Cost and Quality assessment of a Disruptive Reconfigurable Manufacturing System based on MOPSO metaheuristic

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Abstract: Reconfigurable manufacturing system is an active field of research for more than two decades, due to its enhanced efficiency and high throughput. An important aspect of such system is process planning which assigns reconfigurable machines to different operations. This study examines the process planning problem subject to different defects and considers novel optimization criteria based on scrap cost, re-work cost, number of failed and conforming units produced by a process plan. A multi-objective model has been developed to optimize the total cost and the quality decay index of the process plan. Due to NP hard nature of the problem, a heuristic called multi-objective particle swarm optimization has been implemented and a numerical example has been analyzed. The results will help decision makers in understanding the impact of quality on process plan selection and a trade-off between different components of the proposed model.

Keywords: Reconfigurable manufacturing system, cost, quality, disruption, MOPSO.

1. INTRODUCTION

Enormous challenges are faced by modern manufacturing systems in the form of product variety, cost effectiveness and responsiveness. The traditional manufacturing systems are unable to cope with these challenges more effectively. For example, though the dedicated manufacturing line (DML) provides high throughput, it lacks in adjusting for product variety (Koren 2006). On the other hand, the flexible manufacturing system (FMS) responds well to the issue of product variety, however, it requires high initial investment and offers a level of flexibility which is not always needed (ElMaraghy 2005). These challenges have been addressed through Reconfigurable Manufacturing System (RMS) which is designed at its outset for responding to product dynamics, using its functionality and capacity, as per the requirements (Koren et al. 1999).

The increased competition in product market has caused more varieties and shorter product life cycle which is expected to impact the product quality. An effective assessment of quality related issues is imperative for a production system to perform smoothly (Elmaraghy, Nada and ElMaraghy 2008). One of the challenges in RMS is to assess the quality of products and processes. Unlike the traditional manufacturing systems, quality is more difficult to assess in RMS due to its complex structure. According to Koren et al. (2018), RMS offers a large number of production routes due to which two quality related problems are anticipated. One, the variation in product dimensional quality increases and second, if there is a problematic machine, it is hard to identify and trace it merely by inspecting the quality of end product. The literature shows that, among other aspects, the analysis of quality is missing in the design of RMS. On the other hand, FMS contains the analysis of quality; however, a more concrete and quantitative measure of quality is missing in it as well.

This study presents the process planning approach and an important aspect of the analysis is to consider an imperfect RMS system i.e., a system prone to defects and quality related concerns. These defects can stem from multiple sources such as, machine disruption, failure of quality characteristics and tolerance related problems. In order to consider the effect of defects on the process plan, two objectives, i.e., minimization of the total cost and minimization of the quality decay index are analyzed. The total cost comprises of costs related to production, machine usage, scrap and re-work. A novel index of quality decay has been defined in terms of failed operation units, number of machines and conforming operation units.

The rest of the study is organized as follows. Section 2 provides a brief state of the art regarding the choice of objective functions in concerned literature. Section 3 contains the problem statement and mathematical model whereas Section 4 outlines the solution approach. Section 5 provides the main findings and lastly, Section 6 concludes the study and provides future research perspectives.

2. STATE OF THE ART

Since the current study offers novel multi-objective criteria to analyze the cost and quality, hence, the review is presented with respect to existing focus on cost and quality. Furthermore, although cost has been analyzed more often in RMS process planning, there is a dearth of literature focusing on the quality aspects in RMS. On the other hand, FMS, being a production system closer to RMS (in terms of flexibility and responsiveness), offers several studies focusing on the quality aspects. Thus, portion of this section presents the literature analysis of cost in RMS and the remaining portion presents the literature analysis of quality in FMS.

Azab and Elmaraghy (2007) presented a 0-1 based integer model to analyse the reconfigurable process planning problem.

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Beside other objectives, the model was used to optimize the system cost to support the changes posed by a product family. Chaube et al. (2012) used an adapted version of non-sorting genetic algorithm (NSGA-II) to optimize the cost and time of RMS process plan. The components of cost were primarily based on reconfiguration cost, tool changeover cost and transportation cost. Musharavati and Hamouda (2012) used the simulated annealing (SA) algorithm and its variants, to optimize the operating cost and system throughput of RMS process plan, by proposing a joint function of operating cost per throughput. Goyal et al. (2012) defined several criteria, including cost, to optimize the performance of RMS. The cost was defined in terms of machine exploitation and NSGA-II was used to attain non-dominated solutions which were subsequently ranked.

Benderbal et al. (2018) studied modularity in process planning and analysed the system cost, besides system modularity and time. The cost data related to tools, basic and auxiliary modules, machines and their subsequent configurations were taken into account to analyse the system cost. Moghaddam et al. (2019) designed a scalable RMS for part family. An integer programming model was presented to minimize the system design cost while fulfilling the required level of demand. More recently, Touzout and Benyoucef (2019) used three hybrid meta-heuristics to solve the process planning problem by considering the objectives of cost and time. The components of cost included the processing and reconfiguration costs.

It can be argued that, the existing literature on process planning focuses on the aspects of cost and time. A microscopic view of different cost components shows that, components such as, production cost and reconfiguration cost have been analyzed; however, none of the existing models have considered scrap and re-work costs due to different defects. Furthermore, the analysis of quality is an important aspect of any production system, however, the current process planning literature does not take it into account. As stated earlier, the FMS literature contains different studies focusing on the aspect of quality and in the following, we provide renowned contributions related to the analysis of quality in FMS.

Hsu and Tapiero (1989) introduced the process quality control for FMS using Open Queueing Network (OQN) and considered cost components related to inspection, scrap, post-sale failures and waiting. An important assumption of the analysis was that all of the defective items were scrapped and hence, the re-work of such items was not considered. A fuzzy multi-objective approach was presented by Karsak and Kuzgunkaya (2002) to assist in the selection of FMS. The considered objectives were optimization of costs related to labour, scrap, capital and maintenance, reduction in work-in-process, increasing market response and improving quality. Importantly, the objective of quality was defined in terms of a qualitative measure, i.e., weak, fair and good quality.

Li and Huang (2007) analysed the probability of good parts in FMS by using Markov Model. The results suggested that the probability of good part production is independent of number of products. Furthermore, it offered an estimate only for good part production and did not emphasize on the failed/scrapped parts. Wang et al. (2010) studied the quality of FMS system with batch production and used the Markov chain based analytical approach to analyse the sequence of production under different assumptions. More recently, Souier et al. (2019) studied the real-time part routing problem in FMS and proposed the objectives of workload balancing and reliability, under the constraint of maintenance. The objective of reliability was modelled in terms of importance of work station, remaining set-up time and reliability of work station. The study, however, did not quantify the number of failed units due to the reliability issues or costs related to the sub-optimal performance of the system.

To summarize, numerous contributions have been offered to RMS process planning literature, however, it still lacks in analysing the quality of production. In almost all of the studies, a perfectly working RMS has been considered without acknowledging decay in the performance of production system. It is more difficult to assess the quality of production in RMS, as it offers multiple routes to process the same product and each route can have a different impact on the quality of product. On the other hand, although quality has been well analysed in FMS literature, yet it has either been defined in terms of cost or in terms of a qualitative/vague measure (i.e., weak/fair/good quality or probability of good parts). From managerial viewpoint, it is beneficial to know the quantitative impact of different defects on quality, such as, the number of conforming and failed units. Furthermore, in both RMS and FMS, a joint investigation of cost and quality, leading to the discussion on their trade-off and convergence, is missing. Integrating the notion of quality in process planning will help in selecting those configurations which can ensure an improved quality, besides minimizing cost and other efforts.

3. PROBLEM STATEMENT AND MODEL

A set of operations p is to be performed in a disruptive RMS using the available number of machine triplets i ($i \in$ I) such that, a triplet is the combination of machine, its respective configuration and tool(s). The considered defects can be analyzed at the macro and micro levels and these can be explained with the help of Fig. 1. The macro level defect is caused at the level of machine due to poor maintenance. A machine triplet i can produce good quality operation units with capacity (CAP_{ip}), however, due to in-adequate maintenance, it starts disrupting. Thus, its capacity can be divided into an in-control and out-of-control states.

The production capacity in the control state is of good quality (FP_{ip}) while the out of control capacity is of varying quality levels, due to the probability of machine disruption (λ_i). Part of this capacity is failed ($\lambda_i NFP_{ip}$) and it is discarded whereas remaining capacity ((1- λ_i)NFP_{ip}) is sent for inspection. The cost of inspection is negligible and the units are subsequently processed for re-work. An error of type I is committed here as portion of the inspected units are of considerable quality even then they are re-worked. This error can be attributed to human negligence and miss-judgement.

On the other hand, the micro-level defect is caused at the level of tool due to finishing, contouring, milling etc. Each operation is designated by quality characteristic k and failure occurs when k acquires defect at the level of tool. The circles and diamonds in Fig. 1 respectively represent the conforming and failed operation units at the end of the process plan.

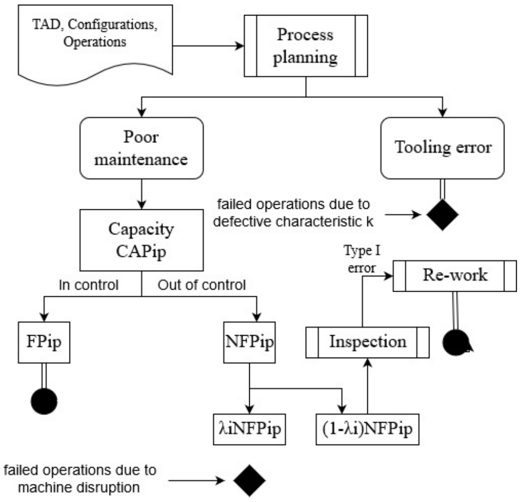

Fig. 1. Nature of the considered defects

The objectives of total cost (TC) and quality decay index (QDI) are to be minimized by respecting the process plan and imposed constraints. The detailed model is presented below:

Indexes

i, i' index for machine triplets; $i, i' = \{1,2 \ldots I\}$

p, p' index for operation; $p, p' = \{1, 2 \ldots P\}$

k index for quality characteristic; $k = \{1, 2 \ldots K\}$

Parameters

fr_{ik} failure rate of quality characteristic k on triplet i

n_s number of operation units entering the RMS

xk_{pk} 1, if characteristic k belongs to operation p; else 0

FP_{ip} feasible capacity of triplet i for operation p

NFP_{ip} non-feasible capacity of triplet i for operation p

f_l conforming fraction of non-feasible units passed through inspection

$1\text{-}f_l$ non-conforming fraction of non-feasible units passed through inspection

rwc_p re-work cost of conforming non-feasible op p

rnc_p re-work cost of non-conforming non-feasible op p

λ_i failure probability due to machine disruption

Ψ probability of type I error due to inspection

mc cost of using a machine

pc_p production cost per unit operation p

sc_p scrap cost per unit failed operation p

d_p required level of demand of operation p

Decision variables

XM_{ip} 1, if triplet i is assigned to operation p; else 0

ω_{ip} number of failed operation units' p on triplet i

NM number of machines required for production

$xo^{i}_{pp'}$ 1, if operations p and p' are performed on i; else 0

P_{nc} number of conforming operation units

QDI quality decay index

TC total cost of the process plan

PC total production cost

SC total scrap cost

RC total re-work cost

3.1. Total Cost (TC)

The first objective is to minimize the total cost in a disruptive RMS. It comprises of production cost (PC), scrap cost (SC) and re-work cost (RC). A process plan is preferred with an overall minimum value of total cost, given by (1) as;

$$TC = PC + SC + RC \qquad (1)$$

The first component in eq. (1) is production cost which encompasses the cost of using a machine and its associated production cost, as given in (2);

$$PC = \sum_{i=1}^{I}\sum_{p=1}^{P}\left(XM_{ip} \times NM \times mc\right) + \sum_{p=1}^{P}\left(n_s \times pc_p\right) \qquad (2)$$

The machine usage cost takes into account the number of machines (NM) required for the entire production. The NM value is calculated as the ratio of demand to production capacity, after discarding the failed units due to machine disruption. Its relationship is provided in (3) as;

$$NM = \frac{\sum_{p=1}^{P} d_p}{\sum_{p=1}^{P}\sum_{i=1}^{I} XM_{ip}\left(FP_{ip} + (1-\lambda_i)NFP_{ip}\right)} \qquad (3)$$

The total scrap cost (SC) is the product of per unit scrap cost and number of failed operation units as illustrated below (4):

$$SC = \sum_{i=1}^{I}\sum_{p=1}^{P} sc_p \times \omega_{ip} \qquad (4)$$

The re-work cost (RC) considers two cost values related to the re-work of conforming (rwc_p) and non-conforming operations (rnc_p), such that $rwc_p < rnc_p$. As part of the conforming units is sent for re-work due to type I inspection error, a probability value of this error (Ψ) has been considered in the calculation of re-work cost, as provided in (5);

$$RC = \sum_{i=1}^{I}\sum_{p=1}^{P} XM_{ip}\begin{pmatrix}[f_1 \times rwc_p \times \Psi + (1-f_1) \times rnc_p] \times \\ (1-\lambda_i)NFP_{ip}\end{pmatrix} \qquad (5)$$

3.2. Quality Decay Index (QDI)

The analysis of quality is an important aspect of any production system as it provides information on the nature of product specifications and their conformance to customer expectations. This study introduces quality decay index (QDI) by integrating failed operation units, conforming operation units and number of machines required for production. As machine exhibits a disruptive profile, less number of machines will ensure an improved quality. The relationship for QDI is provided in (6) and it is the ratio of product of failed operation units and number of machines to conforming operation units. Similar to the cost function, the objective is to minimize QDI either by minimizing the numerator or by maximizing the denominator.

$$QDI = \sum_{i=1}^{I}\sum_{p=1}^{P}\left(\frac{\omega_{ip} \times NM}{P_{nc}}\right) \quad (6)$$

The term of conforming units (P_{nc}) in the above equation is calculated using the relationship provided in (7) as;

$$P_{nc} = \sum_{p=1}^{P}\sum_{i=1}^{I} XM_{ip}\left(FP_{ip} + (1-\lambda_i)NFP_{ip}\right) \quad (7)$$

The defective units are produced due to machine disruption (macro-level defect) and failure of quality characteristic (micro-level defect). The number of failed operations p on machine triplet i is calculated using (8) as;

$$\omega_{ip} = XM_{ip}\begin{pmatrix}\lambda_i NFP_{ip} + \\ n_s \times xk_{pk} \times fr_{ik}\end{pmatrix}; \qquad \forall p = P, \forall i = I \quad (8)$$

The objectives of TC and QDI are to be minimized by respecting the following constraints. Constraint (9) ensures that at a time, one operation is to be performed by a particular machine triplet. Constraint (10) designates an operation to only one machine triplet. Constraints (11) and (12) are respectively demand fulfilment and precedence constraints whereas constraint (13) requires the compatibility of tool approach direction between triplets and operations. Lastly, the non-negativity and binary constraints are provided by (14) and (15) respectively.

$$XM_{ip} + xo^{i}_{pp'} \leq 1; \qquad \forall p,p' = P \;\; \forall i = I \quad (9)$$

$$\sum_{i=1}^{I} XM_{ip} = 1\,; \qquad \forall p = P \quad (10)$$

$$P_{nc} \geq d \quad (11)$$

$$Prec[O_p][O_{p'}] = 1; \qquad p < p' < P \quad (12)$$

$$TAD[m_i] \times TAD[O_p] = 1; \qquad \forall i = I, \forall p = P \quad (13)$$

$$TC,\ PC,\ SC,\ RC, QDI, NM,\ \omega_{ip},\ P_{nc} \geq 0 \quad (14)$$

$$XM_{ip},\ xk_{pk}, xo^{i}_{pp'} \in [0,1] \qquad \forall p,p' = P, \forall i = I \quad (15)$$

Along-with the aforementioned constraints, the following assumptions have been considered for simplifying the problem:

- The production capacity of different machine triplets is pre-defined and it has a fixed (capacitated) value. Moreover, this value is same for all triplets, however, the distribution of capacity into feasible and non-feasible units varies between triplets;
- The probability of machine disruption has the same value for all triplets (λ=λ_i);
- Since each machine is assumed to be in the "out-of-control" state for part of its production which results in non-feasible units, inspection (with negligible cost) is performed on operations after each machine triplet;
- The rate of rejection of conforming units (type I error) is same for all inspection stages.

4. SOLUTION APPROACH

RMS represents the complex class of optimization problems as it is combinatorial and NP-hard. The traditional approaches of branch and bound techniques are not feasible for solving such problems and meta-heuristics are frequently used as solution approaches. We have implemented an adapted version of multi-objective particle swarm optimization (MOPSO), proposed by Coello et al. (2004), to solve the multi-objective problem of TC and QDI. The particle swarm optimization (PSO), proposed by Eberhart and Kennedy (1995), is a single objective based optimization algorithm which is quite popular due to its simplicity, use of relatively less parameters and an equal emphasis on local and global exploration. The PSO is inspired by the behaviour of birds flocking and fish schooling. During implementation, a bird is represented by a particle for single solution and the set of birds is represented by a swarm. The first ever extension of PSO, called MPSO, was proposed by Moore and Chapman (1999), in an unpublished article. Later, Coello et al. (2004) formally introduced the MOPSO, by incorporating the Pareto dominance and a novel mutation operator. An important aspect of MOPSO implementation is the selection of global best position. In this regard, the same roulette wheel mechanism has been used in the current study, as in Coello et al. (2004) and Goyal and Jain (2016), for the selection of global best position (g_{best}) on the basis of crowding distance.

In the field of RMS, Goyal and Jain (2016) used an adapted version of MOPSO to solve the objectives of cost, machine utilization, operational capability and configuration convertibility. The application of MOPSO to current RMS process planning problem, compared to the study of Goyal and Jain (2016), besides the nature of problem, differ in the aspects of mutation, size of search space and refinement (tuning) of input parameters.

During the implementation of MOPSO, due to rapid loss of diversity, a pre-mature convergence issue might arise; hence, it is beneficial to adapt a proper mutation (turbulence) operator. Coello et al. (2004) stated that, due to its high convergence, the algorithm may fall for local optima/false Pareto front. Inspired by this, they introduced a rapidly decreasing mutation operator. Compared to it, Zhan et al. (2009) developed a perturbation based elitist learning strategy (ELS) mutation which uses a Gaussian operator with standard deviation as an elitist learning rate. The ELS offers the advantages of adding more diversity, helps refining the convergence of solutions and it is effective towards global optimal solutions. Thus, due to its enhanced performance, the ELS integrated MOPSO meta-heuristic has been implemented in the current study. Furthermore, in Goyal and Jain (2016), the authors have divided the search space into half, as the number of decision variables were twice compared to the number of operations, due to an isolated information of machines and machine configurations. In our approach, there is no need to divide the search space, as the triplets contain input information of machine and their configurations.

As the parameters of an algorithm are highly sensitive towards changes, hence, Taguchi Design of Experiment (TDE) was used to tune the input parameters of MOPSO. Due to the non-availability of bench mark experiments related to disruptive RMS, a set of hypothetically generated problem instances were tested where a problem instance is defined by i_p (i=triplet, *p*=operation). TDE was executed in Minitab V 19.0 using L_9 factorial design (3 levels of each input parameter) and smaller-the-better signal-to-noise (S/N) ratio.

A typical process plan of RMS is depicted in Table 1 where a set of machine triplets is to be used for certain operations. The process plan involves decision regarding selection of a machine triplet and its assignment to an operation. A matrix of $triplet \times operation\ (M_i \times O_j)$ has been constructed for the encoding process. The non-feasible solutions can cause penalty, hence, to avoid such solutions, continuous variables have been used for encoding (Bensmaine et al. 2013). This helps in attaining feasible solutions only by allocating each cell of the process plan with a value between [0.00-1.00]. At each generation of the algorithm, these values are decoded and rounded off to the nearest integer for selecting the combination of *triplet-operation* to calculate the objective function value.

Table 1. Compatibility between operations and triplets

Op.	O_1	O_2	O_3	O_4	O_5
Triplet	M_1,M_2, M_4,M_6, M_7,M_9	M_3,M_4, M_6,M_8	M_2,M_5, M_7,M_9	M_1,M_3, M_6,M_8, M_{10}	M_2,M_4, M_5,M_7
Op.	O_6	O_7	O_8	O_9	O_{10}
Triplet	M_1,M_2, M_5,M_7, M_{10}	M_1,M_3, M_6,M_8	M_2,M_4, M_5,M_7, M_{10}	M_3,M_5, M_7,M_9	M_1,M_4, M_6,M_8, M_{10}

The process flow is described through Fig. 2. Initially, an operation and triplet are selected and concerning variables, defects and objective function values are calculated upon fulfillment of the compatibility and feasibility constraints. The process is repeated up until all operations are assigned. Then, the complete process plan is provided in the form of a non-dominated solution. The algorithm performs until the stopping criteria is met.

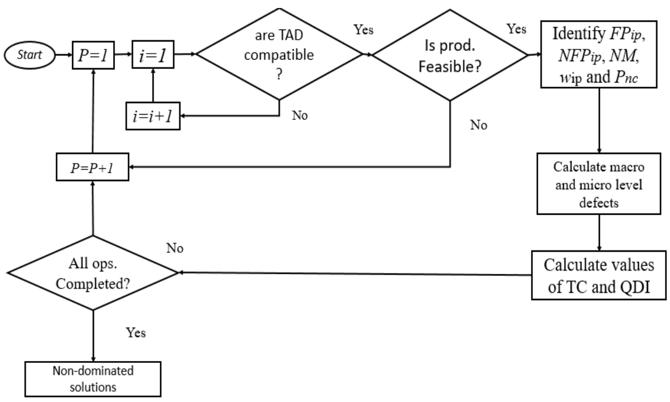

Fig. 2. Illustration of the process flow

5. RESULTS

The algorithm was applied in MATLAB on a computer with specifications Intel Core i5 8th generation, 1.80 GHZ and 8GB RAM. A case study has been used where ten operations (O_1-O_{10}) are to be performed on the available triplets (M_1-M_{10}). The compatibility of operations is given in Table 1 such as, O_1 can be performed by either M_1, M_2, M_4, M_6, M_7 or M_9. The input parameters of the case study are; n_s= 250 units, f_1= 0.3, λ= 0.3, Ψ= 0.3, machine usage cost (mc) varies between \$550-1050 per machine triplet, unit production cost (pc_p) varies between \$7.5-12/op., scrap cost (sc_p)= \$18/op., rwc_p= \$8/op., rnc_p= \$12/op. and d= 250 units (it means that the quantity of each successive operation is equal to 250). The TDE tuned input parameters used by MOPSO are; swarm size = 90, c_1=c_2= 1.5 and maximum number of iterations = 600 while inertia values have been selected as per, maximum intertia = 0.9, minimum intertia = 0.4, according to the suggestion of literature (Singh et al. 2016). Furthermore, the Gaussian operator, defined by (μ,α^2), where μ=mean and α=standard deviation, has been assigned the values of μ=0 and $\alpha_{max} = 1\ and\ \alpha_{min} = 0.1$.

For the experiment, 20 independent runs were performed, using the same termination criteria. The top 10 non-dominated solutions, comprising the objective function values of TC and QDI are presented in Table 2. Clearly, both objectives are in conflict with each other, such as, 3rd solution offers the minimum value of TC equal to \$50800 whereas 9th solution offers the minimum QDI value which is equal to 1.798. If we analyse the inferior objective function values of 3rd and 9th solution respectively, it can be argued that, controlling the value of cost worsens the QDI index and in turn, the quality of production. On the other hand, an optimal quality based solution (s#9) elevates the total cost of process plan. The detailed process plans against minimum TC and minimum QDI based solutions are provided in Table 3. Although the objective functions are conflicting, nonetheless, some level of convergence exists between them. It is due to the fact that TC contains scrap and re-work costs which can be translated into quality. Due to this convergence, some of the operations are performed by same triplets, irrespective of process plan selection on the basis of TC or QDI. For instance, O_3, O_7 and O_8 are respectively performed by M_2, M_6 and M_4 in both cases. Furthermore, the minimum QDI based plan uses 21 machine triplets (NM=21), compared to the minimum TC based plan (NM=24). The lower value of NM in QDI based plan helps in controlling the effect of machine disruption on the quality of production in a process plan.

Table 2. Top 10 non-dominated solutions

S.NO	TC	QDI
1	51870	1.923
2	51972	2.067
3	***50800***	2.575
4	52397	2.375
5	52689	2.996
6	53227	2.138
7	51408	2.934
8	51960	2.418
9	52415	***1.798***
10	53530	2.637

Table 3. detailed plan for min. QDI and TC solutions

Sol.	Operations									
	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9	O_{10}
TC	M_9	M_6	M_2	M_3	M_5	M_5	M_6	M_4	M_7	M_1
QDI	M_2	M_3	M_2	M_6	M_7	M_1	M_6	M_4	M_3	M_6

Another important aspect of the analysis is the failure probability of machine disruption (λ) which potentially affects the decisions such as, number of machines, scrap cost, re-work cost and quality of the process plan. To demonstrate this, the scrap (SC) and re-work (RC) costs of optimal TC based process plan (s#3) were analysed against different input values of probability of machines disruption. The respective results are provided in Fig. 3 which shows a trade-off between scrap and re-work costs subject to different values of probability of machine disruption.

According to the cost based design, a system is more beneficial with maximum re-work and no scrap (i.e., for λ=0) and according to eq. 5, all of the non-feasible units (i.e., NFP_{ip}) are re-worked. However, this is practically an improbable task, as every machine disrupts with the passage of time and with use. In such event, from cost viewpoint, a more sustainable approach is to limit the probability of machine disruption between $0<\lambda \leq 0.3$ to ensure that the combined contribution of SC and RC, towards the total cost value, does not exceed 15%. The combined contribution can be assessed from Fig. 3, by adding the percent contribution of SC and RC at a particular probability value. It is important to control the SC and RC values, as both amount to surplus cost which, from managerial viewpoint, needs to be minimized.

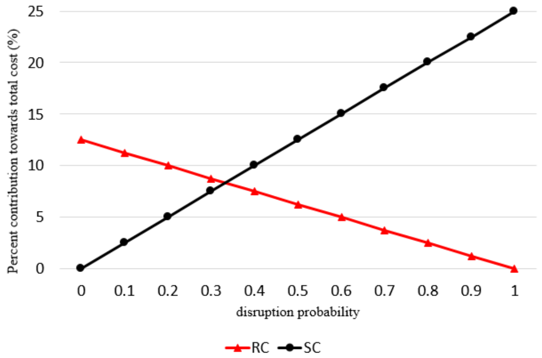

Fig. 3. Effect of change in disruption probability on different costs

6. CONCLUSION AND FUTURE WORK

This study provided the process planning approach in a disruptive RMS. The objective functions of total cost and quality decay index were optimized using MOPSO. The results suggested that quality is an important factor in RMS assessment as it affects the selection of a process plan. Also, it was shown that a convergence existed between the notion of quality and cost. According to the cost based design, a system is better-off with more re-work and less scrap as it warrants a lower cost solution, as much as, a minimum value of total cost is attained when the re-work is maximum with no associated scrap. The results will help the decision makers in assessing the impact of quality on process plan selection in terms of machine assignment, number of machines and different components of cost.

For future, we intend to compare the RMS systems with and without the notion of decay in quality. This will improve our understanding on the role of quality in process plan selection. We will embed a self-adaptation approach for the refinement of input parameters of MOPSO which is a popular technique. Furthermore, currently a deterministic model was considered and as an extension, randomness will be embedded in the mathematical model.

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