Transportation Management (2023) Volume 6
doi:10.24294/tm.v1i3.832

A Simulation Based Optimization Approach to Combine Two Hedging Control Policies in A Transported Degrading Failure-prone Manufacturing System

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ABSTRACT

This paper deals with joint production and corrective maintenance problem of a transported material network failure-prone manufacturing system along which two aspects are supposed. First, each non-identical machine are subject to degradation with failure phenomena. When a failure occurs, system is either repaired or replaced with new one, repairing activity not only degrades machine operating state, but also increases with the next repair time. Second, optimality production control policy called Modified Hedging Point Policy (MHPP) and Modified Hedging Corridor Policy (MHCP) are applied for given network machine. The aim of this article is to find decision variables so as to minimize incurred cost function, including repair costs, stock related costs (i.e., holding costs, backlog and shortage) and setup cost, over an finite-horizon time. Simulation experimental approach with meta-heuristic algorithm is applied to obtain near-optimum decision variables

***Keywords*:** Transported Material Failure-prone Manufacturing System; Simulation; OptQuest; MHCP; MHPP

1. Introduction

In recent years, many articles dealt with failure prone manufacturing systems, along which many uncertainties (i.e. failure and repair rates, demand rate and etc.) have been assumed and described by either homogenous or non-homogenous Markov finite/infinite processes, eventually leads to an optimality production control policy which is described by the HJB equations. In the obtained production policy, a surplus stock level is considered to immune system against shortage/backlog during system down time, this policy often called hedging policies. Hedging concepts (Hedging point policy) originally motivated by Kimemia, Gershwin[1] in a case of one machine- one product system, and extended by many researchers in various manufacturing facilities, that are, M-parallel machines producing one part[2], M-machines producing multiple parts responding constant/random demand rate[3,4]. In spite of all the considerations that have been made to extend the hedging concept to more realistic situations, The vacancy of the deficiency of raw materials has not been taken into account in all above studies, this vital assumption only assumed by Sajadi *et al*.[5] proposing network-FPMS, where m non-identical machine prepare materials to be transported for each downstream machines, leading to produce one commodity at the last machine. In currents paper we extend the proposed concept of FPMS by Sajadi *et al*.[5] to multiple commodity case.

An important aspect of studying each manufacturing systems is consideration of flexibility of machines. In non-flexible manufacturing systems a significant portion of production time is elapsed by set-up activity, In such a case, Elhafsi, Bai[6] obtained a policy, in which, a corridor guides the surplus threshold stock level for setup action, named Hedging corridor policy which was modified by Gharbi *et al*.[7] called MHCP, in contrary to the flexible network machine proposed by Sajadi *et al*.[5] this paper deals with flexible and no-flexible network FPMS, According to the literature considering both flexible and non-flexible machines in an integrated network failure-prone manufacturing system have not be studied yet.

Given the interest of the researchers in this field, they are looking for better hedging value by which system behaves more effectively which might focus on costs, downtime, service level, environmental impact, safety, etc. To be able of controlling the availability of machine is one which guarantees this consideration. In FPMS literature, maintenance activity is the name which is given to this field. Generally, time to failure in such systems is assumed to be random on the basis of well-known probabilistic distribution functions for example, Kenné, Gharbi[2] assumed lognormal, some assumed exponential[8,9] while, some else assumed Weibull distribution[10], As discussed in Ebeling[11] Weibull distribution model is more realistic due to its ability to model various aging classes of life distributions, that are, increasing, constant or decreasing failure rates. The Weibull distribution model is often presented with two parameters: the shape parameter β, and, scale parameter. θ. The scale parameter represents the life (age) of the machine, while the shape parameter characterizes its shape (e.g. $\beta < 1$ represents increasing failure rate). After a machine experienced a large number of breakdowns, repairing costs may become very high, in such a situation, replacing the machine with a new one is more reasonable[12]. In literature two types of replacing strategies has been widely used. First, age-replacement policy, by which machine is replaced whenever the threshold value age X, is achieved[13], and, the block-replacement policy (BRP), by which machine is replaced at predefined period time T,[14,15]. ARP is more popular than BRP, for the sake of incurred cost, for this reason, current paper applied replacing policy according to the threshold age level.

In repairable machines, corrective maintenance operation would be performed either perfect or imperfect, a perfect condition restores machine to as good as new (AGAN) state, while imperfect maintenance just restores machine to as bad as old (ABAO) state, meaning, the failure rate remains at the same value as before repair[16]. In current paper, replacing activity reflects the AGAN strategy, and the repair activity reflects ABAO operation. For FPMS which degrades with age, parameters such as repair time is more reasonable to change with number failures by increasing. In related literature Dehayem Nodem *et al*.[12] considered a non-decreasing arithmetic geometric process which was proposed by Leung[17] to reflect the repair time in their article. The geometric process (GP) has been widely used in reliability engineering, some extensions are: alpha-series processes, threshold geometric process and doubly geometric process where a sequence of non-negative random variables is given (for more information refer to Wu[18]).

Hamilton Jacobi Bellmen equations, are widely used to obtain optimal control policy, for problem with the high dimension, obtaining analytical solution using HJB equations becomes inefficient, for this reason, many methods have been proposed and utilized, for equations in continuous dimension, Kushner, Dupuis[19] proposed numerical methods to solve the HJB equations, for FPMS with high complexity[2] proposed simulation-based experimental approach augmented with response surface methodology to approximate near optimal parameters for joint production and maintenance problem in FPMS. However, in large scale issues, utilizing RSM methodology is not the only solution. In subject of simulation-based optimization approach, some meta-heuristic algorithm such as neural network, scatter search and taboo search becomes more efficient, in market, OPTQUEST software combines mentioned algorithm in a separated single package along with many simulation soft wares, which enables us to optimize large scale problems, in terms of number of decision variables and also the ability of involving mathematical limitations. Many researchers, utilized OPTQUEST, and yielded great results[20-22]. Since current paper deals with large decision variables (nine variable), according to[2] applying RSM becomes time-consuming, And also with regard to the good responses offered by many researchers, optimization procedure is applied on the basis of OPTQUEST package software.

In conclusion, the research gap is that, no work has been carried out a network FPMS, where, each non-identical machine degrades with failure/repair activity. Moreover, contrary to previous studies, this paper considers both flexible and non-flexible in an integrated manufacturing area.

The rest of the paper is as follows: in the next section, industrial context of the problem understudy is provided. In section 3 notation and the problem formulation are provided respectively. An approximation for the production control policy also will be given in the section 4. Simulation-optimization approach in the context of proposed problem will be defined in section 5. A numerical example based on proposed approach is presented in section 6. Finally, section 7 concludes this article and proposes future research opportunity.

2. Industrial context

The study presented in this paper is coincided within many industrial applications, where a network of non-identical flexible machines is positioned so as to prepare multiple products. As stated by Nodem *et al*.[23] there are many engineering systems which their failure can be shown up only by special tests. Filling machines, die-cast machines, grinders, milling, loom machine and many other machining tools are the example of those. They include many sensitive components such as gear box, axis drive components, treadmill, ball screws, spindle heads, water/air jet pump etc. which deteriorate overtime. The main key point of such machines is operable nature of them even though the parts of them are broken up or damaged. Mifdal *et al*.[4] recommended that such a study well matched with a textile company, especially in clothing manufacturing.

This study treated a zipper industrial company, wherein non identical machines including zipper textile fabric weaving (machine 1), zipper chain forming (machine 2), zipper slide head and end stopper (machine 2), assembly machines (machine 3) produce two type of zippers (see **Figure 1**).

3. Notation and problem statement

This section presents the abbreviations, acronyms and notations which have been used to define problem equations.

3.1 Notations

Following notations are used to describe the control model:

$$k \in K = [1, 2, \ldots, n], g \in G = [g1, g2, \ldots, gp], G \subset I$$

MHCP	Modified Hedging Corridor Policy
MHPP	Modified Hedging Point Policy
NFPMS	Network Failure-Prone Manufacturing System
TBF	Time Between Failure
TTR	Time To Repair
$\boldsymbol{M_k}$	Machine *k*
$\boldsymbol{n}$	Number of machines
$\boldsymbol{p}$	Number of commodities (also might see in this article as goods)
$\boldsymbol{B_k}$	Output buffer of product *k*
$\boldsymbol{x_{n-1}(t)}$	stock level of produced parts at intermediate machines
$\boldsymbol{x_n(t)}$	stock level of produced parts at last machine
$\boldsymbol{d_g}$	Demand rate of goods
$\boldsymbol{l_{ik}^k}$	Consumption coefficient of product k from upstream machines denoted by *j* ($j < k$)
$\boldsymbol{u_k(t)}$	Production rate of machine *k* ($\boldsymbol{0 \leq u_k(t) \leq u_k^{max}}$)
$\boldsymbol{n_k(t)}$	Number of failures for machine *k* at time *t* (integer)
$\boldsymbol{a_k(t)}$	Age of machine *k* at time *t* after *n*th failure

$\boldsymbol{TS_g^n}$ Setup time required to switch to good *g*

$\boldsymbol{S_g^n}$ Operation of setup action at machine *n*.

$\boldsymbol{cs_g^n}$ Setup cost to switch to good *g*

$\boldsymbol{c_{rep}^k}$ replacement cost of machine *k*.

$\boldsymbol{c_{cor}^k}$ Corrective maintenance (repair) cost of machine *k*.

$\boldsymbol{c_i^+}$ Inventory cost ($/product/time unit) *i =k*

$\boldsymbol{c_g^-}$ Backlog cost of goods ($/product/time unit)

$\boldsymbol{c_g^{lost}}$ penalty cost of lost sales for goods ($/product/time unit)

$\boldsymbol{\theta_n^k}$ Virtual age of the machine k after the nth repair

$\boldsymbol{\varphi_k}$ Machine age factor of production rate (positive)

$\boldsymbol{q_{\alpha\beta}^k}$ Transition rate of machine from state α to β

$\zeta_k(t)$ $\zeta \in \Omega = \{1,2,3,4\}$ stochastic capacity process of machine *k* at time *t*

$\boldsymbol{Z_{n-1}}$ Inventory threshold level of machine output buffer

$\boldsymbol{Z_g}$ Inventory threshold level of machine output buffer

$\boldsymbol{A_g}$ Setup threshold trigger (for MHCP policy only)

$\boldsymbol{B_g}$ *Necessary* setup threshold trigger (for MHCP policy only)

$\boldsymbol{J}(.)$ cost function

$\boldsymbol{\rho}$ Discount rate

The assumptions on which the mathematical model is presented involve:

1) Unmet demand is either backlogged or missed.
2) Inventory-related costs (i.e. holding, back log) are computed on the mean quantity per unit time ($/unit time).
3) Machines` age increases by production rate.
4) Both customer arrival and its demand rate are assumed to be constant
5) Age-replacement policy applied whenever a threshold level X achieved.
6) Before each replacement, machine needs to be cooled down.

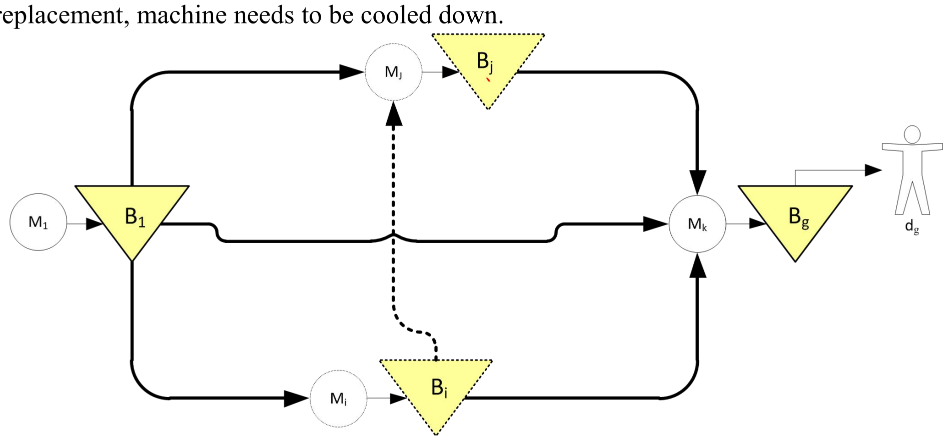


Figure 1; NFPMS problem understudy.

3.2 Problem statement

Figure 1 illustrates the manufacturing system under study, including a network of k non-identical machinery producing two types of commodities. Each machine is fed from its previous output machine. Furthermore, the last machine $M_{k,}$ reflects an assembly machine that turns out two commodities according to predefined consumption rate L_{ii}^{k}.

Lets $u_i(t)$ be the vector of production rate and assume that each machine has a maximal production rate, u_k^{max}, which is neither adjustable, nor depends on kind of product.

$$u_{n-1}^{max} > \sum L_{in-1}^{k}\, u_{n-1}^{max} \quad \forall j < n-1$$

$$u_n^{max} > d_g \quad \forall g \in G \tag{1}$$

Also a set of feasible control policies of process $\zeta_k(t)$ by $K(\alpha)$ would be as follows:

$$K(\alpha) = \{u(t) \in R^n, 0 \le u_k(t) < u_k^{max}, 1 \le k \le n\} \tag{2}$$

The manufacturing system is subject to random events. According to semi-Markov infinite decision process three discrete modes would define system state. Available (starve or operational), denoted by 1; under repair, denoted by 2; under replacement (overhauling), denoted by 3. Then we have $\zeta_k(t) \in \Omega = \{1,2,3\}$. By defining $q_{\alpha\beta}^{k}$ as the transition rate of machine k from state α to β; $\alpha,\beta \in \Omega$. Machines may randomly be at any of the 3 modes over an infinite time horizon. The following equations, statistically describe the dynamic of each machine.

$$P[\zeta_k(t+\delta t) = \beta | \zeta_k(t) = \alpha] = \begin{cases} q_{\alpha\beta}^{k}\delta(t) + O(\delta t) & \text{if } \alpha \neq \beta \\ 1 + q_{\alpha\beta}^{k}\delta(t) + O(\delta t) & \text{if } \alpha = \beta \end{cases} \tag{3}$$

Where

$$q_{\alpha\beta}^{k} \ge 0, \qquad q_{\alpha a}^{k} = -\sum_{\beta} q_{\alpha\beta}^{k}, \ \beta \neq \alpha \in \Omega \tag{4}$$

$$\lim_{t \to 0} \frac{O(\delta t)}{\delta t}$$

In this paper the failure rate q_{12}^{k} depends on Weibull distribution model in wear-out condition as follows:

$$q_{12}^{k} = \frac{\beta}{\theta}\left(\frac{x}{\beta}\right)^{\beta-1} \quad \text{for } \beta < 1 \tag{5}$$

The mean time to failure is also obtained from Eq.5 as follows:

$$\text{MTTF} = \theta\Gamma\left(1 + \frac{1}{\beta}\right) \tag{6}$$

Where $\Gamma(x)$ is gamma function

The age of each machine is an increasing function of production rate as follows:

$$a_k(t_2) = a(t_1) + u_k(t)\varphi_k \tag{7}$$

The repair rate $q_{21}^{k}(.)$ of machine k is an increasing function of following inverse expression:

$$\text{TTR}(n(t)) = \frac{\text{TTR}(1)}{r_b^{n(t)-1}} - (n(t)-1)d_b \tag{8}$$

Where TTR is the duration repair time after failure, which is a non-decreasing arithmetic geometric process with parameters $d_b \le 0$ and $0 < r_b \le 1$[12].

Replacement rate q_{13}^{k} depends on machine age $a_k(t)$ and triggers whenever threshold age level X achieved. Back in available state assumed to be constant rate q_{31}^{k}. Replacement leads to restart machine`s age $a_k(t) = 0$.

Let $x_k(t)$ be the inventory/backlog level of product i. then the state equations could be given as:

$$x_{n-1}(t) = \int_t^{TFIN}\left(u_{n-1}(t) - \sum_{j<n-1} L_{j(n-1)}\, u_{n-1}^{max}\right)dt$$

$$x_n(t) = \int_t^{TFIN}\left(u_n(t) - d_g\right)dt \tag{9}$$

$$d_g = \begin{cases} d_g & \text{if } x_n(t) > -K_g \\ 0 & \text{otherwise} \end{cases}$$

Where $x_k(0) = {}_i^k x_0$; is initial inventory stock level at output buffers.

$$-K_g \le x_n(t) \le Z_g$$

$$0 \le x_{n-1}(t) \le Z_{n-1} \tag{10}$$

Our objective function is to control the production rates so as to minimize the overall costs incurred over an infinite-horizon time, accordingly, the momentary cost function associated with the considered network failure prone manufacturing system (NFPMS) is given by the following expression:

$$g(x(t)) = \sum_i c_k^+ x_k^+ + \sum_h c_g^- x_g^- + \sum_h c_g^{lost} + \sum_k (c_{cor}^k Ind\{\zeta(t) = 2\} + c_{rep}^k Ind\{\zeta(t) = 3\}) + cs_g^n Ind\{S_g^n = 1\} \quad (11)$$

Where

$x_k^+ = \max\{0, x_k\}$, $x_g^- = \max\{0, -x_g\}$.

Total cost function $J(\cdot)$ over an infinite time horizon which is given by

$$J(\alpha,x,u) = E\left[\int_0^\infty e^{-\rho t} g(x(t))dt\ \right] \quad (12)$$

Where ρ is the discount rate.

So the value function is given by:

$$\omega(\alpha,x) = \min_{u \in K(\alpha)} J(\alpha,x) \quad (13)$$

In order to find an optimum solution for value function, an approximation of control policy is given in the next section.

4. Approximate control policy

Due to the high complexity of solving driven HJB equation for such a FPMS[23,24], Simulation-based experimental design augmented with response surface methodology (RSM) has been used so often to approximate relationship between value function and corresponding parameters[2]. In this paper we aim to combine such a simulation-based model with the MHPP as described by Gharbi, Kenné[3] and MHCP as described by[25] For a case of degrading network failure prone manufacturing system described by Sajadi *et al*.[5] augmented with repair/replacement policy described by Dehayem Nodem *et al*.[12].

In this paper machines are assumed non-identical, meaning, transition rate of stochastic process between each state is unique. In current study $x_i(t)$ is a discrete stochastic variable, failure rates depend on machine`s age $a_k(t)$ and also repair time depend on instantaneous number of failures $n(t)$, all these consideration cause an additional increase of the complexity. Given the complexity of HJB equations for proposed problem, the objective of current paper is to experimentally obtain parameters of MHPP and MHCP which give the best approximation of the value for $u_k(t)$.

Every Intermediate machine $_{n-1}$ which produces one kind of part, could be approximated optimally by single threshold surplus level Z_{n-1} which is modified and called as MHPP as follows.

$$u_{n-1}(t) = \begin{cases} 0 & \text{if } x_{n-1}(t) > Z_{n-1} \\ u_{ki}^{max} & \text{if } x_{n-1}(t) + u_{n-1}(t) < Z_{n-1} \\ Z_i^{n-1} - x_{n-1}(t) & \text{otherwise} \end{cases} \quad (14)$$

According to the literature, the most suitable strategy to control production in non-negligible setup duration machines, is well-suited of triple threshold surplus inventory level (Z_g,A_g,B_g). Which named as HCP policy and later modified as MHCP by Gharbi *et al*[7]. Suppose, machine n is assembling part number 1, According to this policy (see Eq.15), setup for part number 2, triggers whenever two condition met simultaneously. The trajectory of part type $g1$ passes over its first threshold level (A_{g1}) and the trajectory inventory level of part number $g2$, has already reached to the below of its second threshold level (B_{g2}); otherwise, the production will be continued until Z_1^n. This paper contributes another criteria before each setup action. Since, setup triggeration is assumed non-negligible, thus, before each triggeration, existing enough material for producing commodity needs to be checked. For this reason, proposed MHCP, by Assid *et al*.[25], is revised and illustrated in **Figure 2**.

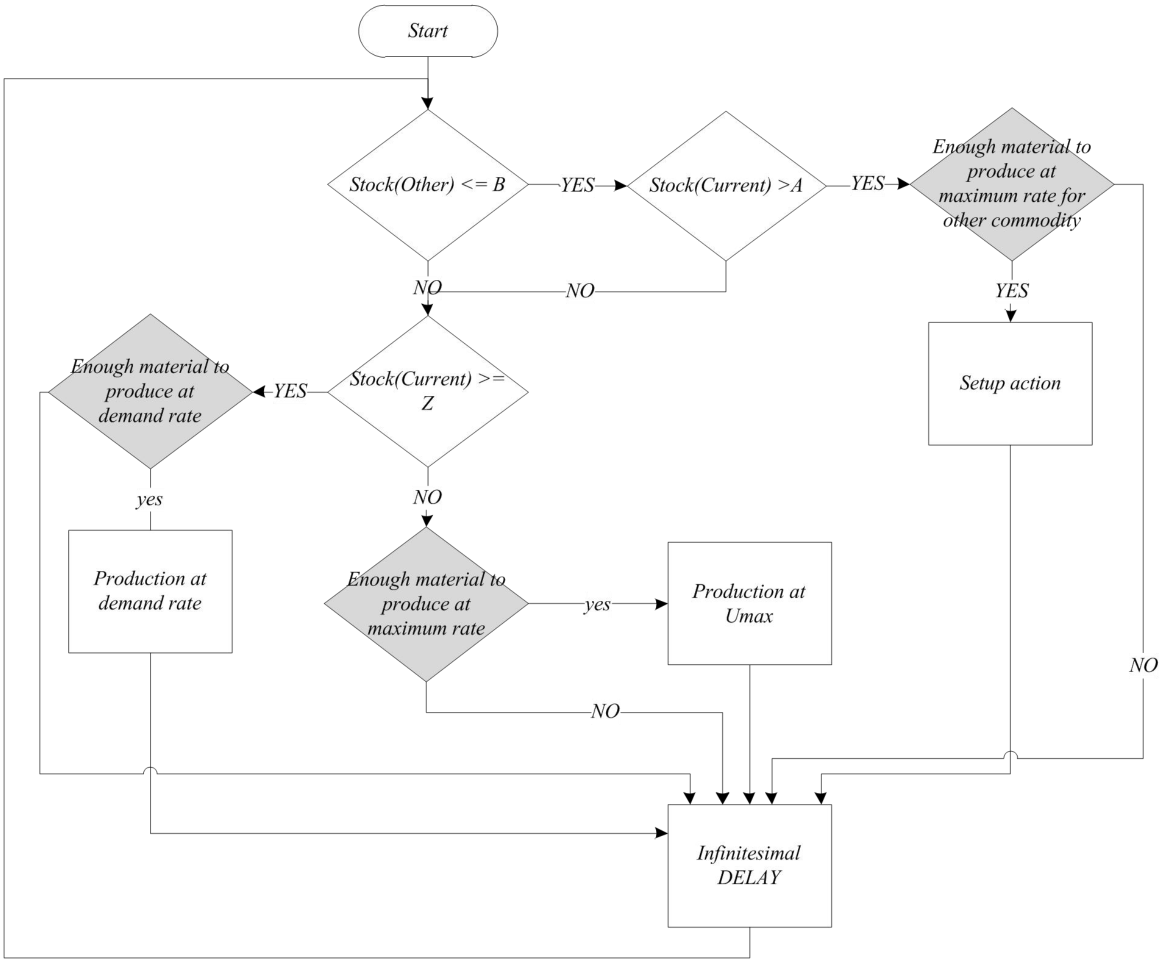


Figure 2; Generalized MHCP**.**

$$S_{g2} = \begin{cases} 1 & \text{if } \left(A_{g1} \le x_{g1} \le Z_{g1}^{n} \; and \; x_{g2} \le B_{g2}\right) \\ 0 & otherwise \end{cases} \quad (15)$$

Production rate would be also considered as:

$$\mathrm{u_g(t)} = \begin{cases} \mathrm{u_g^{max}} & \text{if } \mathrm{x_g < Z_g} \\ \mathrm{d} & \text{if } \mathrm{x_g = Z_g} \\ 0 & \text{otherwise} \end{cases} \quad (16)$$

Following pseudo-code ensures existing enough material for each ignition of production rate $u_k(t)$:

$$\begin{aligned} &\mathrm{For\ j = k-1\ to\ 1\ step\ -1} \\ &\mathrm{u_{k(t)} \times L_{Jk} \le x_j} \\ &\mathrm{next\ j} \end{aligned} \quad (17)$$

To find the optimal control policy, we need to obtain the parameters (Z_{n-1},Z_g,A_g,B_g) given in Eqs. 14 and 16. To achieve this, a simulation model using Arena® is applied to model the behavior of proposed NFPMS, after that, to copy with the complexity of solving experimental design proposed by Kenné, Gharbi[2], OPTQUEST engine optimizer is applied to obtain near-optimum for decision variables. As discussed in Kenné, Gharbi[2], traditional methods of planning FPMS are not sufficient to establish a comfortable level of desired performance, hence, joint analytical and simulation models becomes more interesting. This approach is as follows:

Control problem statement: in this step, all control variables by which the optimal flow control for the considered NFPMS is defined, are presented as HJB equations. (See section 3)

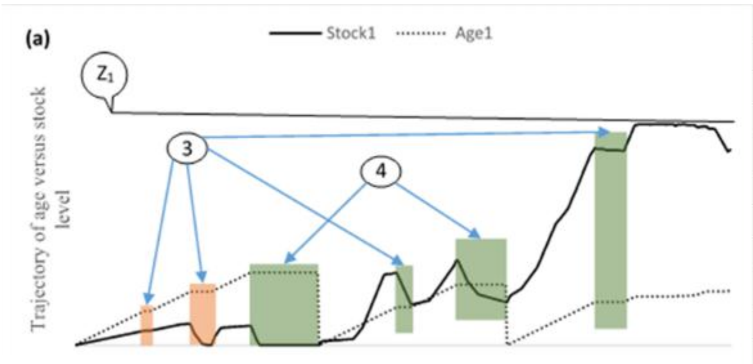
Approximation phase: this step provides a mathematical representation of the desired objective of the previous step, using analytical approach, in terms of design factors as in Equations 14, 15 and 16. The objective of proposed approach is to approximate the relationship between design factors (i.e., Z_{n-1},Z_g,A_g,B_g) as input parameters and response parameter(s) (e.g., cost function, service level, etc.).

Simulation: the dynamic of the proposed near-optimal control policy which was presented in *Approximation* step is modeled using simulation engine.

Experimental analysis: according to the related literature, generally, this step includes two main phase. First, designing appropriate experiments, well-balanced experiments enables us to determine the whole significant interactions between input and output parameters (for more details refer to[26]). Second, Response Surface Methodology (RSM), where, a procedure of regression models (i.e., first order-/second order) in the framework of ANOVA are applied to achieve the most suitable region of response surface, where, design factors ($u(Z_{n-1}$,Z_g,A_g,$B_g))$ approximates the lowest incurred cost. As a matter of fact, obtaining design space with the large input variables using RSM technique is time consuming, as in this paper, we dealt with nine input variables. This paper utilizes the most popular systematic optimum search engine powered by OPTQUEST software. This software combines meta-heuristic method such as taboo search, scatter search and neural network algorithm into simulation model and optimizes the combination of simulation and mathematical model[27].

Let us describe simulation modeling phase. A discrete event simulation (DES), using Arena® software, with C++ subroutines, is applied to present the dynamics of the NFPMS. Such a simulation software is widely used through many applications, for couple of reasons: First, it is consist of several built-in modules, by which a user with lowest programming skill could benefits from it. Seconds, this software interacts with the most popular programming language, VBA, along which, many other Windows®-based software including Microsoft office, .NET, etc. could also benefit from those of high complex simulation models.

Simulation models diagram which most suitable to current study was well adopted by Sajadi *et al*. [5], here, we just focused on simulation validation procedure according to Ben-Salem *et al*.[28]. The trajectory of stock levels and age of each machines are presented in **Figure 3** and **4**. As illustrates in figures, the state of each machines denoted by some digits: 1 denotes production, 2 denotes starve of the machines, means, machine does not able to produce part because of shortage in raw materials (see the pseudo-code provided in Eq.17), 3 denotes failure state and 4 denotes replacement action. Note to the red rectangles in both figures 3 and 4, as can be seen, the width of them, becomes more and more till a replacement take place. This phenomena described in Eq.8, where, the number of failure indicates duration in repair state, also, the time to failure is a random variable generated by Weibull distribution (refer to Eq.6), along which, as the machines becomes older and older, failure happens more frequently.



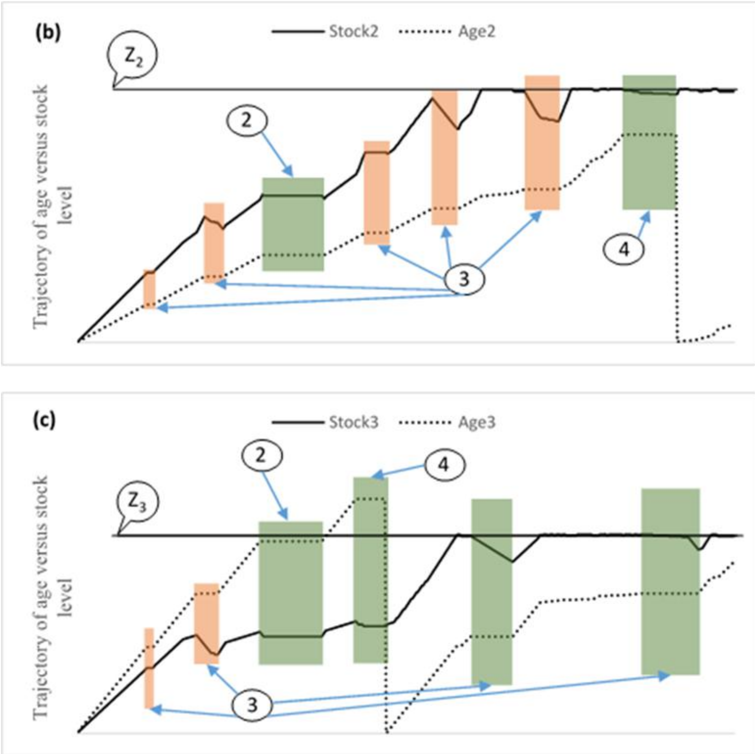


Figure 3; Trajectory of stock level and age for intermediate machine. First machine (a), machine 2 (b), and machine 3 (c).

As can be seen in the trajectory of stock level and age at last machine (**Figure 4**), two setup actions took place (S_2 and S_1, respectively), when the first triggeration occurs, the demand of related commodity $g2$, was in backlog, hence, before filling stock, the production must satisfy backlogged demand. This is shown in **Figure 4**, where, the age level increases while, the stock level remains empty.

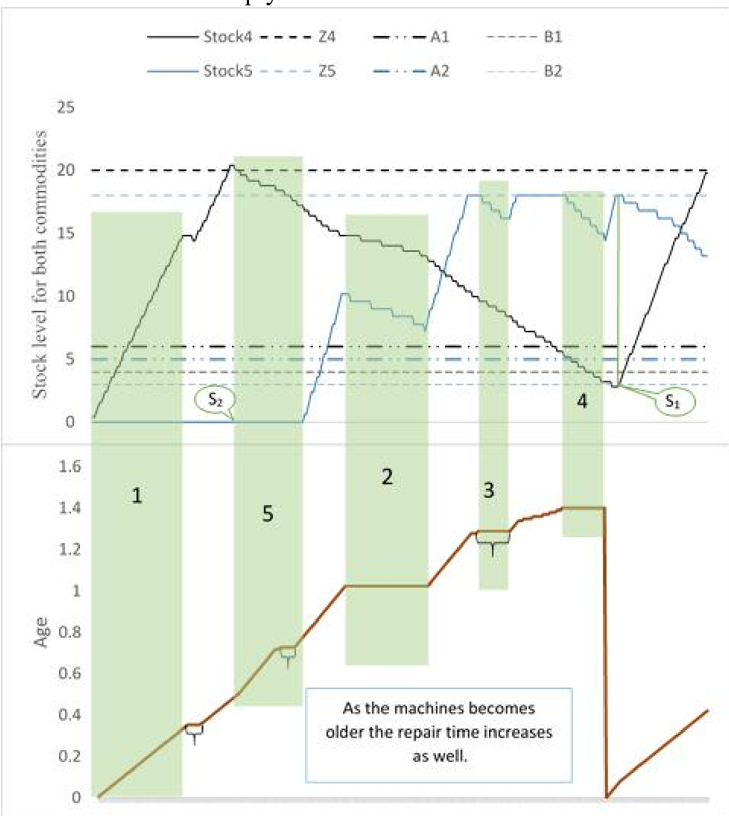


Figure 4; Trajectory of the stock level for two commodities produced at last machine versus machine' age.

5. PTQUEST

As mentioned earlier, simulation optimization technique, is used to find the near-optimal settings of the input variables of approximated optimal control policy for NFPMS $u(\cdot)$, which optimizes the incurred cost function. After each run of the simulation model, the incurred cost, is calculated based on the simulation results over and long-run simulation time, and new series of input parameters (based on mentioned meta-heuristic) are set as input for simulation model. This procedure continues until termination condition met.

In order to Initializing OPTQUEST for optimization, Arena should be prepared to collect statistic data. A set of variables is provided to access information about each type of Arena statistic. The types of variables provided depend upon the statistic type. According to discrete nature of proposed simulation model, DSTAT and OUTPUT variables are used to collect incurred costs, by which some expression is given as **Table 1**.

Type of statistic	purpose
Time-persistent (DSTAT)	Holding costs
Time-persistent (DSTAT)	Backlog costs
Output	Maintenance cost
Output	Setup costs
Time-persistent (DSTAT)	Total costs

Table 1. variable statistic table in Arena

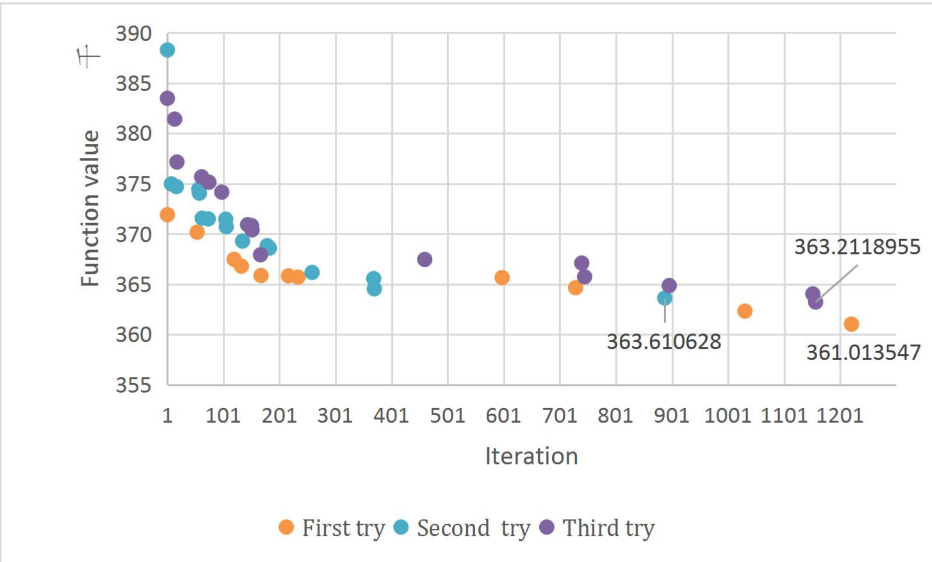


Figure 5; Obtained solution by OPTQUEST**.**

The process of optimization must be terminated at specific condition, this process usually stopped after a finite number of simulation iterations or when the OPTQUEST determines the objective value has stopped improving after 100 simulations. In this paper, the termination condition is left at its default option. Simulation termination length is adjusted as 4000 TMU, which is sufficiently large to ensure that the incurred cost is measured in steady state, with regard to 5 replications for each iteration. To ensure that the OPTQUEST has reached to the best near-optimum solution, the procedure has restarted for three times at different initial values (**Figure 5**), after then, the most propitious solution sets as initial value as final optimization triggeration (**Figure 6**), The minimum obtained value function is depicted in figure 6, where, OPTQUEST struggles to find better solution over 1403 iterations. As can be inferred within figure 6, OPTQUEST could no longer make improvement to the objection value.

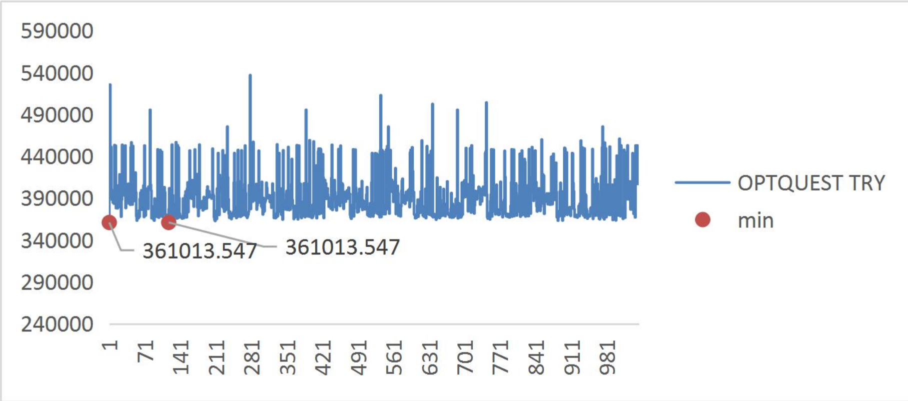


Figure 6; OPTQUEST simulation iterations**.**

6. Conclusion

This paper extended the pervious study on hedging stock level policies in a network degrading non-identical machines, where, age replacement policy is applied for each machine to respond this degradation. The age indicator is used to recognize replacement due dates, if machine breaks down it is either repaired (minimal repair) or replaced whenever mentioned condition met. The proposed problem, was descripted using HJB equations, the optimal production control policy for intermediate machines which produce one part type was assumed on the basis of Modified Hedging Point Policy and, the last machine, Modified Hedging Corridor Policy, respectively. The aim of the study was not to solve the HJB equations, instead, a joint simulation-optimization approach proposed. The OPTQUEST software is applied to obtain optimum parameters for the proposed production policy with regard to minimize incurred cost. The following contributions might also be considered as future study opportunity of current paper:

- To enrich such a NFPMS we would be able to include quality control systems analysis and emission indexes to make the problem closer to the real situation.
- The maintenance activity in this paper assumed based on ARP, further consideration, should be considered more complex PM activities, for the proposed material transportation mechanism.

References

1. Kimemia J, Gershwin SB (1983) An algorithm for the computer control of a flexible manufacturing system. AIIE Transactions 15 (4):353-362
2. Kenné J-P, Gharbi A (2001) A simulation optimization approach in production planning of failure prone manufacturing systems. Journal of intelligent manufacturing 12 (5):421-431
3. Gharbi A, Kenné JP (2000) Production and preventive maintenance rates control for a manufacturing system: an experimental design approach. International Journal of Production Economics 65 (3):275-287
4. Mifdal L, Hajej Z, Dellagi S (2015) Joint optimization approach of maintenance and production planning for a multiple-product manufacturing system. Mathematical Problems in Engineering 2015
5. Sajadi SM, Seyed Esfahani MM, Sörensen K (2011) Production control in a failure-prone manufacturing network using discrete event simulation and automated response surface methodology. The International Journal of Advanced Manufacturing Technology 53 (1):35-46
6. Elhafsi M, Bai SX (1996) Optimal production and setup control of a dynamic two-product manufacturing system: Analytical solution. Mathematical and computer modelling 24 (3):57-78
7. Gharbi A, Kenné J-P, Hajji A (2006) Operational level-based policies in production rate control of unreliable manufacturing systems with set-ups. International Journal of Production Research 44 (3):545-567
8. Gharbi A, Kenne JP (2003) Optimal production control problem in stochastic multiple-product multiple-machine manufacturing systems. IIE transactions 35 (10):941-952
9. Kenné JP, Boukas E, Gharbi A (2003) Control of production and corrective maintenance rates in a multiple-machine, multiple-product manufacturing system. Mathematical and computer modelling 38 (3-4):351-365
10. Gharbi A, Kenné J-P, Beit M (2007) Optimal safety stocks and preventive maintenance periods in unreliable manufacturing systems. International Journal of Production Economics 107 (2):422-434
11. Ebeling CE (1997) An Introduction to Reliability and Maintenance Engineering. McGraw-Hill, Singapore,

12. Dehayem Nodem FI, Kenne J-P, Gharbi A (2011) Production planning and repair/replacement switching policy for deteriorating manufacturing systems. The International Journal of Advanced Manufacturing Technology 57 (5):827-840
13. Pham H, Wang H (1996) Imperfect maintenance. European journal of operational research 94 (3):425-438
14. Berg M, Epstein B (1976) A modified block replacement policy. Naval Research Logistics (NRL) 23 (1):15-24
15. Denkena B, Bluemel P, Kroening S, Roebbing J (2012) Condition based maintenance planning of highly productive machine tools. Production Engineering 6 (3):277-285
16. Van Horenbeek A, Buré J, Cattrysse D, Pintelon L, Vansteenwegen P (2013) Joint maintenance and inventory optimization systems: A review. International Journal of Production Economics 143 (2):499-508
17. Leung K (2006) A note on 'A bivariate optimal replacement policy for a repairable system'. Engineering Optimization 38 (5):621-625
18. Wu S (2017) Doubly geometric processes and applications. Journal of the Operational Research Society:1-13
19. Kushner H, Dupuis PG (2013) Numerical methods for stochastic control problems in continuous time, vol 24. Springer Science & Business Media,
20. Kleijnen JP, Wan J (2007) Optimization of simulated systems: OptQuest and alternatives. Simulation Modelling Practice and Theory 15 (3):354-362
21. Kadry S, Bagdasaryan A, Kadhum M Simulation and analysis of staff scheduling in hospitality management. In: Modeling, Simulation, and Applied Optimization (ICMSAO), 2017 7th International Conference on, 2017. IEEE, pp 1-6
22. Alvandi S, Li W, Kara S (2017) An Integrated Simulation Optimisation Decision Support Tool for Multi-Product Production Systems. Modern Applied Science 11 (6):56
23. Nodem FD, Kenné J, Gharbi A (2011) Simultaneous control of production, repair/replacement and preventive maintenance of deteriorating manufacturing systems. International Journal of Production Economics 134 (1):271-282
24. Ouaret S, Kenné J-P, Gharbi A, Polotski V (2017) Age-dependent production and replacement strategies in failure-prone manufacturing systems. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 231 (3):540-554
25. Assid M, Gharbi A, Hajji A (2014) Joint production and setup control policies of unreliable manufacturing systems minimizing the incurred total cost and taking into account other criteria. Int J Adv Manuf Technol 72:809-826
26. Montgomery DC (2017) Design and analysis of experiments. John Wiley & Sons,
27. Shokohyar S, Mansour S (2013) Simulation-based optimisation of a sustainable recovery network for Waste from Electrical and Electronic Equipment (WEEE). International Journal of Computer Integrated Manufacturing 26 (6):487-503
28. Ben-Salem A, Gharbi A, Hajji A (2015) Environmental issue in an alternative production – maintenance control for unreliable manufacturing system subject to degradation. The International Journal of Advanced Manufacturing Technology 77 (1-4):383-398
29. Afshar-Bakeshloo, M., Mehrabi, A., Safari, H., Maleki, M., & Jolai, F. (2016). A green vehicle routing problem with customer satisfaction criteria. Journal of Industrial Engineering International, 12(4), 529-544.
30. Afshar-Bakeshloo, M., Bozorgi-Amiri, A., Sajadi, S. M., & Jolai, F. (2018). A multi-objective Environmental Hedging Point Policy with customer satisfaction criteria. Journal of Cleaner Production, 179, 478-494.
31. Jolai, F., & Afshar-Bakeshloo, M. (2018). Determining maintenance opportunity window (MOW) in job-shop systems by considering manpower of maintenance. Journal of Quality Engineering and Production Optimization.