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A multi-objective approach for resilience-based system design optimisation of complex manufacturing systems

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Abstract

Disruptive events in complex manufacturing systems (CMS), characterised by labour-intensive processes and repetitive activities, render these systems vulnerable. In order to tackle this challenge, an approach for resilience-based system design optimisation is proposed. The approach: (i) introduces a dynamic multi-dimensional resilience metric; and (ii) formulates the resilience as a multi-objective optimisation problem to improve CMSs resilience by finding an optimal human resource allocation model, considering design factors including redundancy, resources capacity and roles. The case study, selected to test the validity of the presented approach, show improvement in resilience and efficiency, in terms of throughput, resources utilisation and restoration time.

Keywords: Resilience design; complex manufacturing systems; dynamic multi-dimensional resilience; multi-objective optimisation; resource planning

1. Introduction

Designing complex manufacturing systems (CMSs) has raised significant attention in our modern society over the last decades [1]. This ever-growing interest raises the necessity of understanding and handling the complexity of these systems, which may become vulnerable in case of disruptions. In the context of CMSs, the propagation of effects due to disruptive events may be rapid and catastrophic and typically lead to production delays or even partial or full production losses. CMSs' complexity is characterised by parallel interactions between activities due to multiple sub-systems operating simultaneously, time-dependency, diversity, repeating manufacturing modules in multiple sub-systems and complications in the physical structure of (sub)-systems [1][2].

In order to develop practices for prompt response and efficient handling of unwanted events, the resilience of systems is being studied over the past few years. Hollnagel [3] defines resilience as an: "*intrinsic ability of a system to adjust its functioning prior to, during, or following changes and disturbances, so that it can sustain required operations under both expected and unexpected conditions*". Analysing design parameters to determine how to optimally respond to disruptive in CMSs is a rich area for academic research. Thus, this paper addresses the following research question: "How to optimise the dynamic resilience in CMSs under multiple simultaneous disruptions through changes to the system design, by finding the most efficient combination of resources allocation?". This study contributes to knowledge by: (i) proposing a dynamic multi-dimensional resilience metric, considering system *throughput*, *resource utilisation* and *lead times*, to gain fundamental understanding on how to evaluate disruptions in CMSs; and (ii) formulating the resilience as a multi-objective optimisation (MOO) problem to enhance systems' resilience proposing changes to the system design. The MOO finds an optimal resources allocation model, considering design factors including redundancy levels and resources capacity and roles.

2. Concept of system resilience

Resilience, typically defined at the system level, is viewed in Fig. 1 (adapted from [4]) as a system resilience curve (SRC).

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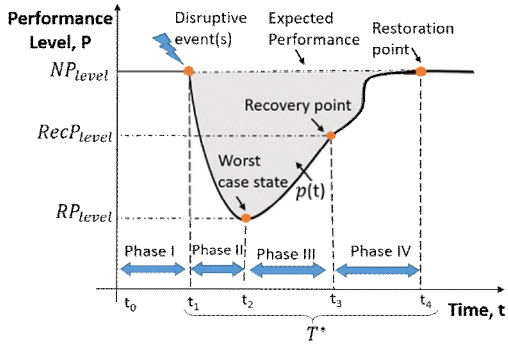

Fig. 1: System resilience curve before, during and after a disruptive event

The SCR shows how the performance levels change over time before, during and after the occurrence of a disruptive event. The system is assumed to operate at a steady-state performance level (NP_{level}) until the occurrence of the disruptive event at t_0 (*Phase I* – normal operation). In *Phase II* (shock and response), the time that covers the period since the disruptive event occurs at t_1 until the worst case performance level of the system reached at t_2, shows the time required for the system to act for mitigating and absorbing the impact of the event (robustness). The worst case performance level at t_1 is expected to be greater or equal to the robustness performance level (RP_{level}) before any recovery action is conducted. Recovery actions are applied to the system in *Phase III* (recovery) until some minimal acceptable recovery performance level ($RecP_{level}$) has been obtained (t_3). This is an intermediate performance level at which some high-priority functionalities of the system have been recovered. In *Phase IV* (performance restoration), the system's restoration completion at t_4, shows the time required for the system to be fully restored and return to steady-state operating conditions at the nominal performance level (NP_{level}). After Phase IV, the system may learn from the disruptive event and improve its resilience against future events with similar behaviour. Resilience is also related to re*storation time/rapidity (T^*)* that describes the speed at which the system fully restores to a desired performance. Following the SRC, optimising system resilience after the occurrence of disruptive events refers to the development of strategies to respond timely (after t_1) and restore to normal operations (NP_{level}) as quickly and efficiently as possible, i.e., at a minimum T^*, while ensuring efficient usage of resources and redundancy. Robustness and rapidity are the two key elements required in measuring system resilience [4]. In this work, robustness and rapidity are examined in terms of system's throughput and lead times, respectively.

The remainder of the paper is structured as: *Section 3* discusses the literature review, *Section 4* presents the proposed approach, *Section 5* validates the approach through a case study, and *Section 6* provides a conclusion to the paper.

3. Literature review

Several research studies examine resilience across a wide spectrum of systems in the literature. Within the context of supply chains, there exists a considerable body of research that explores the concept of resilience [5]. The focus of the majority of this research has mainly relied on handling external disruptions (i.e., fires, earthquakes, floods, etc.). Meanwhile, the literature on resilience from a manufacturing systems perspective is less consistent. According to [6], a certain number of research studies investigates the resilience in manufacturing systems, developing control policies (scheduling and rescheduling policies, tasks reallocation policy, optimal capacity control and inventory policies) for achieving resilient operations. However, the majority of these policies does not provide generic applicability as redundancy or/and flexibility dimensions are barely considered. This may lead to costly and/or isolated solutions.

Within the context of CMSs, optimisation of resilience by changing design factors can expedite the systems' performance recovery and mitigate unwanted impacts [7]. Thus, recovery activities such as resource allocation are employed to minimise the performance loss and recovery time. There is currently an increase in the number of studies [7]–[11] that attempt to improve systems' resilience by optimally allocating available human and equipment resources. It is observed that the majority of these studies simplify the problem focusing on minimising performance losses without considering recovery time. Although individual attempts have been made providing guidelines on how to enhance the resilience of CMSs by finding optimal resource allocation models, the resilience optimisation is a topic that remains unsolved in the literature.

Overall, a resilient system should be typically designed with the capability to satisfy a set of functional requirements including minimal performance loss, quick recovery and preventing excessive use of resources and constraints such as redundancy and flexibility. However, most research studies propose static models to measure resilience and pay limited attention on resource utilisation and constraints [9]. In order to tackle the aforementioned challenges and gain insights on how to design resilient CMSs, an approach for resilience-based system design optimisation, considering reduction in performance losses and restoration time with limited resources, is proposed.

It is noted that CMSs consist of multiple subsystems able to operate simultaneously. In this work, these subsystems are referred to as manufacturing phases comprising of activities. Performing multiple activities in different phases can lead to parallel interactions. Some of the threads may internally occur in CMSs are unexpected/late deliveries; unexpected orders; quality problems; and inventory-related issues.

4. Conceptual framework: Resilience-based system design optimisation approach

Considering a system under disruptions, it can: (i) continue operating if the performance level is at least equal to the minimum acceptable operating level (RP_{level}); and (ii) fully restore, if the performance level is greater or equal to the nominal performance level (NP_{level}). This process highly depends on the changes made to the system design. This work investigates the optimisation of the continuity and restoration plans for CMSs from the perspective of resilience. Thus, a resilience-based optimisation approach using multi-objective theory is proposed to ensure CMSs' continuity and restoration, by minimising loss of performance and restoration time, and preventing excessive use of resources. A multi-dimensional resilience measure and a resumption-recovery strategy, proposing an optimal resource allocation model, are discussed. The design factors considered for the MOO problem formulation are the amount of resources, and inventory and storage capacities. In this work, multi-layered interdependent CMSs being under the occurrence of simultaneous unexpected deliveries and orders are examined.

4.1. Phase I – DES model development of CMSs

The conceptual framework proposed in this work is viewed in Fig. 2. The framework, studying the occurrence of disruptive events in CMSs, comprises of three phases: (i) a discrete-event simulation (DES) model consisting of three layers, i.e. *activity, object and inventory-resource*; (ii) a resilience assessment in CMSs; and (iii) an optimisation engine which operates in conjunction with the simulation model to find the optimal resources allocation. In phase I, a multi-layered DES model is developed, capturing the static and dynamic behaviours of CMSs. The three layers for the construction of DES model in phase I are outlined as:

- ***Activity layer***: this is the backbone of DES model. In this layer, nodes, representing manufacturing activities, are connected by edges to model the paths of a given phase. Multiple interdependent phases may also be modelled in this layer. Characteristics of these nodes are cycle time, resources per node, capacity and effect on inventory.
- ***Object layer***: this layer includes system's objects such as products, raw materials, orders, deliveries and services. Objects characteristics can be type, rate and quantity.
- ***Inventory-Resource layer***: in this layer information about the inventory and resources (human and equipment) is captured. Characteristics of this layer are storage capacity, storage space availability, stock size, resources quantity, schedule, priority tasks and resources utilisation levels.

The three layers communicate interactively through edges, enabling the structural and behavioural imitation of a CMS. Edges between activity nodes can be sequential, parallel, and/or join and and/or split. Inventory-resource edges are unidirectional ending to activity nodes. An activity node can seize more than one inventory/resource node. Object edges are also unidirectional starting from activity nodes. Finally, edges connecting object nodes can be used to demonstrate a series of sub-components assembling a component.
After modelling the behaviour of a CMS, unexpected events are introduced to the system. As seen from Fig. 2, characteristics of these events may be type, start and end dates to realise the duration of the disruptions and rate.

4.2. Phase II – Resilience assessment in CMSs

After performing multiple simulation runs, the resilience is measured in phase II, employing: (i) the number of processed requests to the total number of received requests, in percentage (throughput); (ii) human and equipment resources utilisation (the ratio of total billable hours to the number of total available

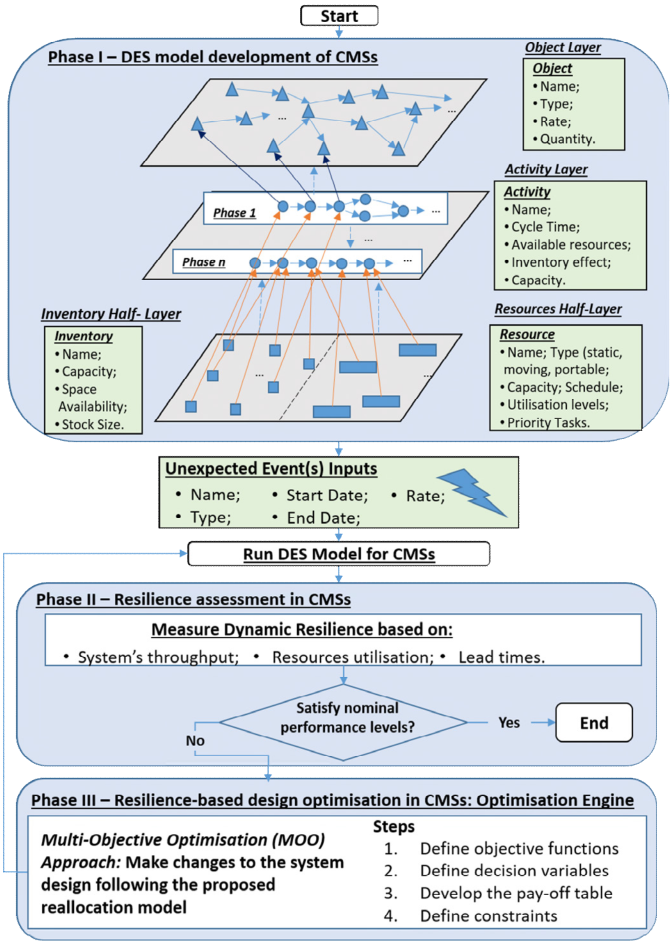

Fig. 2: Framework for measuring and optimising the resilience in CMSs

hours, in percentage); and (iii) restoration time through the lead times of activities. In order to decide if the MOO approach (phase III in Fig. 2) is required, the system resilience is assessed examining if the numbers of daily deliveries and orders are higher than the average.

Once this condition is true, the levels of throughput, resources utilisation and lead times are monitored. The minimum allowable performance levels (RP_{level}) for deliveries and orders are defined at a desired percentage of the total amount of received deliveries and requested orders. Similarly, the maximum allowable resource utilisation level of each human/equipment resource group (RRU_{level}/ $RERU_{level}$) is also defined at a desired percentage of their total working time. With the help of the simulation model, lead times are measured in various parts within the system. If all the aforementioned performance metrics are satisfied, the system is resilient to a given disruption, otherwise a MOO experiment is formulated (phase III in Fig. 2).

4.3. Phase III – Resilience-based design optimisation in CMSs

The philosophy behind the communication between the optimisation engine in phase III and the DES model is as: the optimisation engine suggests design changes to be made to the simulation model in terms of resources in order to improve system's resilience; while after performing these changes, the simulation model is executed to find the improved resilience.

The process is repeated until certain conditions (objective functions, decision variables and requirements), defined by decision-makers, are satisfied. The MOO approach discussed in this work, proposes reallocation of operators within existing groups in order to increase system's flexibility while improving system's throughput, resources utilisation and lead times. In this work, metaheuristics, equally powerful to the classical optimisation algorithms or the stochastic combinatorial optimisation problems [12], are employed. OptQuest™ [13] search engine uses the metaheuristic algorithms of Scatter Search, Tabu Search and Neural Networks, combining them into a single search heuristic. OptQuest™ is used to optimise the resilience of CMSs by generating the Pareto set of MOO problems based on the Weighted Sum Method (WSM).

For the resilience-based design optimisation in CMSs, phase III in Fig. 2, the proposed MOO approach follows four steps:

- The objective functions for the resilience optimisation are defined, in step 1. The objectives are maximising the system's throughput, while minimising both resources utilisation and lead times of assets (restoration time).
- In step 2, decision variables, obtained from the object and inventory-resource layers of DES model, are defined, capturing model's parameters to be optimised. In this work, decision variables refer to the system's resources.
- In step 3, each sub-objective, from step 1, is initially solved as a single-objective problem and then scaled based on the best and worst calculated values (upper and lower bounds for the set of non-dominated solutions). These values are used as requirements in the MOO experiment, giving an indication for the range of values that can be achieved by the non-dominated points. Having defined the lower and upper bounds from the single optimisation problems, it leads to the development of the so called pay-off table.
- In step 4, inventory and storage related constraints for the available assets and spaces in the storage areas are set as: (i) a new order can start only if there exists available at least an asset in the storage or safety storage area; and (ii) a new delivery is accepted only if there is available at least one space in the storage/safety storage area.

After setting the objective functions, decision variables requirements and constraints, the optimisation problem is executed and the optimal resource allocation is generated following heuristic rules. As it is important to simultaneously optimise all the objectives, equal weights for each objective are set, employing the WSM.

5. Validation: case study in a cryogenic warehouse

To demonstrate the validity of the proposed approach to measure and optimise resilience, a CMS at a Cell and Gene Therapy (CGT) cryogenic warehouse, being under simultaneous (beginning at the same moment) disruptive events, is selected. Following the framework in Fig. 2, the system is computationally constructed employing the three-layered DES model (phase I). By the occurrence of disruptive events, performance measures capturing the system resilience are assessed to ensure that certain conditions for the normal operation of the system are satisfied (phase II). Once these conditions are not satisfied, a MOO experiment is carried out to optimise the resilience, by recommending changes to the system design (phase III). In this case study, these changes refer to human resources (HR) reallocation in the shop-floor.

5.1. Cryogenic warehouse: Phase I – DES model development

In this section, the multi-layered DES model (phase I), is developed for the cryogenic warehouse using AnyLogic as:

- ***Activity layer:*** modelling the flow of material and information within the three manufacturing phases of the system: (I) Receipt and Inventory; (II) Storage and Monitoring; and (III) Distribution. The system receives daily a certain amount of: (a) deliveries for storing and monitoring; and (b) orders for distributing cryogenic material to manufacturers and healthcare institutions. The activities execution within the three phases are viewed in the UML Activity diagram in Fig. 3.
- ***Object layer:*** capturing information about the rates of deliveries (12/week) and orders (10/week), and the types of shippers (LN_2) and cryogenic material existing at any time within the system.
- ***Inventory-Resource layer:*** for the development of the *inventory half-layer*, information including the initial stock size of shippers equals to 35 (~ 12% of the storage shippers' capacity) and initial stock size of material equals to 3000 (~ 10% of the storage material capacity) is considered. For the development of the *resource half-layer*, equipment and HRs-related information is required. In terms of *equipment resources*, the company owns 2 trolleys and 4 cryocarts for shippers' transportation, 12 tanks for material storage and pallet racks with total storage capacity of 420 shippers. With regard to *HRs*, the company's working hours is between 8:30am – 17:30pm including a 30-minute lunch break. There exist 6 groups of HRs for: receiving deliveries (2); general tasks (20); shippers filling (4); and for quality checks: QA (4), QC (6), and QP (2). The numbers in the parentheses indicate the amount of operators within each group. Each operator may be trained to carry out multiple activities. The activities in which the operators are trained are: receipt of deliveries (2); receipt of material (9); shipper filling (4); inventory (13); verification (18); and dispatch (12). The numbers in the parentheses show the operators required for each activity.

5.2. Cryogenic warehouse: Phase II – Resilience assessment

After modelling the CGT cryogenic warehouse based on the proposed DES model and performing simulation runs for one year, the system is experiencing unexpected events and thus its resilience is assessed (phase II). The model is running for a ten working day period during which simultaneous unexpected **deliveries** (4 times more than the average daily rates, N_{CD}^{D} = 4*N_{AvgD}^{D}) and **orders** (5 times more than the average daily rates, N_{CD}^{O} = 5*N_{AvgD}^{O}) occur. RP_{level} for deliveries and orders is defined at 75%. However, the analysis of simulation results shows a daily increase in work in progress (WIP) by 100%.

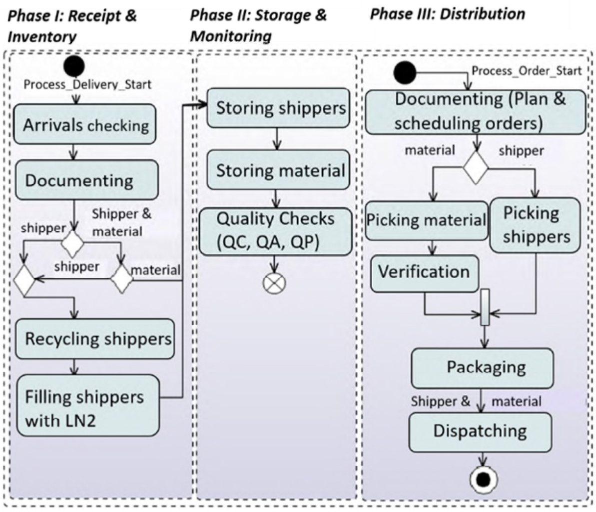

Fig. 3: Case study: UML activity diagram for a cryogenic warehouse

It is also found that once the number of deliveries increases, the **utilisation** of the operators trained in shipper filling (SF) increases at 96%, 16% higher than the robustness level (RU_{level} = 80%). Similarly, the **lead times** for picking and dispatching shippers, at Phase III, increase by 132% and 261% respectively. These activities take longer than normal due to operator's unavailability. From these results, it is seen that the nominal performance levels, as explained in step 4 in Fig. 2, are not satisfied, and hence, the MOO method for resources reallocation is required to improve the system's resilience.

5.3. Cryogenic warehouse: Phase III – Resilience-based design optimisation

For the formulation of resilience optimisation for the cryogenic warehouse (phase III), three objective functions, namely maximising the amount of accepted deliveries and completed orders, minimising the utilisation of SF operators and minimising the lead times for picking and dispatching shippers, are examined (step 1). The decision variables are defined ensuring that the number of operators remains constant and equal to the current number (step 2), as the company has no intention to recruit more operators. For the optimisation process, the upper and lower bounds for the set of non-dominated solutions are found by soling each objective individually. The best and worst values which define the requirements are then used to create the pay-off table (step 3). Due to space constraints the pay-off table is omitted. In step 4, constraints for the inventory capacity and storage spaces are defined. Thus, before an order initiation, if the inventory stock size is greater than zero, then there are available at least one shipper and one product in the storage area and hence the operator can complete the dispatch. Else, the inventory safety stock size is checked and if there are available at least one shipper and one product in the safety storage area, the operator completes the dispatch. Otherwise, operators complete dispatch once a shipper and a product are available. Similarly, before an asset storing (after receiving delivery), if the storage space availability is greater than zero, then there are available spaces for at least one shipper and one product to the storage area. The operator can store the delivered shipper and product. Else, the safety storage space is checked and if there are available spaces for at least one shipper and one product, the operator stores the delivered shipper and product. Otherwise, the operator performs storage once required space becomes available.

The three single objectives, from step 1, are then combined and solved assuming equal weights (i.e. 1/3) for each objective using the WSM. After setting the prerequisites, the MOO experiment is executed. AnyLogic OptQuest® generates the User Interface, showing the current and best feasible solutions, and the dynamic optimisation progress with respect to the number of iterations. The optimisation results are diagrammatically presented in Fig. 4, illustrating the maximisation of the deliveries and dispatches for 2200 iterations. Optimisation results did not change beyond this number of iterations. Following the results obtained, the optimal values of operators required within each role are: receipt of deliveries (2); receipt of material (4); SF (12); inventory (7); verification (9); and dispatch (5).

The proposed reallocation of operators is then embedded into the simulation model. The model is examined for a ten working day period during which experiencing the disruptions previously considered by employing the new allocation of operators. The simulation results show that the system accepts 90 deliveries and completes 92 orders, while achieving the normal utilisation levels of the operators trained in SF (~63%) within average 25 and 7.5 minutes of picking and dispatching shippers, respectively. All the metrics satisfy the nominal performance measures and hence the system is resilient.

Figures 5-7 demonstrate the average daily resource utilisation of SF operators and lead times for picking and dispatching shippers along simultaneous disruptions that occur at 8:30am for three cases: (i) normal system operation; (ii) system under disruptions with no changes to the system design; and (iii) system under disruptions applying the proposed optimal resource allocation. The variations of simulation results applying the current and the optimal operators' allocation show that the optimal solution allows an increase of 21 deliveries and dispatches while reducing the SF utilisation by 29% (Fig. 5). There is a significant improvement on this utilisation percentage which also results within the company's allowable limits, as the normal performance level is set at 60%, whereas the robustness level at 80%. Similarly, the optimal solution increases the amount of deliveries and dispatches by 11%, while reducing the lead times for picking and dispatching the shippers by 23% and 36% respectively (Fig. 6-7). These latter improvements show that the suggested allocation eliminates delaying tasks and promptly provides sufficient operators once required. Finally, while considering the optimal operators' allocation, it is not observed any change in the resources utilisation and lead times that worsen the system's performance.

It is also seen from the plots that if the system is under disruptions and no action is taken, the HR utilisation and lead times increase and remain at high levels, making the system unable to efficiently handle the disruptions (red line). On the contrary, once the HR reallocation, obtained from the MOO, is applied, a significant drop is observed in these measures (blue line). The results from the optimal HR allocation finally show that in all cases they are close to the performance levels at which the system works under normal operation (green line). Hence, the case study demonstrates that the proposed HR reallocation leads to eliminate the WIP, prevent excessive use of resources and quick recovery, improving efficiently the system's resilience. Thus, the proposed resilience-based design approach can be effectively applied for handling disruptions in a cryogenic warehouse and enable users to evaluate the effectiveness of the proposed resumption-recovery strategy. The outcome of this research shows that the proposed approach has a clear impact on the resilience of CMSs by considering the trade-off between the performance loss, restoration rapidity and HRs utilisation.

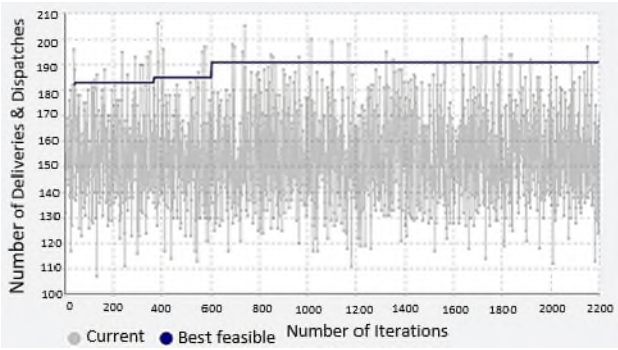

Fig: 4: MOO results - No. of Deliveries & Dispatches vs. No. of Iterations

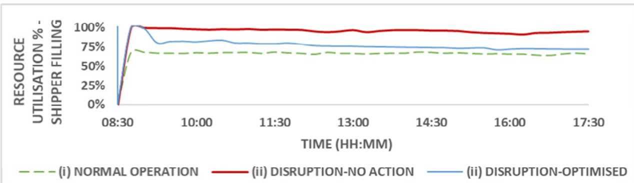

Fig. 5: Resource utilisation of shippers filling operators

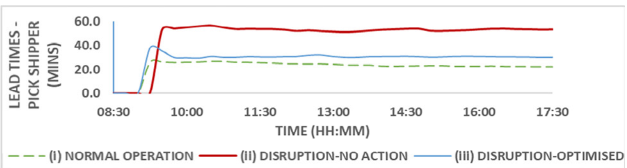

Figure 6: Lead time for picking shippers

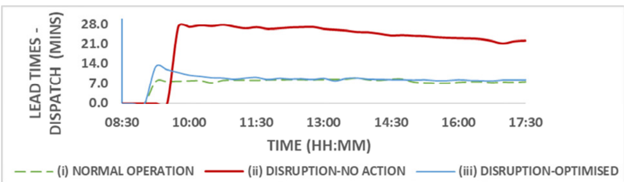

Fig. 7: Lead time for dispatching shippers

6. Conclusions and future work

In this paper, a resilience-based design approach, developed for CMSs being under simultaneous disruptions, is proposed to: (i) measure the resilience via throughput, resources utilisation and lead times; and (ii) assist decision-makers to design a system with optimal resource planning in order to improve the system's resilience (MOO). The contributions of the proposed framework are: introducing a multi-dimensional quantitative resilience metric; considering constrained resources and inventory levels; and examining simultaneous disruptive events, which extend the existing resilience concepts for CMSs that mostly suggest two-dimensional resilience metrics, do not consider the dimension of redundancy and study single disruptions. The proposed approach is demonstrated by its application to an industrial system at a CCT cryogenic warehouse. The results show that, the reallocation of operators at the shop-floor indicated by the proposed MOO method can improve the multi-dimensional system resilience performance. The resilience analysis and recovery capability, capturing the propagation of disruptions in CMSs as well as mitigating their effects, which may be difficult to be predicted due to the dynamic behaviour of these systems, can provide a novel guidance for CMS design. The approach helps CMSs under simultaneous disruptions to become resilient and users to determine the optimal number of assigned operators required on each workstation in a facility. Future work could include the optimisation of resilience in CMSs analysing different scenarios considering each time a different probability of occurrence of a disruptive event, such as optimistic, realistic and pessimistic. The analysis of multiple scenarios can enhance the quality of the proposed approach helping system designers to make informed decisions. Finally, antifragility, which is beyond resilience, is an interesting topic that could be studied in the future extending the current work. The focus should be on understanding how the capacity of CMSs can not only resist disruptive events but benefit from them.

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