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DEVELOPING AGENT-BASED HEURISTIC OPTIMISATION SYSTEM FOR COMPLEX FLOW SHOPS WITH CUSTOMER-IMPOSED PRODUCTION DISRUPTIONS

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ABSTRACT

The study of complex manufacturing flow-shops has seen a number of approaches and frameworks proposed to tackle various production-associated problems. However, unpredictable disruptions, such as change in sequence of order, order cancellation and change in production delivery due time, imposed by customers on flow-shops that impact production processes and inventory control call for a more adaptive approach capable of responding to these changes. In this research work, a new adaptive framework and agent-based heuristic optimization system was developed to investigate the disruption consequences and recovery strategy. A case study using an Original Equipment Manufacturer (OEM) production process of automotive parts and components was adopted to justify the proposed system. The results of the experiment revealed significant improvement in terms of total number of late orders, order delivery time, number of setups and resources utilization, which provide useful information for manufacturer's decision-making policies.

Keywords: agent-based simulation, customer production disruptions, flow-shops, heuritic optimisation algorithm, manufacturing systems.

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INTRODUCTION

The manufacturing system operations can be challenging to model due to the complex behavior and attributes of the system entities that interact in a critical manner, but are crucial to understand for proper representation of the system. The type of model to be developed is based on the level of details the system provides, which is important to the problem under study and the corresponding outcome.

An important part of the supply chain network is the manufacturing system, which is regarded as one of the major contributors to national economy and a significant driving force for growth (BIS, 2017). In the manufacturing sector, automotive manufacturers (AM) play an important role in the delivery automobiles of different types and varieties to their customers. However, automobile manufacturing companies serve as customers to Original Equipment Manufacturers (OEM). OEM can be referred to as a manufacturing system that operates as one of the main sources of the parts and components suppliers for automobile manufacturing customers (CAR, 2010). The OEM finished products (parts and components) constitute material requirements for automotive assembly line operation. For this reason, the automotive manufacturer relies on OEM to a large extent and in the actual sense, the OEM production operations are initiated by order request from their automobile manufacturing customers to be delivered on a time slot daily basis, in which case, OEM production operations are not only controlled by AM order requests but the nature of the order requests, which is irregular in term sequence, time and order request withdrawal. These irregularities are known to cause various types of disruptions for the OEM production flow-shop planning and scheduling. These OEM manufacturing production disruptions could be in the form of customers changing the sequence of order delivery which translates to production sequence change; customers could cancel the order originally requested which means cancellation of production schedules; and most uniquely, customers could change the time for order delivery, resulting in a change in production time on the OEM floor-shop. These disruptions individually and collectively impact the smooth running of the OEM manufacturing flow-shop, with significant consequences on the entire manufacturing system operational performance. Due to this problem of disruption, in most cases, the OEM system suffers the problem of over-utilization or under-utilization of available resources and other risks to the continuous alteration to the production plan and schedule from the customer's point of view.

The concept of thesimulation approach such as the Agent-Based Modeling (ABM) is applicable to the production disruption of such complexity in the manufacturing environment. ABM is a simulation approach that is recently gaining researchers' attention especially for complex systems modeling (Lee et al., 2015; Gilbert, 2008; Gilbert & Bankes, 2002) in a rapidly and continuously changing system environment (Grimm & Railback, 2005). Unlike other traditional simulation modeling approaches such and System Dynamics (SD) and Discrete Event Simulation (DES), ABM is referred to as a modeling technology used across all levels of abstraction (Borshchev & Filippov, 2004).

In this paper, the ABM approach was adopted to be embedded within the proposed disruption recovery framework that uses the proposed heuristic approach and inventory replenishment strategy. The ABM was used to capture more complicated details of the manufacturing system behavior, dependencies and interactions which consequently provide deeper insight of the system model under consideration (Borshchev & Filippov, 2004). The approach demonstrates how ABM integration can be used for simulation modeling of the operational behavior and attributes of the complex manufacturing system in response to customer-imposed production disruptions. The heuristic algorithm was developed to help the production flow-shop to accommodate and adapt to disruptions. The idea of 'borrow' of shortage orders from the inventory due to disruption, to complete customer order in due time and right quantity was implemented, while the inventory replenishment strategy was applied to continuously and gradually maintain the inventory limits up to its maximum level.

The problem presented in this study was that of a flow-shop production line with sequential operations of multiple product types. We specifically considered the problem of customer-imposed OEM production disruptions in terms of (a.) change in sequence of production, (b) order cancellation, and (c) change in order delivery due time. OEM manufacturing systems are faced with production disruption emanating from customer order demand. Disruptions occur from customers when the system experiences production uncertainties affecting the flow process of the assembly line. These uncertain situations affect how, when and what customers demand from the OEM. This is due to customer operation of sequential assembly line in their production processes. From the OEM perspective, manufacturing production processes, plans and schedules are based on customer-requested demand information. These demands come in different and sequential order splits to suit customers' assembly line operation. In as much as the OEM production process depends on customer orders, they are restricted by time. Disruptions still need to be managed to keep the smooth running of the system while equally fulfilling customer demand in due time. The sequence change occurs when customers' assembly line sequence changes due to uncertainties experienced (Chen & Xiao, 2009). Since order splits are processed in the system sequentially by flow-line machines, a change in this sequence significantly disrupts the planned production schedule. Cancellation disruption occurs when customers decide to cancel order(s) that have been initially requested (Yeo & Yuan, 2011). This type of disruption, even though disrupts planned production schedule, it can also reduce the entire process time as well as setup time since cancelled orders or order splits will no longer be processed and required no machine setup. Order delivery due time can be changed by customers to accommodate urgent needs on their assembly line. Change in the order delivery due time affects the already planned production schedule. When this happens, the order or order split in question will be made first priority on the production line with the aim of achieving the due time for delivery. Disruptions that increase the number of setups, cause prolonged processing time which cannot be accommodated by the daily production cycle time constraint. This results in requesting support from the inventory to complete orders that cannot be completed in the daily production cycle. When this continually happens, maintaining an optimum inventory policy is challenging, as the system is at risk of stock-out. For this reason, an effective measure to tackle this problem is significant for uninterrupted system operations.

The rest of the paper presents some selections of relevant and related works in the area of manufacturing disruptions, and the application of ABM in the context of the manufacturing system. It also discusses the application of heuristic algorithm in problems relating to manufacturing systems, followed by the methodology section, which bring to light the proposed framework and its integration with the ABM model. Next is the system development which focuses on the actual ABM system, and then the discussion of the results of the developed system follows. The paper ends with the conclusion and recommendations for future research in the final section.

PREVIOUS RELATED WORKS

Over the years, many researchers have conducted studies in the area of manufacturing production disruption from different perspectives. Also, various disruption recovery strategies and plans have been proposed through different approaches among which simulation modelling is a popular consideration with different integrated solutions intended for better results. In this section, we discuss relevant works related to manufacturing production disruption problems, the use of simulation approaches particularly Agent-Based Modelling (ABM) and consideration for optimization techniques such as heuristic rules or algorithm applications based on previous studies in the production scheduling problem domain.

Manufacturing Production Disruption Problems

A typical supply chain network is associated with many types of disruptions. According to (Paul et al. 2015), these disruptions types are categorized as transportation disruption, supply disruption, demand disruption and production disruption. According to Paul & Essam (2014), among these disruption types, production disruption is more evident in the manufacturing environment. In this situation, disruption can occur as a result of different factors relating to loss of reputation, financial problems which happen internally within the system, and can also be caused by problems from external sources. Production disruptions in this manner create a more difficult problem for the entire manufacturing system resulting into production delays, shortages of resources, and unfulfilled customer order (Paul & Essam, 2014) among others. A typical example of disruption to the manufacturing production is machine breakdown, discussed in Lin and Gong (2006). In this study, the effect of machine breakdown was analyzed using the Economic Production Quantity (EPQ) model. This particular production disruption was identified in a single production system of deteriorating items considering an unchanged time of repair. In Widyadana & Wee (2011), the machine breakdown EPQ model presented in (Lin and Gong, 2006) was extended. It was considered for machines breaking down randomly of which stochastic repair time was engaged using exponential and uniform distributions. The idea of distributed machine breakdown as a cause of production disruption was considered in Chiu (2007), where an EPQ model was developed to determine run-time in production. In the paper, a cost function was developed representing the production system with a single stage. The developed model was tested, with and without the breakdown disruption, to observe the production run-time variations. Other categories of production disruptions are recorded in Chiu et al. (2007); Sargut & Qi (2012); Schmitt & Snyder (2012).

In Moinzadeh & Aggrawal (1997) (s, S) of production-related inventory policy was considered for randomly generated disruptions as well time between breakdowns being distributed exponentially in an bottleneck system which was unpredictable. In Sana (2011) the consideration was for a two-stage supply chain involving the supplier as well as the retailer, in which disruption could happen randomly at both ends, and with the assumption of lost customer demand in the process for unsatisfied orders. However, through the model developed in this study, the predictable annual cost for retailer order quantity was minimized. An inventory model was developed by Schmitt

& Snyder (2012) with the consideration for two types of suppliers; reliable but expensive and unreliable suppliers. In the two instances, an optimal order and storage quantities were determined with uncertain probability of disruption and recovery plan. In Hishamuddin et al. (2012) a model to recover production disruption was developed for a single stage system. The developed model was intended for lost sale and back order as a result of disruptions. In Chiu et al. (2013) there was a consideration for equipment breakdown as a form of disruption, and an optimal replenishment policy was proposed for an EPQ inventory model. In the model assumption, the machine was expected to instantly enter maintenance mode whenever disruption happened after which production could recommence after machine restoration. The disruption in the manufacturing system process was also studied by Taleizadeh et al. (2014) where the EPQ model for inventory was developed. The developed model was considered for a single machine under multiple products where backorders were accepted as shortages. In Qi, Bard and Yu (2004) a one-supplier-one-retailer supply chain under a disruption in demand during the planning horizon was investigated, and they showed that changes to the initial plan induced by a disruption may inflict considerable deviation costs throughout the system. Xia, Xiao, and Yu (2004) studied a lot-for-lot production and inventory system with the raw material supply disruptions that result in the fluctuation of the production cost. Yang, Qi, and Yu (2005) proposed a dynamic programming method for the demand and cost disruption management of a firm. Xiao and Yu (2006) developed an indirect evolutionary game model with two-vertically integrated channels to study evolutionarily stable strategies of retailers in the quantity-setting duopoly situation with homogeneous goods and analyzed the effects of the demand and raw material supply disruptions on the retailers' strategies. They studied the coordination of a supply chain with one manufacturer and two competing retailers after the production cost of the manufacturer was disrupted. They also extended the model to the case with both cost and demand disruptions (Xiao & Qi, 2008). Two coordination models were developed for a supply chain with one manufacturer, one dominant retailer and multiple fringe retailers to investigate how to coordinate the supply chain after demand disruption. They also found that the disrupted amount of demand largely affects the allocation of the supply chain's profit (Chen & Xiao, 2009). Yu, Zeng, and Zhao (2009) identified a risk evaluation for the impacts of supply disruption on the choice between the famous single and dual sourcing methods in a two-stage supply chain with a non-stationary and price-sensitive demand. They obtained the expected profit functions for the two sourcing modes in the presence of supply chain disruption risks, and examined the sensitivity of the buyer's expected profit to various input factors through numerical examples. An approach was proposed by Cauvin, Ferrarini, and Tranvouez (2009) to minimize the impact of disrupting events on the whole system. It was based on an analysis of disrupting events and the characterization of the recovery process, and on a cooperative repair method for distributed industrial systems.

However, disruption on the production line can be caused from outside the actual manufacturing facility, as in the case in OEM manufacturing systems. OEM manufacturing systems face uncontrollable situations emerging from customer-imposed disruptions on the production line. Production disruption in this manner becomes difficult to manage when it has been orchestrated by the customers. In this ongoing study, three production disruption types were identified, in which the ABM system experimentation was conducted upon. These disruptions were: (a) change in sequence of production, (b) order cancellation, and (c) change in order delivery due time.

Agent-based Modeling Approach

The choice of ABM is rationalized by the nature, attributes and behavior of the problem under study. ABM offers flexible, adaptive, robust and autonomous platform for manufacturing system challenges. The approach evolves to accommodate complex problems in manufacturing operations compared to other traditional simulation methods such as the Discrete Event Simulation (DES) and System Dynamics (SD) (Siebers et al., 2010). ABM was applied as a platform for manufacturing systems modeling (Barbosa &Leitao, 2011) where it was applied for a system that exhibits complex phenomena such as the ability to self-organize and emergent behavior. In a changing shop floor environment, Shen et al. (2005) modeled an internet-enabled agent-based intelligent shop floor to control systems implemented to respond quickly to change. Disruption in terms of manufacturing system failure was modelled by Alsina et al. (2004) to simulate the repairable manufacturing system. The ABM model was used to determine the system failure rate, based on machine age as a factor influencing disruptive behavior. Rolon and Martinez (2012) adopted the agent-based modeling and the simulation for production management systems problem of unplanned disruptive events and disturbances such as arrivals of rush orders, shortage and delays of raw material as well as equipment breakdowns. The ABM method is used in the production scheduling problem (Wang et al., 2008) in a framework for distributed manufacturing scheduling framework at the shop floor level. The modelling framework included the multi-agent system modelling of work cells, service oriented into the shop-floor, distributed shop floor control structure and dynamic distributed scheduling algorithms. In a simultaneously loaded station, Hermann (2013) developed a simulation-based priority rules for flow shop scheduling. Wang et al. (2002), considered agent-based modeling and mapping for the manufacturing system. They identified different types of system agents' such as static agents, resources agents, mobile agents, user interface agents, domain agents gateway agents, and factory agents, among others to formulate the entire manufacturing-system architecture. In Cantamessa (1997) the discussion was based on agent utilization in the manufacturing systems and presented that the characteristic agent-based approach played an important role in academic as well as in industrial implementation. In Monostori et al. (2006) the agent-based system was adopted for the intelligent manufacturing and decentralized systems. They introduced multi-agent systems and software agents through a comprehensive survey and concluded with the benefits and potential application of the agent-based modeling technology in the manufacturing environment. Having explored the production disruption problem situation and the possibility of ABM implementation with the proposed framework, it was the aim of this of this paper to apply integrated ABM and the adaptive framework to simulate and optimize complex manufacturing systems and examine the impact and consequences of using OEM manufacturing in a flow-shop located in Coventry, UK, as a case study. The ABM would simulate the system with different combinations of disruption problem-related scenarios, identify gaps in time slots (free time slots) caused by applying different types of disruptions and then apply the heuristic algorithm to accommodate disruption through the replenishment strategy of inventory borrow. The study was expected to provide predictions of the expected favorable outcome from the system; offer reasonable understanding of the emerging production system behavior, and provide critical insight to help manufacturing production decision-making on disruption recovery plans.

Heuristic Optimization Algorithm Applications

Heuristic optimization algorithm has been applied for production disruption problems in supply chain construction (Shu et al., 2014). In this study, they combined different approaches in which optimization algorithm such as genetic algorithm was adopted for Generic bill-of-materials (GBOM)-oriented management of production disruption problem to respond swiftly to market demand and achieve effective management of supply chain cost. Also in Shu et al. (2016) a multi-objective firely algorithm was applied for a supply chain disruption, particularly simultaneous distribution disruption between manufacturing and distribution centers. Heuristics and metaheuristics represent the main types of stochastic methods (Stojanovic et al., 2017). Both types of algorithms can be used to speed up the process of finding a high-quality solution in cases where finding an optimal solution is very hard. The distinctions between heuristic and metaheuristic methods are inappreciable (Stojanovic et al., 2017). Heuristics are algorithms developed to solve a specific problem without the possibility of generalization or application to other similar problems (Marti & Reinelt, 2011). On the other hand, a metaheuristic method represents a higher-level heuristic in the sense that they guide their design. In such a way we can use any of these methods to design a specific method for computing an approximate solution for an optimization problem.

Since the last several decades, there has been a trend among researchers to solve complex optimization problems by using metaheuristic optimization algorithms. Some applications of metaheuristic algorithms include neural networks, data mining, industrial, mechanical, electrical, and software engineering, as well as certain problems from the location theory (Afshar et al., 2015; Banks et al., 2007; Fister et al., 2015). The most interesting and most widely used metaheuristic algorithms are the swarm-intelligence algorithms which are based on the collective intelligence of colonies of ants, termites, bees, flocks of birds, and so on and forth (Karaboga et al., 2012). The reason of their success lies in the fact that they use commonly shared information among multiple agents, so that self-organization, coevolution, and learning during cycles may help in creating the highest quality results. Although not all of the swarm-intelligence algorithms are successful, a few techniques have proved to be very efficient and thus have become prominent tools for solving real-world problems (Banks et al., 2007) Some of the most efficient and the most widely studied examples are ant colony optimization (ACO) (Corne et al., 2012), particle swarm optimization (PSO) (Fister et al., 2015; Corne et al., 2012), artificial bee colony (ABC) (Karaboga et al., 2012;), and recently proposed firefly algorithm (FA) [18, 36–38] and cuckoo search (CS) (Tavares Neto et al., 2013).

Having critically reviewed previous work production disruption areas using simulation and the heuristic optimization approach, it is clear that the idea and the approach explored in this work to investigate the problem domain and as well as the disruption problem perception has received minimum attention in the past. However, this work presented a new and innovative adaptive framework involving the proposed strategy which included ABM, heuristic algorithm and the inventory replenishment strategy. The aim was to help manage the disrupted processes and ultimately reduce to the minimum the sets of consequences caused by these customer-imposed production disruptions on the manufacturing flow-shop.

METHODOLOGY

In this study, we proposed the simulation-based Production Disruption-Inventory Replenishment framework incorporated into the Adaptive Agent-based Heuristic Optimization System (Figure 1). The idea of the proposed framework was for the manufacturing systems to adapt to production flow-shop disruption caused by customers through the application of the adaptive heuristic and replenishment strategy discussed in this research work.

The Framework

Several types of framework have been developed in an attempt to solve complex manufacturing production related problems (Omar & Suppiah, 2011; Vieira et al., 2003; Shi & You, 2016; Yue & You, 2017; Pati et al., 2016). They are sets of steps, procedures, rules, tools, components or materials purposely put together to target particular problem domains. The use of the system framework in the simulation project to solve problems is not new, especially in the supply chain, logistics and manufacturing (Ivanov, 2010; Gunasekaran & Ngai, 2005; Guillen et al., 2007; Fukuta, 2015). What is new is the guided inter-relationship between framework entities trained to solve unique problems in a unique way. In this study, we proposed the Production Disruption Inventory Replenishment framework to facilitate definitive solutions to specific industrial related problems. And more importantly, the framework was experimented using real life data for the manufacturing production system case study.

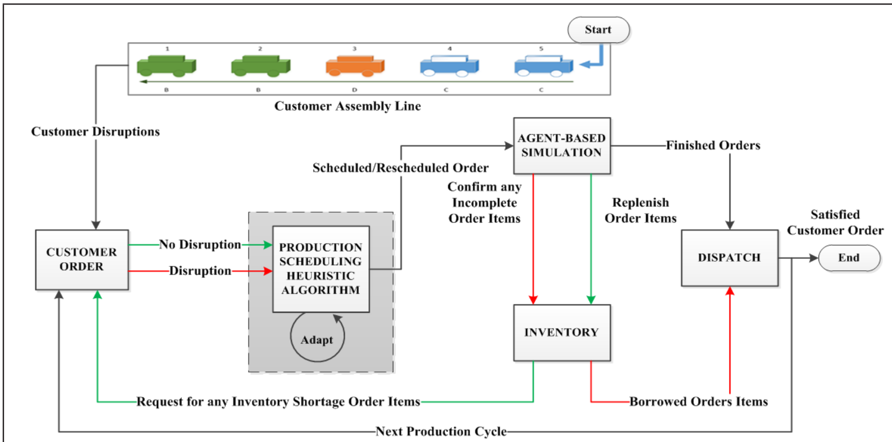

Figure 1. Production Disruption-Inventory Replenishment framework.

In the framework, productions of the manufacturing system are triggered by customer assembly line conditions, which are uncertain and sequential in nature. The sequential process on customer assembly line is the basis for order demand. However, uncertainties on customer assembly line force a change in initial order. 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. In order to respond to the disruption, production scheduling adaptive heuristic algorithm is suggested to reschedule production processes in face of disruption. The heuristic algorithm would not only reschedule the process, but also help determine the system on the number of order items completed or not completed. Through the ABM module, order items not completed could be requested from the inventory storage, which represent a backup plan for a successful implementation of the framework. In case of disruption in this way, all order demands could be completed in time to fulfill customer demand. But then, inventory storage requires to be replenished with items taken from it. Again, heuristic algorithm schedules the replenishment order items to be fixed in 'available time' as the next production process progresses. 'Available time' is defined as the time saved on the production line as a result of disruption. For example, random cancellation which reveals a time gap in between processes or changes in sequence, which can cause orders of the same type to follow each other on the production line as opposed to the original planned schedule; meaning the supposed setup time is now saved. The repetitive process continues in the daily production cycle.

The system framework operates as a typical flow process but adaptive with the aim of adequately satisfying customer order (by delivery orders that meet due date, and require sequence) in spite of production disruptions, while ensuring smooth operation of the production process of the flow-shop. The system process is triggered by order demand coming through from the customer's assembly line. Customer demand is in specified sequence and due time as dictated by the assembly formation. This demand order can be disrupted depending on various constraints that could impact the customer's assembly line. The order demand without disruption goes through a normal production scheduling process. However, the heuristic algorithm for production scheduling process accommodates and adapts the disrupted orders in terms of change in sequence, cancellation and due time change which emanate from customer assembly line constraints. The heuristic algorithm provides a proper/viable production schedule for the flow-shop simulation process. The heuristic algorithm schedule is significant to enhance the efficient utilization of the production resources such as machines, orders and operator in the simulation process. Resource allocation is an important aspect of production scheduling. The autonomous capability of the agent-based system is significant in assigning scheduled order to resources through the attributes and behavioral matching of order and resources. This technique allows order to identify the specific machine as well as the specific operator skill set, enough to work on a specific machine and job. One important function of the agent-based system in the process is the ability to identify and report the order that would not meet customer requirement. The system isolates and drops such orders before requesting for shortage order from the inventory to complete customer order in sequence, and due time. The system also provides possible time slots due to order cancellation or order changing sequences. The inventory serves as an operational storage facility for all order types where shortage products can be borrowed to complete and satisfy customer order demand. In as much as the inventory facility has a shortage limit, a replenishment request of any borrowed order is constantly reported and raised for replenishment in the next possible run. In this case, the shortage orders were replenished using the 'replenishment strategy' proposed in this study. The finished orders as well as any borrowed quantities (to complete the order) reach the dispatch node where customer demand is said to be successfully satisfied and end, or the next production cycle can commence if there is any.

The proposed framework represents significant contribution to knowledge such that it provides a platform for the OEM manufacturing system to adapt to customer production disruptions, maintain the smooth running of the flow-shop while fulfilling customer demands in the right quantity and in due time. The presented work suffices as a bedrock for academic exploitation in this specific research area. From the practical point of view, it provides solutions to particularly impending production disruption challenges where the customer assembly line and the OEM production line have parallel dependencies.

Agent-based Modeling Module

The Agent-based Modeling approach allows the simulation of the complex adaptive system (Botti & Giret, 2008). This approach has been used to solve manufacturing-related problems (Ghosal, 2015; Attri, 2005). The ABM approach was adopted in this study to take advantage of the entity interaction capabilities as well as operational flexibility which are crucial to the complexity of the problem domain. With ABM, message sequence and communication among system entities (agents), which are fundamental to the proposed strategy, is possible to identify gaps in time slots (free time slots) caused by applying different types of disruptions. We incorporated the ABM module into the proposed framework to actualize the reality of the system agents.

The idea of the agent-based modelling and simulation has been more appreciated in manufacturing, probably because of its social engagement, autonomy, and ability to deal with complexity associated with manufacturing operations. In building an agent-based model, manufacturing flow-shop is seen and represented as a social environment where production activities take place. This representation emphasizes production process events and inter-relationships towards others (individual agents) in this 'social environment'.

It is known that there has been a lot of meanings and impressions of the word 'agent'. However, in this context of agent-based model, according to (Wang et al. 2012) agents are software programs that have social ability (able to interact with each other based on certain 'instructions'); are autonomous (able to control their own actions); pro-active (able to undertake goal-directed actions) and reactive (able to perceive their environment and respond to it).

For the manufacturing flow-shop modeling, each entity such as machines, parts and resources are individual agents, each with its own properties and attributes required to meet the desired production goal. As each of these individual agents cannot on their own get the job done except interact; their collection, known as multi-agents perform the simulation goal. And also, the environment in which 'agent' interaction takes place becomes a multi-agent system environment. All of the agents and the environment in which they operate are represented within a computer program (Bersini, 2012).

The developed ABM system demonstrates the identified manufacturing system agents' interaction using the UML message sequence diagram as illustrated in Figure 2.

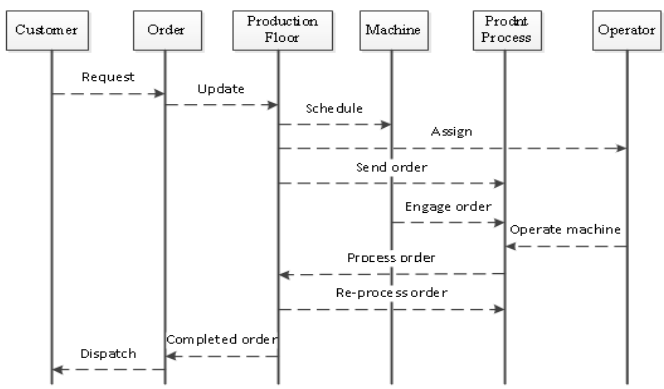

Figure 2. The System Message sequence diagram.

In the messaging sequence diagram in Figure 2, the order request, resources allocation, order production and dispatch information sharing are depicted. The customer send order request, is updated on the production floor. Upon receipt of the customer order request, the production floor schedule machines are based on the order information. The order and machine schedule are used to assign operators on the production job. As a result, the machine that has been allocated to the operator engages order for the production processes. The production processes occurs in a loop of operations until all the assigned orders have been completed. The completed order information is passed on to the production floor for order dispatch to the customer according to the request.

An important aspect of the ABM the UML state transition diagrams which are commonly used in ABM manufacturing production and scheduling problems (Bersini, 2012; Cantemessa, 1997; Ghosal, 2015). The state transition diagrams of individual agents presented in Figure 3 define the states of each agent during the system lifetime which changes with different changing events within the system operation. It is particularly useful in this context for the system to capture timing transitions, which is crucial to the proposed approach.

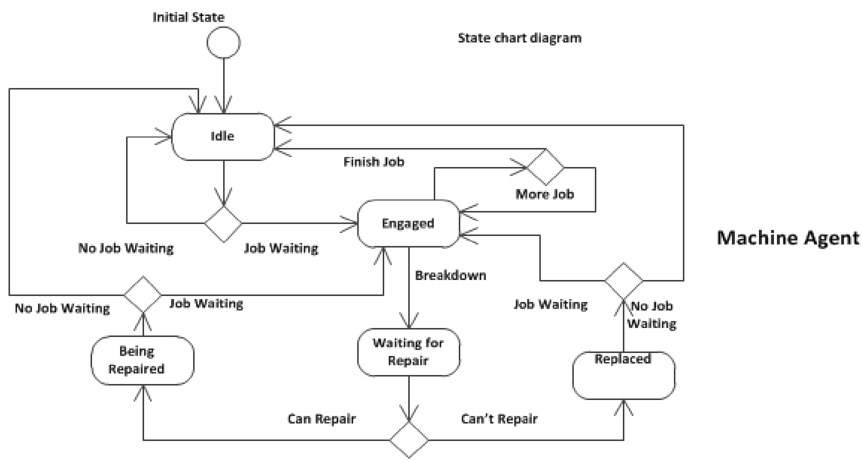

Figure 3. Machine agents state transition diagrams.

In Figure 3, the machine in the initial state idles when no order is being processed or is waiting. The machine becomes engaged as the order arrives, is being processed, or when orders are waiting in queue the machine continues to be engaged. In the case of machine breakdown, three states can occur: which can be waiting for repair, being repaired or being replaced. After this the machine switches back to the idle state provided there is no job waiting to be processed. The state transition also applies for orders and the operator. From the initial state, orders can arrive to be processed. When assigned to machine and operator, orders attain the processed status. The state which changes to progress as the orders moves through different processes. Uncompleted orders are tagged rejected while completed ones are accepted to the finished state. For the operator, the initial state of the available operator is idle, before being allocated to a job on the machine. An operator becomes busy when orders arrive and are being allocated to the machine; the status which they maintain until they become idle again.

The timing of each agent transition is recorded by the system and used in the overall system analysis and decision-making.

The Proposed Hueristic Algorithm

The proposed heuristic algorithm is designed to enable the system to control the inventory while supporting the production process with the aim of adapting to customer-related disruptions.

Step 1: Start.
Step 2: Determine current daily inventory level of all order types and obtain each Order Units (OU).
Step 3: From Simulation, obtain production Available Time (AT), Order Setup Time (ST) and order Process Time (PT).
Step 4: If more than one order is the least and/or Different Inventory Levels (DIL), replenish the least to meet the next least level based on AT provided by the agent-based model (ABM).
Step 5: If more than one order (O) are the Least and the Same Inventory Levels (LSI), replenish them alternatively based on (AT) provided by ABM.
Step 6: If there is no (AT) for (O), check (until) (ST) is less than (AT), [S < AT].
6.1 For [S < AT], replenish Order Unit (Ou) until [S < AT] < (Ou), Else, wait for (AT) the next day.
Step 7: If an order (O) has the least (LI), make its replenishment priority and replenish to meet next order level based on available time (AT) provided by ABM. Do 6.1.
Step 8: If an order (O) meets maximum inventory level, then stop replenishment.
Stop 9: Stop/ Repeat next day.

SYSTEM DEVELOPMENT

Data Collection and System Interaction

Real life simulation data was collected from OEM manufacturing as well as the simulation criteria and parameters. The ABM system was developed using Excel VBA to program and represent the three identified agents. The agents were: Order, Machine, and Operator. These three agents interact within the system environment to execute system rules and strategy. The relationship is shown in Figure 4 below.

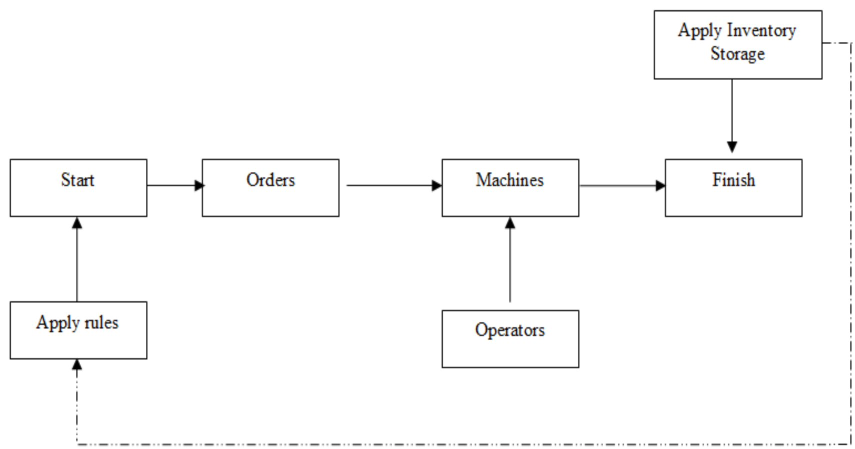

Figure 4. ABM System Interaction.

Figure 4, at the start of the production cycle which was triggered by the order request, the orders related directly with the machine as assigned by the production schedule. Likewise, operators related directly with the machine, as they have been allocated to jobs. At the machine station, orders were processed and completed. However, for uncompleted orders the proposed heuristic algorithm was applied for inventory support. The same rules re-occured at the start of the next production cycle with information of any order borrow from the inventory requiring replenishment.

Simulation System

The developed ABM simulation system environment presented in (Figure 5) shows a visualized operation of the system. It reveals in real-time the states of the individual agents while the system is in operation.

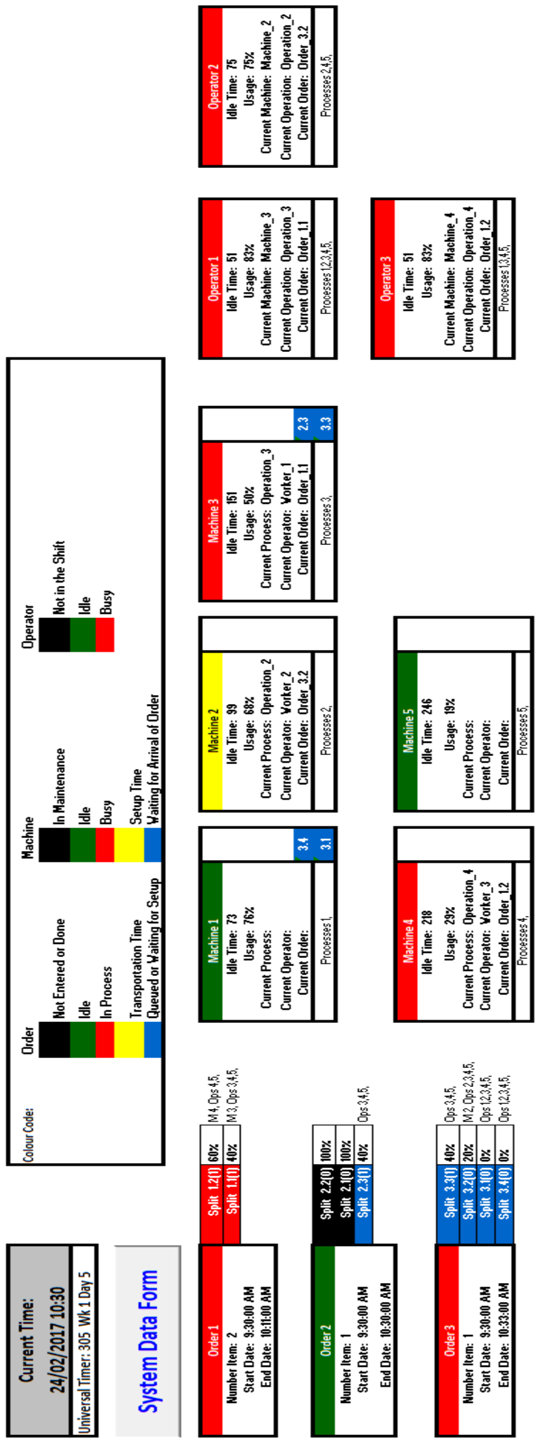

Figure 5. ABM simulation environment.

In Figure 5, the order, machine and operator status changed with activities within the system environment. The interface provided important information about the order processing progress, processing and idle time, number of queues, completion status and the resources utilization, which collectively formed key results for the system analysis of the production disruption problem.

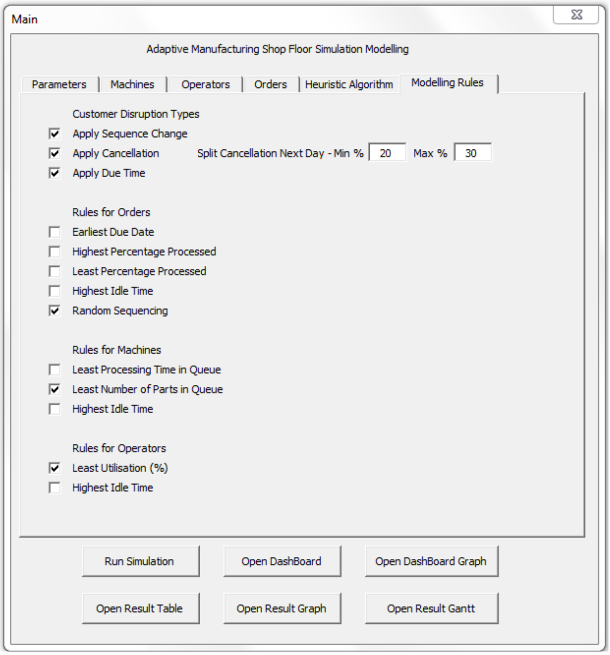

Figure 6. System modelling rules tab.

Figure 6 we shows a tab in the system user form with a set of modeling rules and disruption types used in the experiment.

Agent rules were applied during the simulation experiment to determine the key performance indicators (KPI) that were crucial for analysis and decision-making. The customer disruption types checkbox allowed the system to combine different disruption scenarios to further understand the system behavior in a more in-depth mode. The user form also consisted of other tabs such as the input parameter tab where the number of machines, orders, operators, operations, number of simulation runs, and production time period allowed on the flow-shop were defined. In the machine tab the individual machine was assigned to process, and process times were randomly generated for the machine. The user form also contained the operator tab, where operators were assigned to machines and generated operator-specific machine setup time for each order type. Also, in the order tab orders were given production routes based on customer order information. In this tab, each order

Finally, the heuristic algorithm tab provided opportunity to either apply or not the heuristic and the replenishment strategy to determine the consequences of either option. Some of the relevant functionalities of the ABM approach which were implemented in the model were that it allowed orders to be assigned to the machine and operators to be assigned to the machine with individual agent attributes and behavior.

In the proposed system experiment, we set the order process time and machine setup time based on random distribution fitted from real life data. Using the actual data for order quantity, we proportioned each order quantity with the daily production cycle to give the system flexibility and avoid unrealistic numbers. The simulation environment in Figure 6 was incorporated and run within the Microsoft Excel spreadsheet. This made it user-friendly and could be easily accessible as one of the main software packages in the industry.

RESULTS AND DISCUSSIONS

The input data collected from the real life system was used for the system experiment, and the system was run for 3 disruption scenarios; 1 for change in sequence, 1 for cancellation and 1 for the combination of both, with varying delivery due time. The implementation of the proposed approach was recorded for the scenarios to observe the impact. The results presented were for the production period shown in Table 1. This period was represented in the inventory level result, borrowed order and replenishment behavior. However, for the purpose of illustration, only the results table for 1 day of the week is presented.

Table 1

Production Period

Observation period	**Daily production cycle**
4 weeks (20 days)	8 hours (09:00 – 17:00)

Disruption 1. Change in Sequence

The sequence change occured when the customer's assembly line sequence changed due to the uncertainties experienced. In Table 2, the sequence of the initial order splits were changed and the new sequence of orders were processed for dispatch.

From the system-generated result table, out the 7 order splits, only 4 order splits were successfully completed with their corresponding production information such as the processing and idle time, number of orders completed and not completed, and planned start and end time of each order split. It can be observed that the 3 uncompleted order splits do not have the left end date because they never left the system. The consequences of change in the sequence disruption in the inventory showed a steady decrease as shown in Figure 7. As the number of uncompleted order splits increased, more orders were required from the inventory to support production. The situation continued over a period of 20 days, in which the trend continued to decline. On day 11, the inventory level of order 3 was reduced to zero. This meant no more inventory to support production and hence, inability to satisfy customer demand. This resulted in a number of late orders and production backlogs (see Table 2 and Figure 7).

Disruption 2. Order Cancellation

The order cancellation disruption occurs when a customer decides to cancel order(s) that have been initially requested. In the observed experiment, cancellation created available process time through a reduced number of setups and processing time. The inventory level of the cancelled order remained unchanged over the period of which order type was cancelled. For instance, in Figure 8, order 2 and 3 remain unchanged during the cancellation period. On the day illustrated in the Table 3, one split each of order 1 and 3 underwent cancellation, creating chances for some borrow order to be replenished.

It can also be observed that only 1 order unit could not be completed on that day, which was relatively low compared to Table 2 of the change in sequence disruption with 3 orders requiring inventory support. However, the trend in the inventory level for order cancellation was expected to drop as no replenishment strategy was applied for borrowed order (see Table 3 and Figure 8).

Disruption 3. Combined Disruptions

We combined the two disruptions to test the consequences on the production and the effect on inventory level. This was also used to determine the

Table 2

Disruption 1 Results

Week 1 - Day 4

Order	Initial Number of Items	Disruption	Number Items	Items Completed	Items Not Completed	Total Time	Processing Time	% Processing Time	Idle Time	% Idle	Planned Start Date	Planned End Date	Entered Start Date	Left End Date	Processes
Order_1.1	10	Order_3.2	10	10	0	206	190	92.23	16	7.77	9:00:00 AM	5:00:00 PM	06/04/2017 09:00	06/04/2017 12:26	1,2,3,4,5,6,7,
Order_3.1	7	Order_3.1	7	7	0	229	133	58.08	96	41.92	9:00:00 AM	5:00:00 PM	06/04/2017 09:00	06/04/2017 12:49	1,2,3,4,5,6,7,
Order_1.2	19	Order_3.3	4	4	0	237	76	32.07	161	67.93	9:00:00 AM	5:00:00 PM	06/04/2017 09:00	06/04/2017 12:57	1,2,3,4,5,6,7,
Order_3.2	10	Order_1.1	10	10	0	374	210	56.15	164	43.85	9:00:00 AM	5:00:00 PM	06/04/2017 09:00	06/04/2017 15:14	1,2,3,4,5,6,7,
Order_2.1	30	Order_2.1	30	0	30	481	340	70.69	141	29.31	9:00:00 AM	5:00:00 PM	06/04/2017 09:00		1,2,3,4,5,6,7,
Order_3.3	4	Order_1.2	19	0	19	481	95	19.75	386	80.25	9:00:00 AM	5:00:00 PM	06/04/2017 09:00		1,2,3,4,5,6,7,
Order_3.4	9	Order_3.4	9	0	9	481	27	5.61	454	94.39	9:00:00 AM	5:00:00 PM	06/04/2017 09:00		1,2,3,4,5,6,7,

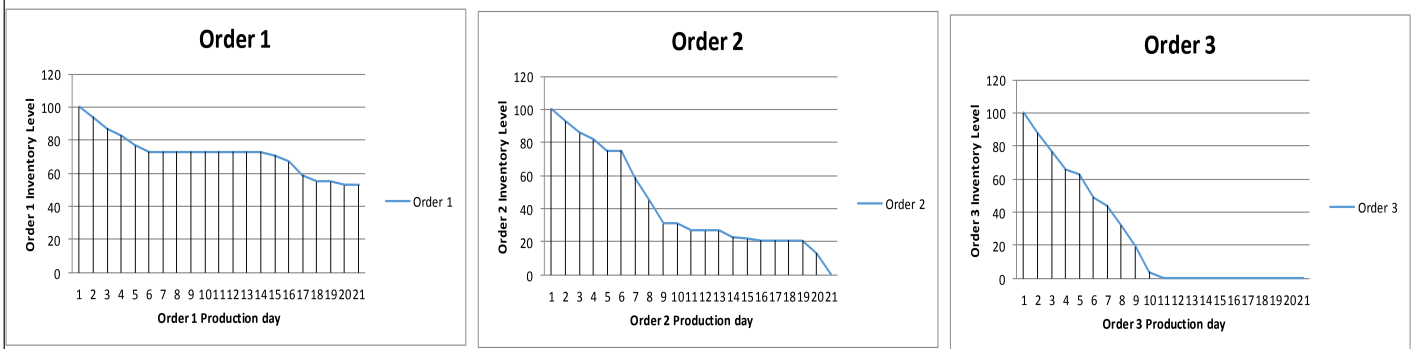

Figure 7. Disruption 1 inventory behavior

Table 3

Disruption 2 Results

Order	Initial Number of Items	Disruption	Number Items	Items Completed	Items Not Completed	Total Time	Processing Time	% Processing Time	Idle Time	% Idle	Planned Start Date	Planned End Date	Entered Start Date	Left End Date	Processes
Order_3.1	6	Order_3.1	17	17	0	337	323	95.85	14	4.15	9:00:00 AM	5:00:00 PM	10/04/2017 09:00	10/04/2017 14:37	1,2,3,4,5,6,7,
Order_2.1	30	Order_2.1	8	8	0	356	160	44.94	196	55.06	9:00:00 AM	5:00:00 PM	10/04/2017 09:00	10/04/2017 14:56	1,2,3,4,5,6,7,
Order_1.1	9	Order_1.1	6	6	0	371	126	33.96	245	66.04	9:00:00 AM	5:00:00 PM	10/04/2017 09:00	10/04/2017 15:11	1,2,3,4,5,6,7,
Order_3.2	9	Order_3.2	3	3	0	380	57	15	323	85	9:00:00 AM	5:00:00 PM	10/04/2017 09:00	10/04/2017 15:20	1,2,3,4,5,6,7,
Order_3.3	1	Order_3.3	1	0	1	481	3	0.83	477	99.17	9:00:00 AM	5:00:00 PM	10/04/2017 09:00		1,2,3,4,5,6,7,
CANCELED															
Order_1.2	20		23												
Order_3.4	14		2												

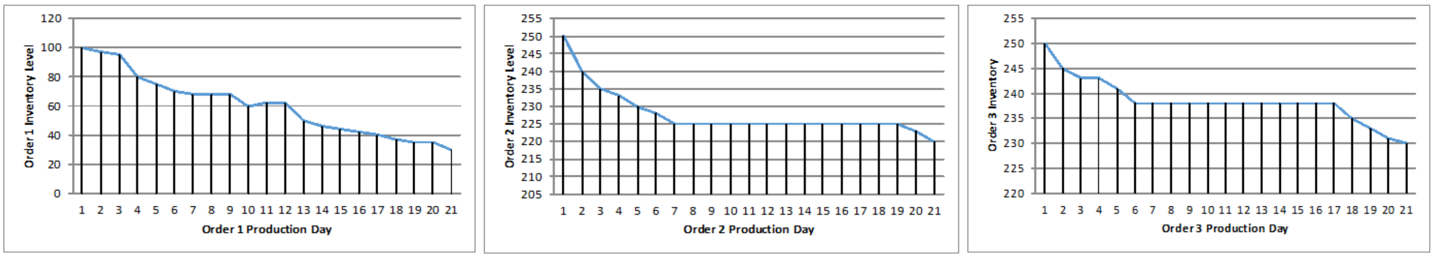

Figure 8. Disruption 2 inventory behavior.

effectiveness of the proposed replenishment strategy. Through the proposed strategy, the system was able to accommodate these disruptions through inventory support and continuous replenishment. The system utilized the saved production time slot achieved through the order cancellation time slot, reduced number of setup from sequence changed, and replenished the inventory. In Table 4 and Table 5, the result of the combined disruptions show 4 order splits cancelled and 2 units of order and 2 splits uncompleted. Over a period of 20 days, the system showned instances of order borrowed from which the system responded through the replenishment strategy. In Figure 10, we observed the impact of the proposed strategy in an attempt to maintain the inventory to the maximum while production was being supported.

Combined Disruptions with Replenishment Strategy

The impact of the proposed heuristic algorithm and replenishment strategy is evident as shown in Figure 10. The levels of inventory of all order types appeared to respond to the different types on the flow-shop in accordance to the proposed strategy of gradually and continuously replenishing the inventory and keeping the inventory at the maximum level based on the inventory control conditions. Orders 2 and 3 showed this responsiveness by gradually maintaining the optimal level even with instances of order borrowing due to disruptions.

In this experiment, order 1 was managed at the maximum level expect for two instances of inventory and immediate replenishment as shown in Figure 10. This was due to the fact that only two instances of shortage were recorded for order 1 and hence, required no inventory borrow. Based on the system generated results of the application of the proposed replenishment strategy, the inventory level was consistently replenished; borrowed orders were considerably replenished utilising production available time; disruptions were clearly managed through inventory support and replenishment while customer orders were satisfied.

Table 4

Combined Disruption

Week 1 - Day 2

Order	Initial Number of Items	Disruption	Number Items	ns Comple	Items Not Completed	Total Time	Processing Time	% Processing Time	Idle Time	% Idle	Planned Start Date	Planned End Date	Entered Start Date	Left End Date	Processes
Order_3.1	20	Order_3.1	20	20	0	397	380	95.72	17	4.28	9:00:00 AM	5:00:00 PM	04/04/2017 09:00	04/04/2017 15:37	1,2,3,4,5,6,7,
Order_3.2	5	Order_3.2	5	0	5	481	70	14.55	411	85.45	9:00:00 AM	5:00:00 PM	04/04/2017 09:00		1,2,3,4,5,6,7,
Order_1.2	5	Order_2.3	8	0	8	481	60	12.47	421	87.53	9:00:00 AM	5:00:00 PM	04/04/2017 09:00		1,2,3,4,5,6,7,
Order_2.2	11	Order_1.3	11	0	11	481	55	11.43	426	88.57	9:00:00 AM	3:00:00 PM	04/04/2017 09:00		1,2,3,4,5,6,7,
Order_3.3	5	Order_3.3	5	0	5	481	15	3.12	466	96.88	9:00:00 AM	5:00:00 PM	04/04/2017 09:00		1,2,3,4,5,6,7,
Order_2.3	8	Order_1.2	5	0	5	481	25	5.2	456	94.8	9:00:00 AM	3:00:00 PM	04/04/2017 09:00		1,2,3,4,5,6,7,
Order_1.3	11	Order_2.2	11	0	11	481	55	11.43	426	88.57	9:00:00 AM	5:00:00 PM	04/04/2017 09:00		1,2,3,4,5,6,7,
CANCELED															
Order_1.1	13		13												
Order_2.1	11		11												

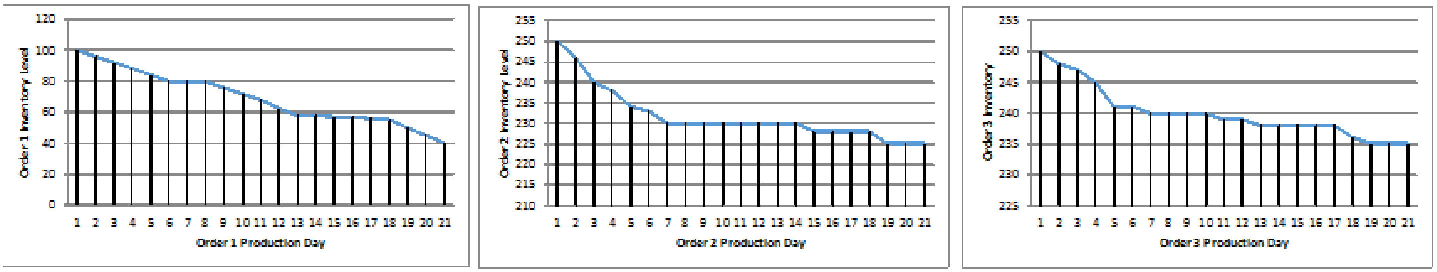

Figure 9. Combined disruption inventory behavior.

Table 5

Proposed Strategy Result Table

Order	Number o	Disruption	umber Items	Comple	Not Comp	Total Time	ocessing Ti	ocessing T	Idle Time	% Idle	Planned Start Date	Planned End Date	Entered Start Date	Left End Date	Processes
Order_1.1	3	Order_2.2	3	3	0	33	24	72.73	9	27.27	9:00:00 AM	5:00:00 PM	28/04/2017 09:00	28/04/2017 09:33	1,2,3,
Order_3.1	20	Order_3.1	5	5	0	72	50	69.44	22	30.56	9:00:00 AM	5:00:00 PM	28/04/2017 09:00	28/04/2017 10:12	1,2,3,
Order_2.1	13	Order_2.1	23	23	0	222	184	82.88	38	17.12	9:00:00 AM	5:00:00 PM	28/04/2017 09:00	28/04/2017 12:42	1,2,3,
Order_2.2	18	Order_1.1	20	20	0	451	240	53.22	211	46.78	9:00:00 AM	5:00:00 PM	28/04/2017 09:00	28/04/2017 16:31	1,2,3,
Order_2.3	1	Order_2.3	2	0	2	481	10	2.29	470	97.71	9:00:00 AM	5:00:00 PM	28/04/2017 09:00		1,2,3,
CANCELED															
Order_3.2	8		12												
Order_1.2	29		20												
Order_3.3	9		10												
Order_2.4	4		2												

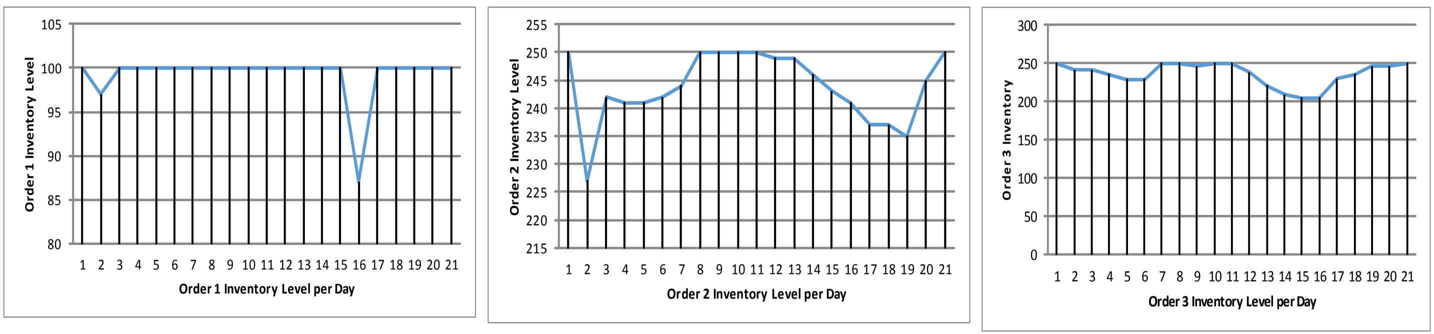

Figure 10. The proposed strategy inventory behavior.

CONCLUSION AND RECOMMENDATIONS

This paper presents the results of the integrated approach which involved the use ABM technique and heuristic algorithm application as well as the inventory replenishment strategy for the flow-shop production scheduling process in the OEM manufacturing industry. The system was developed to investigate customer-imposed production disruption problems. This was to determine the impact and consequences of the proposed change, without affecting production and inventory. The system was also able to determine resources utilization, production performance and inventory control under different combinations of disruptions. This enhances the ability to adapt and manage the system, accommodate disruption, and encourage better decisions in terms of production scheduling and operation, which eventually improves the delivery of the right quantity of finished orders in a timely manner, irrespective of disruptions. Through the experimental application of the proposed system in this ongoing research, the following significant improvements were achieved:

- At the end of every production process, 100 % inventory level was achieved
- Even though there was a number of shortage of orders, no impact of it was experienced in the delivery as production was constantly supported by inventory which was continuously being replenished
- The inventory level was maintained at the maximum for much longer days.

This research and the developed integrated system have improved the understanding of several entities of inter-relationship within the OEM manufacturing plant. The process of building the system and studying the interaction of the system entities of a real-life factory environment have given an insight into the operational specifics of the OEM manufacturing system, especially in dealing with disruption problems. The adopted approaches in the development of the system and its analysis as well as the problem domains have not only exposed significant opportunities for further research exploitations, but have also been useful to scheduling managesr since they offer an exhaustive understanding on the actual system behavior instead of the expected behavior of the system. Ultimately, the platform provided in this work is a solution for tackling related problems or a useful tool to embark on modified problem areas. As for further developments, the problem related to the change in the production and delivery due time ought to be focused and specifically explored using the developed heuristic and replenishment strategy. As a matter of further justification, the proposed solution can be compared with results of other traditional and current means of dealing with such problems in the manufacturing flow-shop. Likewise, more factors such as machine breakdown and cost factor can be included in more details to determine the possible impact on the proposed system.

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