PREVENTIVE MAINTENANCE EFFECT ON THE AGGREGATE PRODUCTION PLANNING MODEL WITH TOW-PHASE PRODUCTION SYSTEMS: MODELING AND SOLUTION METHODS

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Abstract:

This paper develops two mixed integer linear programming (MILP) models for an integrated aggregate production planning (APP) system with return products, breakdowns and preventive maintenance (PM). The goal is to minimize the cost of production with regard to PM costs, breakdowns, the number of laborers and inventory levels and downtimes. Due to NP-hard class of APP, we implement a harmony search (HS) algorithm and vibration damping optimization (VDO) algorithm for solving these models. Next, the Taguchi method is conducted to calibrate the parameter of the metaheuristics and select the optimal levels of factors influencing the algorithm's performance. Computational results tested on a set of randomly generated instances show the efficiency of the vibration damping optimization algorithm against the harmony search algorithm. We find VDO algorithm to obtain best quality solutions for APP with breakdowns and PM, which could be efficient for large scale problems. Finally, the computational results show that the objective function values obtained by APP with PM are better than APP with breakdown results.

1 Introduction

Aggregate production planning (APP) is a medium range capacity planning method that typically encompasses a time horizon anywhere from 2 to 18 months. In general, its aim is to determine the production quantity and inventory level in an aggregate term in such a way that the expected demand is met by utilizing the resources of an organization efficiently and effectively [1]. A survey of models and methodologies for APP has been represented in [2]. Ashayeri et al. proposed a model optimizing total maintenance and production costs in discrete multi-machine environment with deterministic demand [3]. Lee studies a two-machine flow shop scheduling problem with an availability constraint. He assumes that a machine may not always be available. Also if a machine

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continues to process those unfinished jobs that were scheduled in the previous planning period, then it is not available at the beginning of the period [4]. He studies the problem in a deterministic environment. Namely, he assumes that the unavailable time is known in advance. He proves that the problem is NP-hard and develops pseudo-polynomial dynamic programming algorithm to solve the problem optimally. At the tactical level, there are only a few papers discussing this issue. Wienstein and Chung presented a three-part model to resolve the conflicting objectives of system reliability and profit maximization. An aggregate production plan is first generated, and then a master production schedule is developed to minimize the weighted deviations from the specified aggregate production goals. Finally, work center loading requirements, determined through rough cut capacity planning, are used to simulate equipment failures during the aggregate planning horizon. Several experiments are used to test the significance of various factors for maintenance policy selection. These factors include the category of maintenance activity, maintenance activity frequency, failure significance, maintenance activity cost, and aggregate production policy [5]. Lee and Chen studied the problem of processing a set of n jobs on m parallel machines where each machine must be maintained once during the planning horizon. Their objective is to schedule jobs and maintenance activities so that the total weighted completion time of jobs is minimized [6]. Aghezzafet et al. presented an integrated production and preventive maintenance planning model for a single-line production systems which can be minimally repaired at failure. They assumed that maintenance actions carried out on the production line reduce its capacity, and proposed a mathematical programming model to establish an optimal integrated production and maintenance plan for the single-line production systems [7]. Cassady and Kutanoglu compared the optimal value of total weighted tardiness under integrated production scheduling with preventive maintenance planning with that under separate production scheduling and preventive maintenance planning. They assume that the uptime of a machine follows a Weibull distribute; the machine is minimally repaired when it fails; and the preventive maintenance restores the machine to a state as good as new. Their results indicate that there is an average of 30 % reduction i the expected total weighted tardiness when the production schedule and preventive maintenance planning are integrated [8]. Wang and Liang presented a novel interactive possibility linear programming (PLP) approach for solving the multi-product aggregate production planning (APP) problem with imprecise forecast demand, related operating costs, and capacity [9]. Sortrakul et al. proposed an integrated maintenance planning and production scheduling model for a single machine minimizing the total weighted expected completion time to find the optimal PM actions and job sequence [10]. Aghezzaf and Najid discuss the issue of integrating production planning and preventive maintenance in manufacturing production systems. In particular, it tackles the problem of integrating production and preventive maintenance in a system composed of parallel failure-prone production lines. It is assumed that when a production line fails, a minimal repair is carried out to restore it to an 'as-bad-as-old' status. Preventive maintenance is carried out, periodically at the discretion of the decision maker, to restore the production line to an 'as-good-as-new' status. It is also assumed that any maintenance action, performed on a production line in a given period, reduces the available production capacity on the line during that period [11]. Yu-Lan et al. extended this research where PM actions can be performed under flexible intervals (instead of equal intervals), which lead to more efficient solutions [12]. Pan et al. suggested an integrated scheduling model incorporating both production scheduling and preventive maintenance planning for a single machine in order to minimize the maximum weighted tardiness [13]. Hajej et al. investigated stochastic production planning and the maintenance scheduling problem for a single product and a single machine production system with subcontracting constraints [14]. Nourelfath's and Chatelet's paper deals with the problem of integrating preventive maintenance and tactical production planning for a production system composed of a set of parallel components, in the presence of economic dependence and common cause failures. Economic dependence means that performing maintenance on several components jointly costs less money and time than on each component separately. Common cause failures correspond to events that lead to simultaneous failure of multiple components due to a common cause [15]. Yalaouiet al. proposed an extended linear programming model as a hybrid approach for computing the optimal production plan with minimum total cost. This program is not only considering cases of multi-lines, multi-periods and multi-items but also taking into account the deterioration of the lines. This deterioration is represented in the model as a reduction of production line capacities as a function of time evolution. Maintenance operations are supposed to provide lines in an operational state as good as new, i.e. with a maximum capacity. Also, a ‘‘Fix and Relax heuristic’’ is developed for complex problems [16]. Fitouhin and Nourelfath presented an integrated model for production and general preventive maintenance planning for multi-state systems. It determines an integrated lot-sizing and preventive maintenance strategy of the system that will minimize the sum of preventive and corrective maintenance costs, setup costs, holding costs, backorder costs, and production costs, while satisfying the demand for all products over the entire horizon. The model is first solved by comparing the results of several multi-products capacitated lot-sizing problems. Then, for large-size problems, a simulated annealing algorithm is developed and illustrated through numerical experiments [17]. Cui et al. proposed a proactive joint model which simultaneously determines the production scheduling and maintenance policy to optimize the robustness of schedules. Then, a three-phase heuristic algorithm is devised to solve the mathematical model. Computational results indicate that the performance of the solution can be significantly improved using their algorithm compared with the solutions by the traditional way [18]. Ramezanian et al developed a mixed integer linear programming (MILP) model for general two-phase aggregate production planning systems. The goal is to minimize costs and workforce instabilities at inventory levels. They presented genetic algorithm and Tabu search for solving this problem [19]. The aggregate production planning (APP) problem is an optimization problem which can be solved by an Adaptive Simulated Annealing Penalty Simultaneous Perturbation Stochastic Approximation algorithm (ASAPSPSA) that uses an Adaptive Simulated Annealing algorithm (ASA) presented by Hami and Kardy [20]. In this paper we develop Ramezanian et al. model. The goal of APP is to forecast future demand swings. On the other hand, maintenance system identifies the proper time for PM and restrains from breakdowns and reduces maintenance costs. In recent years, there have been generated different models independently. The current research has developed two MILP models for an integrated APP system with return products, breakdowns and preventive maintenance. First, we develop a combined aggregate production planning model and machine breakdowns in the first model. Second, we develop a combined production planning model for two phase production systems and preventive maintenance in an aggregate production planning in the second model. Then we use Harmony search algorithm and Vibration damping optimization to solve the problems. Finally, we evaluated the effect of downtime and maintenance on the objective function.

The remainder of this paper is organized as follows: Section 2 is methodology; Section 3 describes an aggregate production planning Model with machine breakdowns, and a MILP formulation of the aggregate production planning Model with preventive maintenance. The solution approaches harmony search and vibration damping are presented in Sections 4 and 5. Section 6 presents computational experiments. The conclusions and suggestions for future studies are included in Section 7.

2 Methodology

We develop two MILP models. The proposed models are coded with LINGO 8 software, and the new implemented model compared two metaheuristic algorithms by statistical analysis. The former is harmony search, and the latter is vibration damping optimization. The Taguchi method is conducted to calibrate the parameter of metaheuristics and to select the optimal levels of the factors influencing algorithm’s performance. Finally, we compared two models.

3 Problem formulation

3.1 The APP model and breakdowns

In this section, we present an aggregate production planning model with machine breakdowns. This model is relevant to multi-period, multi-product, multi-machine, two-phase production systems.

3.1.1. Assumptions

- The quantity shortage at the beginning of the planning horizon is zero.

- The quantity shortage at the end of the planning horizon is zero.
- Breakdown decision variable, if setup to be performed, the decision variable is equal to one, and otherwise it is zero.
- There is a setup cost of producing a product only once at the beginning of a period, and the setup cost after a failure is not considered.
- Lead time equal to one.

3.1.2. Model variables

P_{i2t}: Regular time production of second-phase product *i* in period *t* (units),

O_{i2t}: Over time production of second-phase product *i* in period *t* (units),

C_{i2t}: Subcontracting volume of second phase product *i* in period t (units),

B_{i2t}: Backorder level of second-phase product *i* in period *t* (units),

I_{i2t}: The inventory of the second phase product *i* in period *t* (units),

H_t: The number of the second group workers hired in period *t* (man-days),

L_t: The number of the second group workers laid off in period *t* (man-days),

W_t: Second workforce level in period *t* (man-days),

Y_{i2t}: The setup decision variable of second-phase product *i* in period *t*, a binary integer variable,

$X_{R_{i2t}}$: The number of the second-phase returned products of product *i* that was remanufactured in period *t*,

$X_{RI_{i2t}}$: The number of the second-phase returned products of product *i* held that in inventory at the end of period *t*,

$X_{D_{i2t}}$: The number of the second-phase returned products of product *i* that disposed in period t,

P_{k1t}: Regular time production of first-phase product *k* in period *t* (units),

O_{k1t}: Over time production of first-phase product *k* in period *t* (units),

C_{k1t}: Subcontracting volume of first-phase product *k* in period *t* (units),

B_{k1t}: Backorder level of first-phase product *k* in period *t* (units),

I_{k1t}: The inventory of the first-phase product *k* in period *t* (units),

H'_t: The number of first group workers hired in period *t* (man-days),

L'_t: The number of the first group workers laid off in period *t* (man-days),

W'_t: First workforce level in period t (man-days),

Y_{k1t}: The setup decision variable of first-phase product *k* in period *t*, a binary integer variable..

3.1.3. Parameters

p_{k1t}: Regular time production cost of first-phase product *k* in period *t* ($/units),

o_{k1t}: Over time production cost of first -phase product *k* in period *t* ($/units),

c_{k1t}: Subcontracting cost of first-phase product *k* in period *t* ($/units),

h_{k1t}: Inventory cost of first-phase product k in period t ($/units),

a_{k1l}: Hours of machine l per unit of first-phase product k (machine-days/unit),

u_{k1l}: The setup time for first-phase product k on machine l (hours),

r_{k1lt}: The setup cost of first-phase product k on machine l in period t ($/machine-hours),

R'_{kt}: The regular time capacity of machine l in period t (machine-hours),

hr'_t: Cost to hire one worker in period t for first group labor ($/man-days),

l'_t: Cost to layoff one worker of first group in period t ($/man-days),

w'_t: The first group labor cost in period t ($/man-days),

I_{k10}: The initial inventory level of first-phase product k in period t (units),

w'_0: The initial first group workforce level (man-days),

B_{k10}: The initial first group backorder level (man-days),

e_{k1}: Hours of labor per unit of first-phase product k (man-days/unit),

α'_t: The ratio of regular-time of first group workforce available for use in overtime in period t,

β'_{lt}: The ratio of regular time capacity of machine l available for use in overtime in period t,

$w'_{max\ t}$: Maximum level of first group labor available in period t (man-days),

D_{i2t}: Forecasted demand of second-phase product i in period t (units),

p_{i2t}: Regular time production cost of second-phase product i in period t ($/units),

o_{i2t}: Over time production cost of second-phase product i in period t ($/units),

c_{i2t}: Subcontracting cost of second-phase product i in period t ($/units),

h_{i2t}: Inventory cost of second-phase product i in period t ($/units),

a_{i2j}: Hours of machine j per unit of second-phase product i (machine-days/unit),

u_{i2j}: The setup time for second-phase product i on machine j (hours),

r_{i2jt}: The setup cost of the second-phase product i on machine j in period t ($/machine-hours),

R_{jt}: The regular time capacity of machine j in period t (machine-hours),

hr_t: Cost to hire one worker in period t for second group labor ($/man-days),

l_t: Cost to layoff one worker of second group in period t ($/man-days),

w_t: The first group labor cost in period t ($/man-days),

I_{i20}: The initial inventory level of the second-phase product i in period t (units),

w_0: The initial second group workforce level (man-days),

B_{i20}: The initial second group backorder level (man-days),

e_{i2}: Hours of labor per unit of second-phase product i (man-days/unit),

α_t: The ratio of regular-time of the second group workforce available for use in overtime in period t,

β_{jt}: The ratio of regular time capacity of machine j available for use in overtime in period t,

f: The working hours of the labor in each period (man-hour/man-day),

$w_{max\ t}$: Maximum level of second group labor available in period t (man-days),

$C_{max\ it}$: Maximum subcontracted volume available of second-phase product i in period t (units),

f_{ik}: The number of unit of first-phase product k required per unit of first-phase product i,

TR_{i2t}: The number of the second-phase returned products of product i in period t,

$XD_{max\ i2t}$: The maximum number of the second-phase returned products of product i that could be disposed in period t,

$XR_{max\ i2t}$: The maximum number of the second-phase returned products of product i that could be remanufactured in period t,

hX_{i2t}: Inventory cost of second-phase returned products of product i in period t ($/units),

$C1_{l1t}$: Failure cost of first-phase machine l in period t ($),

$C3_{j2t}$: Failure cost of second-phase machine j in period t ($),

$C5_{i2t}$:The cost of returned products of the second-phase product i that disposed in period t ($)

$C6_{i2t}$: The cost of returned products of the second-phase product i that remanufactured in period t ($),

m : Percentage of machine capacity in each period (due to lack of maintenance in the previous period) is lost due to failure,

LT: Lead time,

M: A large number.

3.1.4. First proposed model

$$\begin{aligned} MinZ =& \sum_{i=1}^{N}\sum_{t=1}^{T}(p_{i2t}P_{i2t}+o_{i2t}O_{i2t}+c_{i2t}C_{i2t})+\sum_{k=1}^{K}\sum_{t=1}^{T}(p_{k1t}P_{k1t}+o_{k1t}O_{k1t}+c_{k1t}C_{k1t})+ \\ & \sum_{t=1}^{T}\sum_{i=1}^{N}h_{i2t}I_{i2t}+\sum_{t=1}^{T}\sum_{k=1}^{K}h_{k1t}I_{k1t}+\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j=1}^{J}r_{i2jt}Y_{i2t}+\sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{l=1}^{L}r_{k1lt}Y_{k1t}+\sum_{i=1}^{N}\sum_{t=1}^{T}b_{i2t}B_{i2t}+ \\ & \sum_{i=1}^{N}\sum_{t=1}^{T}b_{k1t}B_{k1t}+\sum_{t=1}^{T}(hr_tH_t+l_tL_t)+\sum_{t=1}^{T}w_tW_t+\sum_{t=1}^{T}(hr'_tH'_t+l'_tL'_t)+\sum_{t=1}^{T}w'_tW'_t+ \\ & \sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{k=1}^{K}C1_{l1t}Y_{k1t}+\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i=1}^{I}C3_{j2t}Y_{i2t}+\sum_{i=1}^{N}\sum_{t=1}^{T}C5_{i2t}XD_{it}+\sum_{i=1}^{N}\sum_{t=1}^{T}C6_{i2t}XR_{it}+ \\ & \sum_{i=1}^{N}\sum_{t=1}^{T}hX_{i2t}XRI_{i2t} \end{aligned} \tag{1}$$

$$\begin{aligned} & P_{i2t}+O_{i2t}+C_{i2t}+XR_{i2t}+B_{i2t}-B_{i2,t-1}+I_{i2,t-1}-I_{i2t}=D_{i2t}; \\ & i=1,2,...,N \qquad t=1,2,...,T \end{aligned} \tag{2}$$

$$\begin{aligned} & P_{k1t}+O_{k1t}+C_{k1t}+B_{k1t}-B_{k1,t-1}+I_{k1,t-1}-I_{k1t}=\sum_{i=1}^{N}f_{ik}(P_{i2,t+LT}+O_{i2,t+LT}); \\ & k=1,2,...,K \qquad t=1,2,...,T \end{aligned} \tag{3}$$

$$C_{k10}+I_{k10}=\sum_{i=1}^{N}f_{ik}(P_{i2,LT}+O_{i2,LT}); \quad k=1,...,K \tag{4}$$

$$\sum_{i=1}^{N}(a_{i2j}P_{i2t}+U_{i2j}Y_{i2t})+m\,R_{jt}Y_{i2t}\le R_{jt}; \qquad i=1,2,...,N \quad t=1,2,...,T \quad j=1,2,...,J \tag{5}$$

$$\sum_{i=1}^{N}(a_{i2j}O_{i2t})+m\,\beta_{jt}\,R_{jt}Y_{i2t}\le \beta_{jt}R_{jt}; \qquad i=1,2,...,N \quad t=1,2,...,T \quad j=1,2,...,J \tag{6}$$

$$\sum_{i=1}^{N}(a_{k1l}P_{k1t}+U_{k1l}Y_{k1t})+m\,R'_{lt}Y_{k1t}\le R'_{lt}; \quad k=1,2,...,K \quad t=1,2,...,T \quad l=1,2,...,L \tag{7}$$

$$\sum_{i=1}^{N}(a_{k1j}O_{k1t})+m\,\beta_{lt}\,R'_{lt}Y_{k1t}\le \beta_{lt}R'_{lt}; \qquad k=1,2,...,K \quad t=1,2,...,T \quad l=1,2,...,L \tag{8}$$

$$P_{k1t} + O_{k1t} \le MY_{k1t}; \quad k = 1,2,...,K \quad t = 1,2,...,T \tag{9}$$

$$P_{i2t} + O_{i2t} \le MY_{i2t}; \quad i = 1,2,...,N \quad t = 1,2,...,T \tag{10}$$

$$W_t = W_{t-1} + H_t - L_t; \quad t = 1,2,...,T \tag{11}$$

$$W'_t = W'_{t-1} + H'_t - L'_t; \quad t = 1,2,...,T \tag{12}$$

$$\sum_{k=1}^{K} e_{k1} P_{k1t} \le fw'_t; \quad t = 1,2,...,T \tag{13}$$

$$\sum_{k=1}^{K} e_{k1} O_{k1t} \le \alpha'_t fw'_t; \quad t = 1,2,...,T \tag{14}$$

$$\sum_{i=1}^{N} e_{i2} P_{i2t} \le fw_t; \quad t = 1,2,...,T \tag{15}$$

$$\sum_{i=1}^{N} e_{i2} O_{i2t} \le \alpha_t fw_t; \quad t = 1,2,...,T \tag{16}$$

$$w_t \le w_{\max t}; \quad t = 1,2,...,T \tag{17}$$

$$w'_t \le w'_{\max t}; \quad t = 1,2,...,T \tag{18}$$

$$C_{i2t} \le C_{\max i2t}; \quad i = 1,2,...,N \quad t = 1,2,...,T \tag{19}$$

$$B_{i2t}.I_{i2t} = 0; \quad i = 1,2,...,N \quad t = 1,2,...,T \tag{20}$$

$$B_{k1t}.I_{k1t} = 0; \quad k = 1,2,...,K \quad t = 1,2,...,T \tag{21}$$

$$XR_{i2t} = XRI_{i2,t-1} - XD_{i2t} - XR_{i2t} + TR_{i2t}; i = 1,2,...,N \quad t = 1,2,...,T \tag{22}$$

$$XD_{i2t} \le XD_{\max i2t}; \quad i = 1,2,...,N \quad t = 1,2,...,T \tag{23}$$

$$XR_{i2t} \le XR_{\max i2t}; \quad i = 1,2,...,N \quad t = 1,2,...,T \tag{24}$$

$$Y_{i2t} \in \{0,1\}; \qquad i = 1, 2, ..., N \quad t = 1, 2, ..., T \tag{25}$$

$$Y_{k2t} \in \{0,1\}; \qquad k = 1, 2, ..., K \quad t = 1, 2, ..., T \tag{26}$$

$$B_{i\,2T} = 0; \qquad i = 1, 2, ..., N \tag{27}$$

$$B_{k\,1T} = 0; \qquad k = 1, 2, ..., k \tag{28}$$

The first term in objective function (1) is total production cost, which is associated with the regular-time production, overtime production and subcontracting cost for the second-phase products. The second term in objective function (1) is total production cost, which is associated with the regular-time production, overtime production and subcontracting cost for the first-phase products. The third and fourth terms in (1) are inventory cost for the second-phase and first-phase products. The fifth and sixth terms in (1) are total setup cost for the second-phase and first-phase products. The seventh and eighth terms in (1) are backorder setup cost for the second-phase and first-phase products. The ninth and tenth terms in (1) are total labor cost and hiring and layoff cost associated with the change of workforce level for the second-phase. The eleventh and twelfth terms in (1) are total labor cost and hiring and layoff cost associated with the change of workforce level for the first-phase. The thirteenth term in (1) is failure cost for the first-phase. The fourteenth term in (1) is failure cost for the second-phase. The fifteenth term in (1) is disposed cost for the second-phase products. The sixteenth term in (1) is remanufactured cost for the second-phase products. The seventeenth term in (1) is inventory cost for the second-phase products.

Constraint (2) is relevant to satisfy demands for the second-phase products. Constraint (3) ensures production, subcontracting and inventory equilibrium for first-phase products that associated to the total production of second-phase products. Constraint (4) certifies that the initial inventory level and the subcontracting volume of first-phase products in the beginning of planning horizon should b equal or greater than the total production of second phase products at the firs LT periods to satisfy the products demand. Constraints (5) and (6) limit the regular time production to the available second group machines capacity and the overtime production to the available overtime for this group of machines respectively. Setup times are considered in the machine capacity constraint (5). Also, total production of first-phase products in each period of regular time and overtime is limited by the available production capacity for the first group machinesby constraints (7) and (8), respectively. Constraints (9) and (10) are relevant to the total regular time production and over time production limits after setup in this model for first-phase products and second-phase products, respectively. Constraints (11) and (12) are relevant to workforce level for the both groups of workers. Constraints (13) – (16) imply workforce capacity constraints at regular time and overtime at each period for the both groups of workers. Constraints (17) and (18) limit the workforce level to the available labor for the both groups of workers. Constraint (19) limits the subcontracting level to the available subcontracting volume. Naturally, in order to minimize the objective function, the constraints (20) and (21) are not necessary and we can ignore them. Constraint (22) is a balance of return products. Constraint (23) limits the disposed level to the available disposed volume. Constraint (24) limits the remanufactured level to the available remanufactured volume. Constraints (25) and (26) are the setup decision variable for the both phase. Constraints (27) and (28) are the quantity shortage at the end of the planning horizon.

3.2 The APP model and PM

In this section, we present an aggregate production planning model with preventive maintenance. This model is relevant to multi-period, multi-product, multi-machine, two-phase production systems.

3.2.1. Assumptions

- The quantity shortage at the beginning of the planning horizon is zero.

- The quantity shortage at the end of the planning horizon is zero.
- Maintenance decision variable, if maintenance is to be performed, the decision variable is equal to one, but otherwise it is zero.
- There is a setup cost of producing a product only once at the beginning of a period, And the setup cost after a failure is not considered.
- If maintenance is not performed in period *t*, the time and cost of maintenance will not apply to the model, the failure costs will be considered in period *t+1* instead, and downtime will be deducted from available machine capacity.
- Lead time equal to one.

3.2.2. Model variables

In the second model, we have first model variables and appendix variable:

PMF_{lt}: The preventive maintenance decision variable of first-phase machine *l* in period *t*, a binary integer variable.

PMS_{jt}: The preventive maintenance decision variable of second-phase machine *j* in period *t*, a binary integer variable.

3.2.3. Parameters

In the second model, we have first model parameters and appendix parameters:

MTS_{jt}: The preventive maintenance time of second-phase machine *j* in period *t* (minutes).

MTF_{lt}: The preventive maintenance time of first-phase machine *j* in period *t* (minutes).

$C2_{l1t}$: Maintenance cost of first-phase machine *l* in period *t* ($).

$C4_{j2t}$: Maintenance cost of second-phase machine *j* in period *t* ($).

3.2.4. The second proposed model

$$\begin{aligned} MinZ = &\sum_{i=1}^{N}\sum_{t=1}^{T}(p_{i2t}P_{i2t}+o_{i2t}O_{i2t}+c_{i2t}C_{i2t})+\sum_{k=1}^{K}\sum_{t=1}^{T}(p_{k1t}P_{k1t}+o_{k1t}O_{k1t}+c_{k1t}C_{k1t})+\\ &\sum_{t=1}^{T}\sum_{i=1}^{N}h_{i2t}I_{i2t}+\sum_{t=1}^{T}\sum_{k=1}^{K}h_{k1t}I_{k1t}+\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j=1}^{J}r_{i2jt}Y_{i2t}+\sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{l=1}^{L}r_{k1lt}Y_{k1t}+\sum_{i=1}^{N}\sum_{t=1}^{T}b_{i2t}B_{i2t}+\\ &\sum_{i=1}^{N}\sum_{t=1}^{T}b_{k1t}B_{k1t}+\sum_{t=1}^{T}(hr_tH_t+l_tL_t)+\sum_{t=1}^{T}w_tW_t+\sum_{t=1}^{T}(hr'_tH'_t+l'_tL'_t)+\sum_{t=1}^{T}w'_tW'_t+\\ &\sum_{l=1}^{L}\sum_{t=1}^{T}C1_{l1t}(1-PMF_{l,t-1})+\sum_{l=1}^{L}\sum_{t=0}^{T-1}C2_{l1t}PMF_{lt}+\sum_{j=1}^{J}\sum_{t=1}^{T}C3_{j2t}(1-PMS_{j,t-1})+\\ &\sum_{l=1}^{J}\sum_{t=0}^{T-1}C4_{j2t}PMS_{jt}+\sum_{i=1}^{N}\sum_{t=1}^{T}C5_{i2t}XD_{i2t}+\sum_{i=1}^{N}\sum_{t=1}^{T}C6_{i2t}XR_{i2t}+\sum_{i=1}^{N}\sum_{t=1}^{T}hX_{i2t}XRI_{i2t} \end{aligned} \tag{29}$$

$$\begin{aligned} &P_{i2t}+O_{i2t}+C_{i2t}+XR_{i2t}+B_{i2t}-B_{i2,t-1}+I_{i2,t-1}-I_{i2t}=D_{i2t};\\ &i=1,2,\ldots,N \qquad t=1,2,\ldots,T \end{aligned} \tag{30}$$

$$\begin{aligned} &P_{k1t}+O_{k1t}+C_{k1t}+B_{k1t}-B_{k1,t-1}+I_{k1,t-1}-I_{k1t}=\sum_{i=1}^{N}f_{ik}(P_{i2,t+LT}+O_{i2,t+LT});\\ &k=1,2,\ldots,K \qquad t=1,2,\ldots,T \end{aligned} \tag{31}$$

$$C_{k10}+I_{k10}=\sum_{i=1}^{N}f_{ik}(P_{i2,LT}+O_{i2,LT}); \qquad k=1,\ldots,K \tag{32}$$

$$\begin{aligned} &\sum_{i=1}^{N}(a_{i2j}P_{i2t}+U_{i2j}Y_{i2t})+PMS_{jt}MTS_{jt}+(1-PMS_{j,t-1})m\,R_{jt}\le R_{jt};\\ &t=1,2,\ldots,T \qquad j=1,2,\ldots,J \end{aligned} \tag{33}$$

$$\sum_{i=1}^{N}(a_{i2j}O_{i2t})+(1-PMS_{j,t-1})m\,\beta_{jt}\,R_{jt}\le\beta_{jt}R_{jt}; \quad t=1,2,\ldots,T \qquad j=1,2,\ldots,J \tag{34}$$

$$\begin{aligned} &\sum_{i=1}^{N}(a_{k1l}P_{k1t}+U_{k1l}Y_{k1t})+PMF_{lt}MTF_{lt}+(1-PMF_{l,t-1})m\,R'_{lt}\le R'_{lt};\\ &t=1,\ldots,T \qquad l=1,\ldots,L \end{aligned} \tag{35}$$

$$\sum_{i=1}^{N}(a_{k1j}O_{k1t})+(1-PMF_{l,t-1})m\,\beta'_{lt}\,R'_{lt}\leq\beta'_{lt}\,R'_{lt};\quad t=1,2,...,T\quad l=1,2,...,L \tag{36}$$

$$P_{k1t}+O_{k1t}\leq MY_{k1t};\qquad k=1,2,...,K\quad t=1,2,...,T \tag{37}$$

$$P_{i2t}+O_{i2t}\leq MY_{i2t};\qquad i=1,2,...,N\quad t=1,2,...,T \tag{38}$$

$$W_t=W_{t-1}+H_t-L_t;\qquad t=1,2,...,T \tag{39}$$

$$W'_t=W'_{t-1}+H'_t-L'_t;\quad t=1,2,...,T \tag{40}$$

$$\sum_{k=1}^{K}e_{k1}P_{k1t}\leq fw'_t;\qquad t=1,2,...,T \tag{41}$$

$$\sum_{k=1}^{K}e_{k1}O_{k1t}\leq\alpha'_t\,fw'_t;\qquad t=1,2,...,T \tag{42}$$

$$\sum_{i=1}^{N}e_{i2}P_{i2t}\leq fw_t;\qquad t=1,2,...,T \tag{43}$$

$$\sum_{i=1}^{N}e_{i2}O_{i2t}\leq\alpha_t fw_t;\qquad t=1,2,...,T \tag{44}$$

$$w_t\leq w_{\max t};\qquad t=1,2,...,T \tag{45}$$

$$w'_t\leq w'_{\max t};\qquad t=1,2,...,T \tag{46}$$

$$C_{i2t}\leq C_{\max i2t};\qquad i=1,2,...,N\quad t=1,2,...,T \tag{47}$$

$$B_{i2t}.I_{i2t}=0;\qquad i=1,2,...,N\quad t=1,2,...,T \tag{48}$$

$$B_{k1t}.I_{k1t}=0;\qquad k=1,2,...,K\quad t=1,2,...,T \tag{49}$$

$$XR_{i2t}=XRI_{i2,t-1}-XD_{i2t}-XR_{i2t}+TR_{i2t};\quad i=1,2,...,N\quad t=1,2,...,T \tag{50}$$

$$XD_{i2t}\leq XD_{\max i2t};\qquad i=1,2,...,N\quad t=1,2,...,T \tag{51}$$

$$XR_{i2t}\leq XR_{\max i2t};\qquad i=1,2,...,N\quad t=1,2,...,T \tag{52}$$

$$Y_{i2t}\in\{0,1\};\qquad i=1,2,...,N\quad t=1,2,...,T \tag{53}$$

$$Y_{k2t}\in\{0,1\};\qquad k=1,2,...,K\quad t=1,2,...,T \tag{54}$$

$$PMF_{lt}\in\{0,1\};\qquad l=1,2,...,L\quad t=1,2,...,T \tag{55}$$

$$PMS_{jt}\in\{0,1\};\qquad j=1,2,...,J\quad t=1,2,...,T \tag{56}$$

$$B_{i2T}=0;\qquad i=1,2,...,N \tag{57}$$

$$B_{k1T}=0;\qquad k=1,2,...,k \tag{58}$$

$$PMF_{l0}=1;\qquad l=1,2,...,L \tag{59}$$

$$PMS_{j0}=1;\qquad j=1,2,...,J \tag{60}$$

In the second model, we have first model Constraints and appendix Constraints: the thirteenth term in (29) is failure cost for the first-phase. The fourteenth term in (29) is maintenance cost for the first-phase. The fifteenth term in (29) is failure cost for the second-phase. The sixteenth term in (29) is maintenance cost for the second-phase. The seventeenth term in (29) is disposed cost for the second-phase products. The eighteenth term in (29) is remanufactured cost for the second-phase products. The nineteenth term in (29) is inventory cost for the second-phase products. Constraints (33) and (34) limit the regular time production to the available second group machines capacity, the overtime production to the available overtime and the preventive maintenance time for this group of machines, respectively. Constraints (35) and (36) limit the regular time production to the available first group machines capacity, the overtime production to the available overtime and the preventive maintenance time for this group of machines, respectively. Constraints (37) and (38) are relevant to the total regular time production and over time production limits after setup in this model for first-phase products and second-phase products, respectively. Constraints (55) and (56) are the preventive maintenance decision variable for the both phase. Constraints (59) and (60) are the preventive maintenance decision variable for the both phase at the beginning of the planning horizon.

4 Harmony search

A harmony search algorithm was developed in an analogy with music improvisation processes where music players improvise the pitches of their instruments to obtain better harmony [21]. The steps in the procedure of HS are as follows [22]:

1. Initialize the problem and algorithm parameters.
2. Initialize the harmony memory.
3. New harmony improvisation.
4. Update the harmony memory.
5. Check the stopping criterion.
6. The pseudo-code of the original harmony search algorithm for the problem is shown in Fig. 1.

The search process stops if some specified number of generations is reached without improvement of the best known solution. In our experiments we accepted Stop = 100.

5 Vibration damping optimization

Recently, a new heuristic optimization technique based on the concept of the vibration damping on mechanical vibration was introduced by Mehdizadeh and Tavakkoli - Moghaddam named vibration damping optimization algorithm [23]. The VDO algorithm is illustrated in the following steps:

1. Generating feasible initial solution
2. Initializing the algorithm parameters which consist of: initial amplitude (A_0), maximum Number of Sub-iteration (sub-it), number of generations without improvement (Stop), damping coefficient (γ), and standard deviation (σ =1). Finally, parameter S is set in one (S=1)
3. Calculating the objective value U_0 for initial solution
4. Initializing the internal loop

In this step, the internal loop is carried out for l =1 and repeat while l ≤ sub-it.

Harmony search
Objective function f (x_i), i=1 to N
Define HS parameters: HMS, HMCR, PAR, and BW
Generate initial harmonics (for i=1 to HMS)
Evaluate f (x_i)
While (until terminating condition)
Create a new harmony: x_i^{new}, i=1 to N
If (U (0, 1) ≥HMCR),
$x_i^{new}=x_j^{old}$, where x_j^{old} is a random from {1,…, HMS}
Else if (U (0, 1) ≤PAR),
$x_i^{new}=x_L(i)+ U(0, 1)\times[x_U(i) - x_L(i)]$
Else
$x_i^{new}=x_j^{old} + BW [(2\times U (0, 1))-1]$, where x_j^{old} is a random from {1,…, HMS}
End if
Evaluation f (x_i^{new})
Accept the new harmonics (solutions) if better
End while
Fine the current best estimates

Figure 1. Pseudo code of the original harmony search.

5. Neighborhood generation
6. Accepting the new solution

Set $\Delta = U - U_0$ Now, if $\Delta < 0$, accept the new solution, else if $\Delta > 0$ generate a random number between (0, 1);

If $r < 1 - \exp\left(\frac{-A_S^2}{2\sigma^2}\right)$, then accept a new solution;

Otherwise, reject the new solution and accept the previous solution.
If $l >$ sub-it, then $S + 1 \rightarrow S$ and go to step 7; otherwise $l + 1 \rightarrow l$ and go back to step 5.

7. Adjusting the amplitude

In this step, $A_S = A_0 \exp(\frac{-\gamma S}{2})$ is used for reducing the amplitude at each iteration of the outer cycle of the algorithm. If S>Stop return to step 8; otherwise, go back to step 4.

8. Stopping criteria, in this step, the algorithm will be stopped after a number of generations without improvement, we accepted Stop = 100.

At the end, the best solution is obtained.

5.1 Representation scheme

To design VDO algorithm for mentioning the problem, a suitable representation scheme that shows the solution characteristics is needed. In this paper, each gene is a total aggregate production (X) of second-phase products and a chromosome is a production plan. The X is decomposed to the regular time production, overtime production, and returned products that could be remanufactured by subcontracting the volume. The general structure of the solution representation performed for running the VDO on second-phase with six periods and two products is shown in Fig. 2.

5.2 Neighborhood scheme

In this paper we use swap and insertion scheme, Fig. 3 and 4 illustrate this operation on second-phase with the six periods and two products. Swap and insertion select the Roulette Wheel method.

Total aggregate production for second-phase product 1	X_{121}	X_{122}	X_{123}	X_{124}	X_{125}	X_{126}
Total aggregate production for second-phase product 2	X_{221}	X_{222}	X_{223}	X_{224}	X_{225}	X_{226}

Figure 2. Chromosome representation.

Parent	X_{121}	X_{122}	X_{123}	X_{124}	X_{125}	X_{126}
	X_{221}	X_{222}	X_{223}	X_{224}	X_{225}	X_{226}

Offspring	X_{126}	X_{122}	X_{123}	X_{124}	X_{125}	X_{121}
	X_{221}	X_{222}	X_{224}	X_{223}	X_{225}	X_{226}

Figure 3. Illustration of the swap structure.

Parent	X_{121}	X_{122}	X_{123}	X_{124}	X_{125}	X_{126}
	X_{221}	X_{222}	X_{223}	X_{224}	X_{225}	X_{226}

Offspring	X_{122}	X_{123}	X_{121}	X_{124}	X_{125}	X_{126}
	X_{221}	X_{223}	X_{224}	X_{222}	X_{225}	X_{226}

Figure 4. Illustration of insertion structure.

6 Results

In order to evaluate the performance of the metaheuristic algorithms, 30 test problems with different sizes are randomly generated for each model. The proposed models are coded with LINGO 8 software using the LINGO solver for solving the instances. Furthermore, for the small and medium sized instances of two phases APP with breakdown and PM, LINGO optimization solver is used to figure out the optimal solution in comparison with HS and VDO results. The harmony search and Vibration Damping optimization are coded in MATLAB R2011a and all tests are conducted on a notebook at Intel Core 2 Duo Processor 2.00 GHz and 2 GB of RAM.

6.1 Parameter calibration

Appropriate design of parameters has significant impact on the efficiency of metaheuristics. In this paper the Taguchi method was applied to calibrate the parameters of the proposed methods namely HS and VDO algorithms. The Taguchi method was developed by Taguchi [24]. This method is based on maximizing performance measures called signal-to-noise ratios in order to find the optimized levels of the effective factors in the experiments. The signal-to-noise ratio refers to the mean-square deviation of the objective function that minimizes the mean and variance of quality characteristics to make them closer to the expected values. For the factors that have significant impact on signal-to-noise ratio, the highest signal-to-noise ratio provides the optimum level for that factor. As mentioned before, the purpose of the Taguchi method is to maximize the signal-to-noise ratio. In this subsection, the parameters for experimental analysis are determined. Table 1 lists different levels of the factors for HS and VDO. In this paper according to the levels and the number of the factors, the Taguchi method L_{25} is used for the adjustment of the parameters. Fig. 5 and 6 show signal-to-noise ratios. Best level of the factor for each algorithm is shown in Table 2.

6.2 Computational results

Computational experiments are conducted to validate and verify the behavior and the performance of the harmony search algorithm and the vibration damping optimization algorithm to solve the aggregate production planning model with breakdowns and preventive maintenance. In order to evaluate the performance of the metaheuristic algorithms, 30 test problems with different sizes are randomly generated for each model. These test problems are classified into three classes: small size, medium size and large size. The number of products, machines and periods has the most significant impact on hardness problem. The

Table 1. Factors and their levels

Factors	Algorithms	Notations	Levels	Values
Harmony memory size		HMS	5	5, 10, 15, 20, 25
Harmony memory considering rate	HS	HMCR	5	0.7, 0.75, 0.8, 0.85, 0.9
Pitch-adjusting rate		PAR	5	0.1, 0.15, 0.2, 0,25, 0.3
Bandwidth		BW	5	0.2, 0.5, 0.8, 0.9, 0.99
Max of iteration at each amplitude		sub-it	5	5, 10, 15, 20, 25
Damping coefficient	VDO	γ	5	0.01, 0.05, 0.1, 0.5, 0.9
Initial amplitude		A_0	5	4, 5, 6, 7, 8

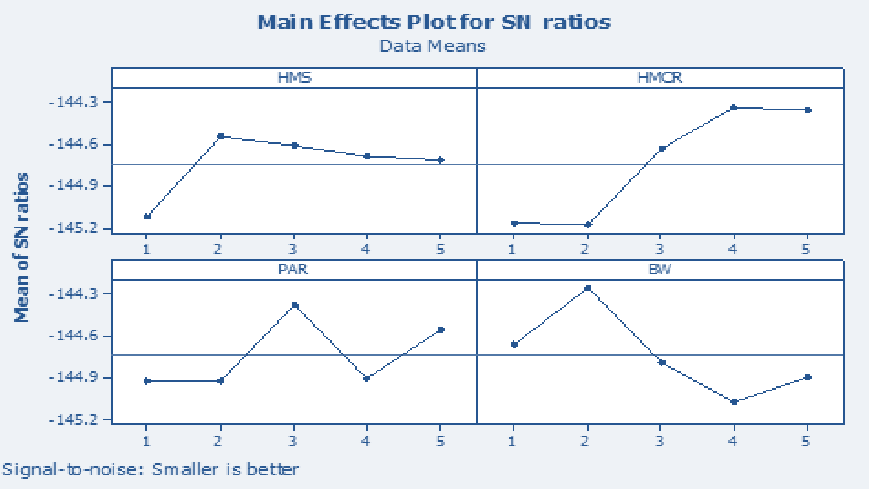

Figure 5. The signal-to-noise ratios for harmony search.

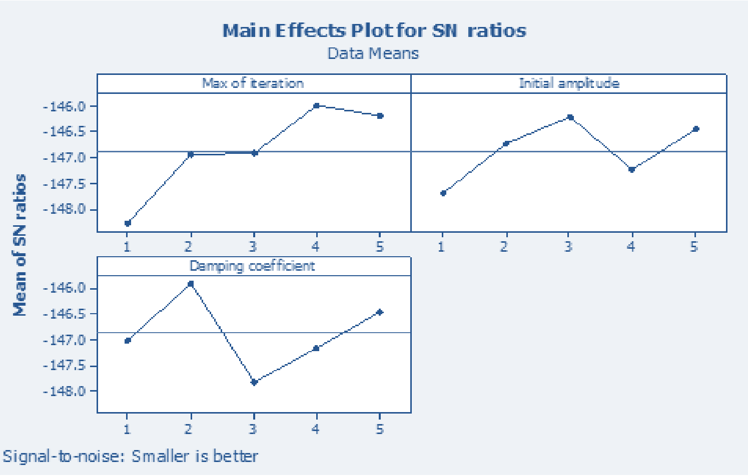

Figure 6. The signal-to-noise ratios for vibration damping optimization.

Table 2. Best level for parameters

Factors	Algorithms	Notations	Values
Harmony memory size		HMS	10
Harmony memory considering rat	HS	HMCR	0.85
Pitch-adjusting rate		PAR	0.2
Bandwidth		BW	0.5
Max of iteration at each amplitude		sub-it	20
Damping coefficient	VDO	γ	6
Initial amplitude		A_0	0.05

approaches are implemented to solve each instance in five times to obtain more reliable data. Table 3 shows all the details of computational results obtained by solution methods for all test problems for the APP and breakdowns. Table 7 shows all the details of computational results obtained by solution methods for all test problems for the APP and PM. The presented statistical analysis (the variance analysis outcome) were reported for problems with small, medium, and large dimensions between algorithms, in Tables 4, 5 and for APP with breakdowns, and in Tables 8, 9 and 10 and for APP with PM, which according to the values of the survey (or P-Value), we can choose the better algorithm with use ANOVA related:

- The objective values obtained by HS and VDO are close to each other for small dimension problems for both models.
- The objective values obtained by HS and VDO are no different from each other in the medium dimension test problems for both models.
- The objective values obtained by VDO are better than HS results for large dimension test problems for both models.

Table 3. Details of computational results for APP and breakdowns

No.	Prob. size	i.j.k.l.t	Lingo	Time (s)	HS	Time (s)	VDO	Time (s)
1		2.1.2.1.3	7475340	1	7475340	6.3	7475340	8.9
2		2.1.2.2.3	7779851	1	7779851	14.3	7779851	15.9
3		2.2.2.1.3	8669761	1	8669761	7.7	8669761	19.9
4		2.1.3.2.3	7801244	2	7801244	60	7801244	211.4
5	Small	2.1.4.1.3	8036987	2	8036987	1012.4	8036987	967.3
6		2.1.2.1.4	9874857	5	10091601	19.5	9874948.2	17.5
7		2.2.2.1.4	12103410	5	13602447	14.9	12719174.2	23
8		2.1.3.1.4	11338530	34	12898652.2	126.9	11930817	130.1
9		2.2.2.1.5	14701090	78	16131986.4	25.7	15624600	28.7
10		2.1.2.1.6	16912130	140	17804354.2	30.4	17384485	32.5
11		2.1.3.2.4	12240940	189	13643066	163.2	12272302	20.2
12		2.1.2.2.5	15181490	2320	17292317.4	26.4	16076467.4	118.1
13		4.1.2.1.3	---	---	16230083	31.2	14210346	44
14	Medium	3.1.2.1.5	---	---	22656268	60.8	20634663.6	44.1
15		2.1.4.1.5	---	---	18672008.2	3105.1	15937179.4	3310
16		4.1.2.1.5	---	---	34718455.6	254.4	28748901.8	319.5
17		2.1.2.2.6	---	---	17012202	43.6	16330562	222.1
18		2.2.2.2.6	---	---	23034849.4	58	21194881.6	122.4
19		3.1.2.1.6	---	---	33017550.4	160.8	27858379	140.3
20		4.1.2.1.6	---	---	46314730.2	257.1	40237750.8	228.2
21		2.1.3.2.6	---	---	26547746.4	1848.7	13619441.2	1102.3
22		2.1.2.1.8	---	---	34564240.8	50.8	20680498	380.2
23		2.1.2.2.8	---	---	31141170.2	109.4	15336160.8	185.1
24	Large	2.2.2.1.8	---	---	36790408.6	72.3	22114772.8	452.7
25		2.1.2.1.12	---	---	70206467.6	212.2	36220294.6	190.2
26		2.1.2.2.12	---	---	78730248.4	317.4	51703746.2	870.6
27		3.1.2.1.12	---	---	126332620.4	811.3	84180332.6	1155
28		2.1.2.1.16	---	---	120606150.6	197.9	72526220.4	1370.2
29		2.1.2.2.16	---	---	103364728.8	375.9	63864712.6	1618.2
30		2.2.2.1.16	---	---	109493429	393.9	69927890.6	342

--- Means that a feasible and optimum solution has not been found after 3600 s of computing time.

Table 4. Analysis of variance for test problems with small size, between HS and VDO

Source	SS	DF	MS	F_0	P
Small size	7.98008E+11	1	7.98008E+11	0.06	0.813
Error	2.49444E+14	18	1.38580E+13		
Total	2.50242E+14	19			

Table 5. Analysis of variance for test problems with medium size, between HS and VDO

Source	SS	DF	MS	F_0	P
Medium size	4.83297E+13	1	4.83297E+13	0.52	0.481
Error	1.67981E+15	18	9.33227E+13		
Total	1.72814E+15	19			

Table 6. Analysis of variance of test problems with large size, between HS and VDO

Source	SS	DF	MS	F_0	P
Large size	3.36969E+15	1	3.36969E+15	3.06	0.097
Error	1.98203E+16	18	1.10113E+15		
Total	2.31900E+16	19			

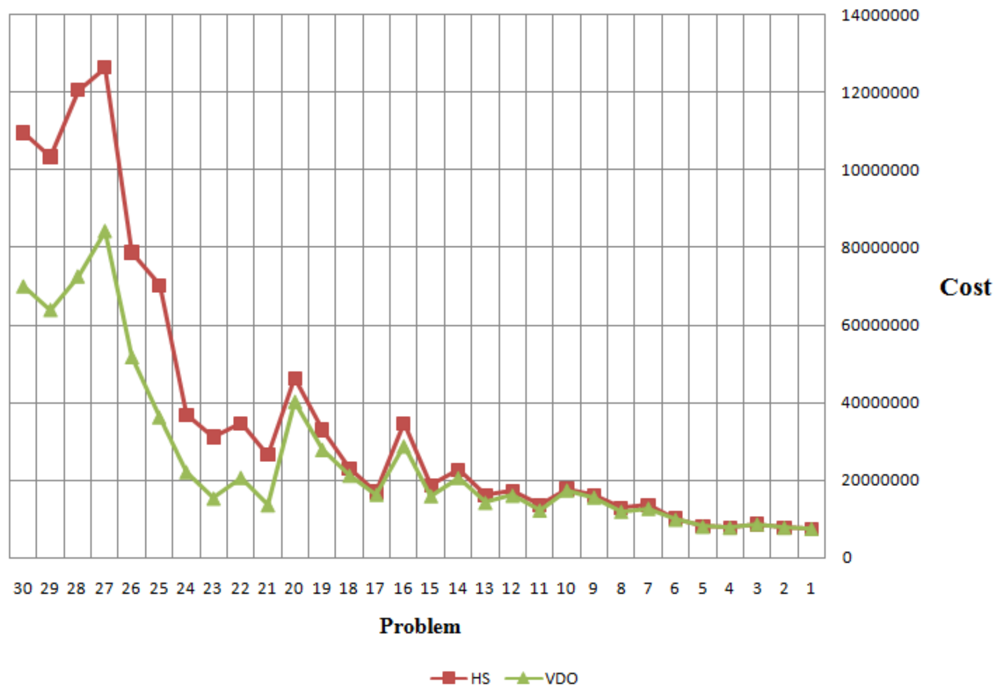

Figure 7. Comparison between solution quality of the HS and VDO, for APP and breakdowns.

Table 7. Details of computational results for APP and PM

No.	Prob. size	i.j.k.l.t	Lingo	Time(s)	HS	Time (s)	VDO	Time (s)
1		2.1.2.1.3	6720124	1	6720124	10.6	6720124	12.7
2		2.1.2.2.3	7093831	1	7093831	18.2	7093831	29.2
3		2.1.3.2.3	7345570	1	7345570	32.6	7345570	1013
4		2.1.4.1.3	7585061	1	7585061	824	7585061	1987
5	Small	2.2.2.1.3	7594855	3	7594855	13.7	7594855	18.8
6		2.1.2.1.4	8522935	3	8522935	6.5	8522935	23.7
7		2.2.2.1.4	9939956	4	9939956	15.4	9939956	48.6
8		2.1.2.1.6	13931320	6	14142746	31.2	14119881	32.4
9		2.1.3.1.4	10185920	7	10525717.8	75.1	10386292.2	152.5
10		2.2.2.1.5	11858890	28	12088009.2	25.8	12022934.6	54
11		2.1.3.2.4	11042530	31	11420786	392.5	11210416	24.6
12		2.1.2.2.5	12824550	172	13627122.4	74	13531169.4	63.8
13		2.1.2.2.6	15105320	1035	16394869.4	37.7	15176125.8	96
14	Medium	2.2.2.2.6	16202530	2002	17340630.2	76.2	16560223.4	61.9
15		4.1.2.1.3	---	---	13750161	51	12435647	113.4
16		3.1.2.1.5	---	---	17321010	108.5	15010929	94.4
17		4.1.2.1.5	---	---	24351300.8	357.1	21996169.2	159.4
18		2.1.4.1.5	---	---	13170435.2	2213	11823412	2830
19		3.1.2.1.6	---	---	27788070.6	105.9	24912403.4	345.6
20		4.1.2.1.6	---	---	36965194.4	493.5	30281600.2	197.6
21		2.1.3.2.6	---	---	19765159.2	1439.7	11412775.2	2681.2
22		2.1.2.1.8	---	---	30847836.2	149.8	18458592	235.2
23		2.1.2.2.8	---	---	29067560.4	88.8	13299469.4	81.1
24	Large	2.2.2.1.8	---	---	31525137.6	114.5	16876372.6	42
25		2.1.2.1.12	---	---	63658096	118.3	31973604.8	89.7
26		2.1.2.2.12	---	---	63231299.6	312.5	34977358.8	112.6
27		3.1.2.1.12	---	---	91273845	676.1	57783215.8	601.3
28		2.1.2.1.16	---	---	83846588.6	120.2	42431013.2	703.5
29		2.1.2.2.16	---	---	76633081	214	45096091.6	811.4
30		2.2.2.1.16	---	---	85097596.6	226.1	51294712.8	947.1

--- Means that a feasible and optimum solution has not been found after 3600 s of computing time.

$p_{k1t} \in [20,24], o_{k1t} \in [22,27], c_{k1t} \in [70,77], h_{k1t} \in [40,45], h_{k1t} \in [40,45], a_{k1l} = 1, u_{k1l} = 0.1,$

$r_{k1lt} \in [4,7], R'_{lt} \in [21000,40000], hr'_t \in [200,480], l'_t \in [200,480], w'_t \in [60,65], I_{k10} = 500,$

$w'_0 = 3500, B_{k10} = 0, e_{kl} = 0.2, \alpha'_t = 0.2, \beta'_{lt} = 0.5, w'_{\max t} \in [3000,7000], D_{i2t} \in [6000,24000],$

$p_{i2t} \in [20,25], o_{i2t} \in [22,27], c_{i2t} \in [100,106], h_{i2t} \in [60,67], a_{i2j} \in [0.4,0.5], u_{i2j} = 0.2,$

$r_{i2jt} \in [10,15], R_{jt} \in [21000,40000], hr_t \in [200,460], l_t \in [200,460], w_t \in [61,64], I_{i20} = 500,$

$w_0 = 3500, B_{i20} = 0, e_{i2} = 0.4, \alpha_t = 0.2, \beta_{jt} \in [0.4,0.5], f \in [120,190], w_{\max t} \in [3000,7000],$

$C_{\max it} \in [2000,9500], f_{ik} = 2, C1_{l1t} \in [100000,220000], C2_{l1t} \in [10000,50000],$

$C3_{j2t} \in [100000,220000], C4_{j2t} \in [10000,50000], C5_{i2t} \in [11,14], C6_{i2t} \in [4,7],$

$MTS_{jt} \in [1500,5000], MTF_{lt} \in [1500,5000], TR_{i2t} \in [300,800], XD_{\max i2t} \in [300,600],$

$XR_{\max i2t} \in [400,650], hX_{i2t} \in [60,65];, m = 0.1, LT = 1.$

Table 8. Analysis of variance oftest problems with small size, between HS and VDO

Source	SS	DF	MS	F_0	P
Small size	2584746709	1	2584746709	0.00	0.984
Error	1.08476E+14	18	6.02647E+12		
Total	1.08479E+14	19			

Table 9. Analysis of variance for of test problems with medium size, between HS and VDO

Source	SS	DF	MS	F_0	P
Medium size	1.84157E+13	1	1.84157E+13	0.35	0.563
Error	9.52142E+14	18	5.28968E+13		
Total	9.70557E+14	19			

Table. 10 Analysis of variance for test problems with large size, between HS and VDO

Source	SS	DF	MS	F_0	P
Large size	1.84979E+15	1	1.84979E+15	3.13	0.094
Error	1.06282E+16	18	5.90453E+14		
Total	1.24779E+16	19			

Fig. 7 and 8 illustrate the comparison between solution quality of the HS and VDO of the instances:

- The HS and VDO can find good quality solutions for small dimension problems for both models.
- The HS and VDO algorithms can solve all test problems for both models.
- The objective values obtained by VDO and HS are close to each other for medium size problems for both models.
- For small dimension test problems, the HS can find good quality solutions but its results will be worse when the problem size increases for both models.

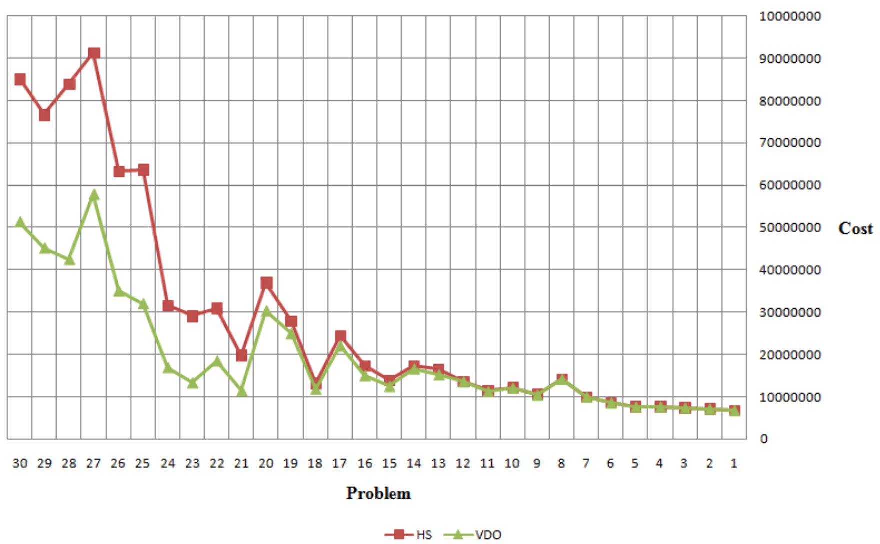

Figure 8. Comparison between solution quality of the HS and VDO, for APP and PM.

We can reach the conclusion that the VDO has shown its usefulness in large dimension problems as compared to the HS.

6.3 PM effect on the objective function

As the objective values obtained by VDO are better than HS results for large dimension test problems for both models, we used a VDO algorithm to show PM effectiveness of the objective function. Table 11 shows not only details of computational results between APP with breakdowns and APP with PM but also the amount of cost reduction and percentage of cost reduction. Also, Fig. 15 depicts a comparison between solution quality of the APP with breakdowns and APP with PM of the instances. So, the objective values obtained by APP with PM are better than APP with breakdown result

Table 11. Details of computational results between APP with breakdowns and APP with PM

No.	i.j.k.l.t	APP with breakdowns	APP with PM	Amount of cost reduction	Percentage of cost reduction (%)
1	2.1.2.1.3	7475340	6720124	755216	10
2	2.1.2.2.3	7779851	7093831	686020	9
3	2.1.3.2.3	7801244	7345570	455674	6
4	2.1.4.1.3	8036987	7585061	451926	6
5	2.2.2.1.3	8669761	7594855	1074906	12
6	2.1.2.1.4	9874948.2	8522935	1352013	14
7	2.2.2.1.4	12719174.2	9939956	2779218	22
8	2.1.2.1.6	17384485	14119881	3264604	19
9	2.1.3.1.4	11930817	10386292.2	1544525	13
10	2.2.2.1.5	15624600	12022934.6	3601665	23
11	2.1.3.2.4	12272302	11210416	1061886	9
12	2.1.2.2.5	16076467.4	13531169.4	2545298	16
13	2.1.2.2.6	16330562	15176125.8	1154436	7
14	2.2.2.2.6	21194881.6	16560223.4	4634658	22
15	4.1.2.1.3	14210346	12435647	1774699	12
16	3.1.2.1.5	20634663.6	15010929	5623735	27
17	4.1.2.1.5	28748901.8	21996169.2	6752733	23
18	2.1.4.1.5	15937179.4	11823412	4113767	26
19	3.1.2.1.6	27858379	24912403.4	2945976	11
20	4.1.2.1.6	40237750.8	30281600.2	9956151	25
21	2.1.3.2.6	13619441.2	11412775.2	2206666	16
22	2.1.2.1.8	20680498	18458592	2221906	11
23	2.1.2.2.8	15336160.8	13299469.4	3036691	17
24	2.2.2.1.8	22114772.8	16876372.6	5238400	21
25	2.1.2.1.12	36220294.6	31973604.8	6246690	14
26	2.1.2.2.12	51703746.2	34977358.8	16726387	28
27	3.1.2.1.12	84180332.6	57783215.8	27397117	28
28	2.1.2.1.16	72526220.4	42431013.2	34095207	40
29	2.1.2.2.16	63864712.6	45096091.6	21768621	28
30	2.2.2.1.16	69927890.6	51294712.8	19633178	24
			Average	**6503332**	**18**

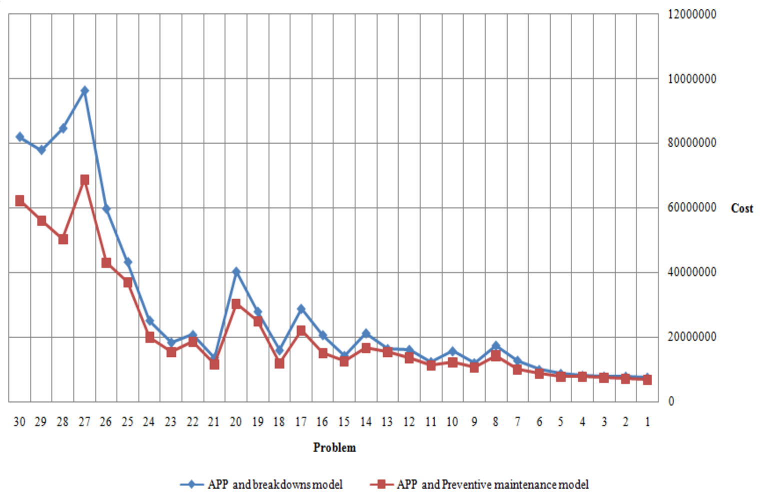

Figure 15. Comparison between solution quality of the APP with breakdowns and APP with PM.

7 Conclusion

The focus of this paper is on multi-period, multi-product, multi-machine, two stage systems, setup decisions, return products, machine breakdowns and preventive maintenance. We develop a mixed integer linear programming model that can be used to compute the optimal solution for the problems with an operation research problem solver. Due to the complexity of the problem, two metaheuristics algorithms named harmony search (HS) algorithm and vibration damping optimization (VDO) algorithm were used to solve the problem. Furthermore, an extensive parameter setting by performing the Taguchi method was conducted for selecting the optimal levels of the factors that affect the algorithm performance. Due to a large class of APP, the computational results show that VDO algorithm obtains good solutions for APP with breakdown and PM. Also, the computational results show that the objective values obtained by APP with PM are better than APP with breakdown results. Therefore, there is one straightforward opportunity for future research, which could extend the assumption of the proposed model by including real conditions of production systems, such as uncertainty return products, breakdowns and preventive maintenance, etc.

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