42	41	40	49
Actual Production		43	41	42	0	40	42	40	40	44	40	40	40	40	42	41	40	42	40	40	42
Production PLUS Replenishment		43	41	42	0	40	42	40	40	44	40	40	40	40	42	41	40	42	40	40	42
Borrow		0	0	0	0	7	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory	10	10	10	10	10	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cancellation		0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		43	41	42	0	47	42	43	40	44	40	40	40	40	42	41	40	42	40	40	42
Late/Unsatisfied orders		0	0	0	0	0	0	2	9	0	8	3	1	7	0	3	3	0	1	0	7

Table 5.b Second selected order results (average order volume vs critical inventory level)

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		44	50	42	45	43	47	43	45	41	50	48	45	47	42	43	44	48	45	46	47
Demand After Disruption		44	50	42	45	43	47	43	45	5	50	48	0	47	42	43	44	48	29	46	47
Actual Production		40	40	42	40	41	40	40	40	5	40	42	0	40	42	43	40	40	29	40	43
Production PLUS Replenishment		40	40	42	40	41	40	40	40	10	40	42	6	40	42	43	40	40	34	40	43
Borrow		4	6	0	0	0	0	0	0	0	5	0	0	6	0	0	0	0	0	5	0
Replenishment		0	0	0	0	0	0	0	0	5	0	0	6	0	0	0	0	0	5	0	0
Inventory	10	6	0	0	0	0	0	0	0	5	0	0	6	0	0	0	0	0	5	0	0
Cancellation		0	0	0	0	0	0	0	0	36	0	0	45	0	0	0	0	0	16	0	0
Production with Inventory Support		44	46	42	40	41	40	40	40	5	45	42	0	46	42	43	40	40	29	45	43
Late/Unsatisfied orders		0	4	0	5	2	7	3	5	0	5	6	0	1	0	0	4	8	0	1	4

Table 5.c Third selected order results (average order volume vs critical inventory level)

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		45	44	42	48	45	50	47	46	43	49	45	50	44	41	40	40	49	41	49	48
Demand After Disruption		45	44	42	48	45	50	47	46	43	49	45	50	44	41	40	40	49	41	49	48
Actual Production		45	44	42	48	40	40	40	46	43	40	45	40	42	41	40	40	40	41	40	40
Production PLUS Replenishment		45	44	42	48	40	40	40	46	43	40	45	40	42	41	40	40	40	46	40	40
Borrow		0	0	0	0	5	5	0	0	0	0	0	0	0	0	0	0	0	0	5	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0
Inventory	10	10	10	10	10	5	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0
Cancellation		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		45	44	42	48	45	45	40	46	43	40	45	40	42	41	40	40	40	41	40	40
Late/Unsatisfied orders		0	0	0	0	0	5	7	0	0	9	0	10	2	0	0	0	9	0	4	8

The effect of disruptions on the three order examples show many instances of late or unsatisfied customer orders. This is because the inventory limits were not sufficient to support production shortages caused by disruptions. The critical levels of inventory here mean that inventories are exhausted quickly. It appears more damaging when there are fewer replenishment opportunities. In Table 5.b, where inventory replenishment occurred on 3 occasions, they were not enough to accommodate disruptions. Over 10 days of the production period, the actual production is less than the demand after disruptions. Apart from the critical inventory condition, the inability of the production flow-shop to match production of demand after disruption can be further understood from the resource utilisation point of view.

Order inventory in Table 5.c tend toward zero level within first half of the production period. This is because the orders experienced more and quicker borrow due to disruption causing more unsatisfied customer orders. The impact of the disruption is felt with high number of unsatisfied orders during the constant zero level of inventory. This continues for a longer period as there were no instances of inventory replenishment, especially in Table 5.a. When there are replenishments, as the case in Table 5.b and one instance (day 18) in Table 5.c, they were not enough to support the declining production levels.

For the low order, critical inventory scenario, Tables 6.a, 6.b and 6.c display results of three selected orders to present the impact of disruption on the inventory behaviour including the best possible replenishment plan.

Table Error! No text of specified style in document.**.a** First selected order results (low order volume vs critical inventory level)

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		21	22	21	20	24	20	22	25	20	25	23	22	24	24	20	25	20	22	24	23
Demand After Disruption		21	22	21	0	24	20	0	25	20	0	23	22	24	24	20	25	20	22	24	23
Actual Production		21	22	21	0	24	20	0	25	20	0	23	22	24	24	20	25	20	22	24	23
Production PLUS Replenishment		21	22	21	0	24	20	0	25	20	0	23	22	24	24	20	25	20	22	24	23
Borrow		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Cancellation		0	0	0	20	0	0	22	0	0	25	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		21	22	21	0	24	20	0	25	20	0	23	22	24	24	20	25	20	22	24	23
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table Error! No text of specified style in document.**.b** Second selected order results (low order volume vs critical inventory level)

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		24	20	20	21	23	25	21	23	22	21	24	21	23	20	23	21	25	23	21	20
Demand After Disruption		24	20	20	21	23	25	21	23	22	21	24	21	23	20	23	21	25	23	21	20
Actual Production		24	18	16	21	20	20	21	23	22	21	20	21	23	20	20	18	20	20	21	20
Production PLUS Replenishment		24	18	16	27	20	20	29	23	22	21	20	21	23	20	20	18	20	20	21	20
Borrow		0	2	4	0	3	5	0	0	0	0	4	0	0	0	3	3	0	0	0	0
Replenishment		0	0	0	6	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory	10	10	8	4	10	7	2	10	10	10	10	6	6	6	6	3	0	0	0	0	0
Cancellation		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		24	20	20	21	23	25	21	23	22	21	24	21	23	20	23	21	20	20	21	20
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	3	0	0

Table Error! No text of specified style in document.**.c** Third selected order results (low order volume vs critical inventory level)

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		24	21	20	25	21	24	20	20	24	21	22	22	20	21	21	25	25	20	20	23
Demand After Disruption		24	21	20	25	21	24	20	20	24	21	22	22	20	21	21	25	25	20	20	23
Actual Production		24	21	20	25	21	24	20	20	24	21	22	22	20	21	21	25	25	20	20	23
Production PLUS Replenishment		24	21	20	25	21	24	20	20	24	21	22	22	20	21	21	25	25	20	20	23
Borrow		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Cancellation		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		24	21	20	25	21	24	20	20	24	21	22	22	20	21	21	25	25	20	20	23
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Even at critical level of inventory, production appears not affected by disruptions. In Tables 6.a-6.c, the inventory level remains unchanged throughout the entire production period. In every instance of the low order volumes, the impact of disruptions has no threat on production levels and hence inventories were kept at considerable high level.

For all the above scenarios, it can be established that the effects of disruptions can be managed when inventory support is sufficient.

7. Sensitivity Analysis

In order to validate and establish the effectiveness of the proposed heuristic approach in this study, comparison with approaches is essential. However, other approaches mentioned in the literature, which have no direct factors and variables as in the experimental setting for the proposed approach, are inadequate for comparison. The irregularities would rather be biased and could give unreliable judgment. Therefore, a sensitivity analysis study is conducted to study the performance based on dependent variables such as the demand volumes and inventory limits. The sensitivity analysis is used to explore the robustness and accuracy of the developed model outcomes under uncertain demand conditions (Rahman and Mohamad-Saleh 2018). The number of late orders is selected as the Key Performance Indicator (KPI) or the target variable against the changing demand volumes and altering different level of inventory limits. Table 7 presents a comparison between the 'As-Is' scenario and three other method of inventory replenishment including sequential, Instantaneous replenishment and the proposed methods.

Table 7 Comparison for Late Order KPI

Data Set- Parameters		**"As-Is"**	**Sequential**	**Instantaneous Replenishment Method**	**Proposed Heuristic**
High Order High Demand (In Vol.)	Full Inventory	785	521	455	383
	Safe Inventory	710	408	311	209
	Critical Inventory	1152	1005	856	675
Average Order Average Demand (In Vol.)	Full Inventory	164	125	37	0
	Safe Inventory	205	384	178	33
	Critical Inventory	248	254	190	153
Low Order Low Demand (In Vol.)	Full Inventory	0	0	0	0
	Safe Inventory	0	0	0	0
	Critical Inventory	15	0	0	0
Total		**3279**	**2697**	**2027**	**1453**

As indicated in Table 1 under the proposed heuristic column, it is clear that the order demand volume as well as the inventory limits significantly impact the number of late orders, most especially for High and Average order and demands.

For the purpose of justification, the proposed heuristic approach for inventory replenishment of this study is compared with the selected closely related approaches; a sequential and instantaneous replenishment approaches by Adediran and Al-Bazi (2018) against the current state "As-Is". The idea of non-instantaneous and gradual inventory replenishment strategy of this study makes both the sequential and instantaneous methods comparable. This is related to the variable levels of inventory at the time of replenishment. The proposed heuristic algorithm is developed to logically replenish inventory based on each level of inventory, order volume and process time availability. In the sequential approach, the inventory replenishment is done in order sequence by considering the required order number or each order inventory per time. For the instantaneous approach, order replenishment to inventory is done instantly.

From Table 7, a small change in high order and demand at full inventory level results in a significant change in the number of late orders. The highest number of late orders are recorded for high order demand. However, the lowest number of late orders at 383 reveals the better performing proposed approach compared to others. The average level of order demand variation has a corresponding level of effect on late orders. Under the average order and demand, the performance of the proposed approach shows superiority with 0, 33 and 153 late orders at full, safe and critical inventory levels respectively compared to other approaches. On all variable circumstances, except for "As-Is" critical inventory, the effect of low order and demand is insignificant as no late order is recorded for all approaches. This is an indication that high demand variation has no significant effect on late orders when high, safe or critical inventory levels are maintained. And the proposed approach 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. However, based on the outcomes of the comparison, the proposed approach of this study is most effective with the least total number of late orders of 1453 under all variable conditions.

8. Conclusion and Recommendation

Measuring the impact of disruption on production and inventory replenishment is an essential requirement to find ways of resolving disruption problems. This study has focused on identifying and measuring the impact of disruptions in terms of process times and order quantities. This paper earlier noted that disruptions affect production causing shortages, and resources' idleness and also causes inventory levels to become low or critical in some cases, creating further problem of large backlogs, higher number of unsatisfied orders and even production shutdown. The study helped production planners working at the UEES to minimise the consequences of the damages on production schedules and inventory control by presenting the framework in which the ABM module was used to identify and measure these consequences in terms of process times and order quantities. In addition, the improved framework was developed with the aim of assisting production planners in flow-shop system to manage disruptions, which is crucial to customer satisfaction. However, the work is limited to the strategy of an organisation to produce products based on anticipated demand rather than other strategies such as make to stock, etc.

To demonstrate the effectiveness of the proposed framework, computational real-life experiments were conducted for low, average and high order volumes against critical inventory levels, where disruptions occur on production in random combination.

The outcome of the experiments clearly reveals the actual times saved or lost, and the actual order quantities that were short or borrowed (Tables 1, 2 and 3). This knowledge allows appropriate types of orders to borrow, and the rescheduling and replenishment of borrowed orders. This is essential for production planners to make decisions when disruptions occur.

The impact of disruption on the level of inventory and the replenishment plan for these experiments were identified in terms of how to efficiently utilise the idle time resulting from customer disruption and use it for replenishing the inventory (Tables 4a-c, 5a-c, and 6a-c). Also, the proposed approach for inventory replenishment was compared with other methods (Table 7) in terms of the number of late orders. The results of the comparison show that the proposed approach outperformed the others under the same inventory level condition. 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 6).

The findings of this study can be explored further by implementing more sophisticated meta-heuristic and optimisation algorithms. This can be incorporated into the ABM module of the framework with the aim of further neutralising the effect of disruption. This can be achieved through production process re-orientation and production behavioural pattern learning through historical data when disruptions occur. The messaging model could be developed further by embedding the heuristics optimisation rules as additional protocols within the agents' interactions in messaging model for better and faster computations.

References

Adediran T.V., Al-Bazi A. (2017). Agent Based Model for Complex Flow-Shop Manufacturing Systems with Customer-Related Production Disruptions. In Information Technology (ICIT), 17-18 May 2017 8th International Conference (767-773), Amman Jordan. IEEE.

Adediran T. V., Al-Bazi A., (2018) Developing Agent-Based Heuristic Optimisation System for Complex Flow-Shops with Customer-Imposed Production Disruptions. Journal of Information and Communication Technology, 18(2), 291-322

Darmoul, S., Pierreval, H. and Hajri–Gabouj, S., (2013). Handling disruptions in manufacturing systems: An immune perspective. Engineering Applications of Artificial Intelligence, 26(1), pp.110-121.

Omega, R.S., Noel, V.M., Masbad, J.G. and Ocampo, L.A., (2016). Modelling supply risks in interdependent manufacturing systems: A case study. Advances in Production Engineering & Management, 11(2), pp.115-125.

Schmitt, T.G., Kumar, S., Stecke, K.E., Glover, F.W. and Ehlen, M.A., (2017). Mitigating disruptions in a multi-echelon supply chain using adaptive ordering. Omega, 68, pp.185-198.
Lam, J.S.L. and Yip, T.L., (2012), Impact of port disruption on supply chains: A Petri net approach. In International conference on computational logistics (pp. 72-85). Springer, Berlin, Heidelberg.
Ocampo, L., Masbad, J.G., Noel, V.M. and Omega, R.S., (2016). Supply-side inoperability input–output model (SIIM) for risk analysis in manufacturing systems. Journal of Manufacturing Systems, 41, pp.76-85.
Bhat, J.A. and Yadav, P.S., (2017) Analysing Disruption in Operational Practices and its Impact on the Efficiency of Handicraft Firms.
Li, B., Barker, K. and Sansavini, G., (2017). Measuring community and multi-industry impacts of cascading failures in power systems. IEEE Systems Journal, 12(4), pp.3585-3596.
Rolon M., Martınez E., (2012) Agent-Based Modeling and Simulation of an Autonomic Manufacturing Execution System. Computers in Industry 63, 53-78.
Li S., Shan H., Lui L., (2011) Multi-Agent-Based Cooperative Coevolutionary Model for Dynamic Shop Floor Reconfiguration Considering Process Planning. Journal of Advanced Manufacturing Systems 10 (1), 53 – 60.
Pan A., Leung S. Y. S., Moon K. L., Yeung K. W., (2009) Optimal Reorder Decision-Making in the Agent-Based Apparel Supply Chain, International Journal of Expert Systems with Application, 36, 8571 -8581.
Rahman, I. and Mohamad-Saleh, J., (2018) 'Hybrid bio-Inspired computational intelligence techniques for solving power system optimization problems: A comprehensive survey'. Applied Soft Computing 69, 72-130.