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Hybride Particle Swarm Optimization to Solve Fuzzy Multi-Objective Master Production Scheduling Problems with Application

Raghad M. Jasim

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Abstract: Multi-objective Master production scheduling problem is NP-hard problem, therefore because there is no algorithm that can identify the proper solution to this problem, the processing time required to solve it grows exponentially as the size of the problem increases, So, finding optimal solution is considered very difficult, and that is why meta-heuristics algorithm such as genetic algorithm (GA), simulated annealing (SA) and memetic algorithm (MA)are used to obtain the optimal solution. This article presented a hybrid particle swarm optimization (HPSO) technique for the purpose of solving fuzzy multi-objective master production schedules (FMOMPS). The fundamental concept is to integrate PSO and GA mutation operations. The purpose of this work is to apply the FMOMPS to an industrial case study involving a textile facility in Mosul, Iraq. The application includes decide the gross requirements by forecasting of demand using artificial neural networks, in addition to locate available production rate of every production line by using geometric process model for all stops and failures, and calculate availability values. The proposed method confirmed its usefulness in locating optimal solutions for MPS issues when compared to genetic algorithms for fuzzy and non-fuzzy models, as the results clearly demonstrated HPSO's superiority over GA, SA, and MA across all objectives.

Keywords: *Fuzzy Logic, Particle Swarm Optimization, Master production scheduling, Multi-Objective Optimization.*

1. Introduction

Production planning at the tactical level, commonly referred to as Master Production Scheduling (MPS), is a theory that has been adopted by numerous businesses for many years. One of the challenges inherent in developing tactical production plans is the fact that demand fluctuates over time due to a variety of unforeseeable factors. However, due to the industry's limited resources, it is impossible to estimate demand perfectly. These factors make the production planner's job extremely difficult. One could recommend increasing capacity during periods of high demand, but this wastes time and money, and in addition, the business will have even more unused capacity during periods of low demand Vieira (2004).

The search for an optimal solution to the master production schedule problem deals with several factors and performance indexes. Among the multiple objectives to be considered, maximizing the level of customer service, minimizing of Inventory level, reduction overtime, and reduced inventory levels below the safety stock level. All of this is in a scenario composed of resource capacity constraints, production rates that vary according to the productive resources and the products to be manufactured, preparation times, a seasonal demand that is close to or, often, higher than the installed capacity Higgins and Browne (1992)

The remainder of the essay is structured as follows: The following part discusses a brief change of master production scheduling, and Section 3 discusses the proposed technique for solving FMOMPS

Department of Veterinary Public Health , College of Veterinary Medicine,
University of Mosul, Mosul, Iraq
raghad.m.j81@uomosul.edu.iq

In such an environment, the aforementioned objectives constitute an arduous mission to be accomplished, as some are in conflict with each other, for example: service level versus stock level. For if there is ademand in a certain period above the productive capacity. It is necessary to raise the level of stocks in the previous periods in order to maintain the level of service.

Garey and Johnson (1979) established mathematically that this problem is NP-Hard, namely, unlikely to have an algorithm that can discover an optimal solution to the problem in polynomial time when capacity limitations and preparation durations are taken into account. Therefore, due to difficulties in solving the problem, it may be advisable to use heuristics algorithms, whether they are constructive, probabilistic or stochastic based on artificial intelligence techniques, which are called meta-heuristics.

It is important to note that heuristics algorithms do not guarantee the achievement of an optimal solution to the problem. However, in most cases, they arrive at a solution close to the optimum in a reasonable computational time Ribas (2003).

Hybrid evolutionary algorithm (HPSO) has been proposed to tackle the fuzzy multi-objective MPS problem in this study, PSO and GA mutations are integrated into this algorithm. The purpose of this article is to implement FMOMPS in a textile manufacturing facility. The application uses artificial neural networks to estimate demand and determine the gross requirement for each production line.

difficulties. In Section 4, an FMOMPS has been developed for the purpose of conducting an industrial case study. Section 5 contains a comparison of HPSO and GA. Section 6 contains of the study conclusion.

2. Foundation Of MPS

The production schedule master calendar. MPS management is a basic issue in the manufacturing process that might result in a low service level because it relates directly between customer service and the optimal use of production resources. MPS management is a critical interface between marketing and manufacturing.

According to the APICS dictionary(American Production and Inventory Control Society), Cox in 2001, master production schedule is “The expected construction schedule that includes a group of plans that drive the material requirement planning (MRP). The company plans represent a description of the special shapes, quantities, and dates. The main production schedule does not represent the sales forecast that describes the demand situation only, but it takes into consideration the forecast, the production plan, and other important considerations such as pending orders, available materials, available energy, production policy, etc. In other words, the master production schedule represents a description of demand, forecast, accumulated orders, available inventory and agreed quantities.” Cox (2001).

Proud in 1999 considered that the real challenge is to develop the master production schedule to achieve the balance between supply and demand Proud. As the request may include the expectation, the customer’s requests (which may or may not be part of the expectation), long-term contracts and agreements, the requirements of the subsidiary store (the refilling of distribution centres) or requests from another department within the company if the product is considered one. The components are in another part of the company, as well as for special works such as industrial exhibitions and for increasing safety storage needs. All of these requests are referred to as gross Vollmann, et al. (1997).

To achieve these requirements, the master production schedule needs availability of materials and production capacity (production lines or machines). It includes those materials that are produced internally in addition to those that are obtained from external sources, beside the product itself. Other parameters such as quantities, dates and time of supply must be taken into consideration. While capacity includes workers and equipment. Both of which are united with its processing. Time, capacity and capital are also important parameters that must be taken into consideration Slack(2001).

The improvement in mathematical programming methods greatly led to a significant improvement in the MPS production schedule in various production systems, as well as in objectives and limitations. Chu in (1995) developed a linear programming system to obtain an optimal or near-optimal solution to the MPS problem to increase profits subject to demand, supply and labor resources. Vieira in (2004) proposed a practical heuristic algorithm to solve the MPS problem, and provided an example that illustrated the important and complex details of creating the optimal MPS capable of maximizing system throughput. Wu et al. in (2002), constructed a mathematical model of MPS problem and developed it by using genetic algorithm, in addition to combining several techniques such as branch and bound to achieve constraints of production scheduling problem in order to obtain the optimum solution of production lines. Vieira and Ribas in (2004) have solved MPS problem by using simulated annealing. The study revealed that evolutionary algorithms are able to overcome the Local Optimum. Vieira et al. in (2004) compared between Genetic Algorithm GA and Simulated Annealing SA in solving the MPS problem. Soares and Vieira(2008) introduced a new evolutionary algorithm to tackle the MPS problem. The study developed a fitness function to minimize inventory levels, requirement not met levels, overtime, and inventory below safety stock levels Soares and Vieira(2008).On the other hand, Supriyanto in (2011) proposed fuzzy MPS model and used genetic algorithm as a way to compare the fuzzy model with the classic model. The results showed significant improvement in some objectives. Sadiq et al. in (2020) suggested a memetic algorithm for resolving the problem of master production scheduling. The findings demonstrated the algorithm's capability when compared to GA and SA .

2.1 Mathematical Model of FMOMPS

Supriyanto (2011) detailed the comparable crisp model for fuzzy multi-objective MPS as follows: .[13]

$$max \quad w_1\mu_{z1}(x) + w_2\mu_{z2}(x) + w_3\mu_{z3}(x) + w_4\mu_{z4}(x)$$
$$s.t.$$
$$\mu_{z1}(x) \le \frac{Z_1^1 - Z_1(x)}{Z_1^1 - Z_1^0}$$
$$\mu_{z2}(x) \le \frac{Z_2^1 - Z_2(x)}{Z_2^1 - Z_2^0}$$
$$\mu_{z3}(x) \le \frac{Z_3^1 - Z_3(x)}{Z_3^1 - Z_3^0}$$
$$\mu_{z4}(x) \le 1 - \frac{Z_4^1 - Z_4(x)}{a}$$
$$\mu_{z4}(x) \le 1 - \frac{Z_4(x) - Z_4^1}{b}$$
$$CUH_{rp} - AC_{rp} \le OL_{max}$$
$$w_1 + w_2 + w_3 + w_4 = 1$$
$$\mu_{zi} \in [0,1]; i = 1,2,3,4$$
$$x_{krp} \ge 0 \text{ and integer} \tag{1}$$

Where

$$Z_1(x) = \frac{\sum_{k=1}^{K}\sum_{p=1}^{P} EI_{kp}}{TH} \tag{2}$$
$$Z_2(x) = \frac{\sum_{k=1}^{K}\sum_{p=1}^{P} RNM_{kp}}{TH} \tag{3}$$
$$Z_3(x) = \frac{\sum_{k=1}^{K}\sum_{p=1}^{P} BSS_{kp}}{TH} \tag{4}$$
$$Z_4(x) = \sum_{r=1}^{R}\sum_{p=1}^{P} OC_{rp} \tag{5}$$

$$BI_{kp} = \begin{cases} OH_k & if (p = 1) \\ EI_{k(p-1)} & if (p > 1) \end{cases} \tag{6}$$
$$EI_{kp} = max\left[0, \left(\left(MPST_{kp} + BI_{kp}\right) - GR_{kp}\right)\right] \tag{7}$$
$$MPST_{kp} = \sum_{r=1}^{R} MPS_{kpr} \tag{8}$$
$$MPS_{kpr} = BN_{kpr} * BS_{kpr} \tag{9}$$
$$RNM_{kP} = max\left[0, \left(GR_{kp} - \left(MPST_{kp} + BI_{kp}\right)\right)\right] \tag{10}$$
$$BSS_{kp} = \max\left[0, \left(SS_{kp} - EI_{kp}\right)\right] \tag{11}$$
$$CUH_{rp} = \sum_{k=1}^{K} \frac{\left(MPS_{krp}\right)}{UR_{kr}} \tag{12}$$
$$OC_{rp} = max\left[0, \left(CUH_{rp} - AC_{rp}\right)\right] \tag{13}$$

The characters of this formulation describe as follows: wi: represents the weighting coefficients used to determine the priority of each fuzzy goal; and x: the MPS solution; When the objective function has a value of Z i0 or Z i1, then the degree of membership function is 0 or 1, respectively; a and b: the upper and lower limits of permissible violations of the overtime object; K: Total amount of various items; R: Total amount of various producing resources; P: Number of planning periods in total; TH: Time horizon for planning; EI kp: End-of-period inventory level for product k at period p; RNM kp: Requirements for product k that were not met during period p; BSS kp: Quantity below the level of safety inventory for product k during period p; OC rp: Required excess capacity at resource r during period p; BI kp: The initial inventory level of the product k at the beginning of the period p; OH k: Initial inventory available (on-hand) at the start of the scheduling period; GR kp denotes the gross need for product k during period p; BS kp: Lot size standard for product k during period p; NR kp: Net requirement for product k during period p, taking infinity capacity into account; SS kp: Level of safety inventory for product k during period p; UR kr: Units per hour of production of product k at resource r; AC rp: Capacity available, in hours, at resource p during period p; BN kpr: The number of standard lot sizes required to produce the product k at the resource r during the period p (number of lots); MPS kpr: Total quantity of product k to be made at resource r during period p; MPST kp: Total quantity of product k to be manufactured during period p (taking into account all available resources); CUH rp: Capacity consumed by the resource r during the time p; OL_{max}: Allowed maximum overtime.

3. Solving FMOMPS Using HPSO

Particle Swarm Optimization (PSO) was developed by Kennedy and Eberhart in 1995 and is based on the social behavior of flocks of birds. In PSO, each individual represents a particle that travels through a solution space of the problem. Each particle is assigned a position, which represents a possible solution to the problem to be solved, and a velocity value, which regulates the movement in the position of the particle. The quality of the position of each particle (fitness) is related to one or more objective functions that represent the problem to be solved. To promote broad exploration of the search space Hansheng et al. in (1999). The initial positions and velocities assigned to each particle are randomly generated Hansheng et al. (1999).

As the algorithm progresses, velocity and position change as a function of social interaction based on the social tendency of each individual to emulate the success of other individuals in the population. The change in the position of each particle depends on its own knowledge and environment, since in this change the best position visited by the particle and the best position visited by some individual in the swarm (pbest) is considered. As the algorithm progresses, the particles are concentrated in areas with good quality solutions of the search space (gbest)Baweja, and Saxena (2018).

Upon completion, the algorithm returns the best solution visited by some individual in the swarm Zhan et al. (2009).

A. FMOMPS Information :

For FMOMPS problems, the proposed algorithm takes into observance many parameters presented in real industrial milieu:

desired level of performance for each objective function.

products number, productive resources number (production lines, workstations, machines), time periods number and duration for each period.

on-hand (initial) inventories, gross requirements and production rate.

lot sizes, setup time and available capacity.

safety stock (safety inventory) level.

B. The Objective Function :

The equation 1 is designed to maximize weighted additive of the membership function of objectives. Due to the fact that HPSO minimizes the objective function, it is possible to decrease to obtain the maximum optimum solution. Assuming that DM's preference (w1=w2=w3=w4=0.25) holds true, the objective function for HPSO can be stated as follows :

function z=f(x)

$\mu_{z1}(x) = \cdots$

$\mu_{z2}(x) = \cdots$

$\mu_{z3}(x) = \cdots$

$\mu_{z4}(x) = \cdots$

$g(x) = \cdots$

z=- (0.25$\mu_{z1}(x)$+0.25 $\mu_{z2}(x)$+0.25 $\mu_{z3}(x)$+ 0.25$\mu_{z4}(x)$)+ $g(x)$;

end

C. Particle Structure :

A single vector structure is not used for describing particle content and shape in MPS issues, unlike the bulk of representations found in the literature. For a scenario with three products, four resources, and two time periods, the structure of a particle is shown in Figure 1.

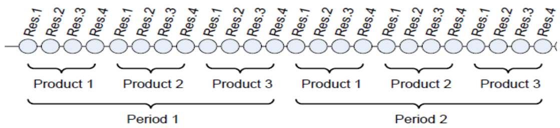

Fig. 1. MPS Particle Structure

The particle is made up of several layers of smaller components (objects). Each item is an integer positive number that represents the quantity of a product that one of the resources can make over a given time period.

D. Initial Population Creation :

By Generating a good initial population, HPSO algorithm could reache better solution in short time. This study presents a method for creating an initial population using uniform random integer numbers that are proportional to the production batch size, which is defined as:

$$\boldsymbol{Particle = randint(N_{pop}, N_{var}, [VarMin\ \ VarMax])} \quad (\mathbf{14})$$

Where $\boldsymbol{N_{pop}}$ represents size of population; $\boldsymbol{N_{var}}$ represents the length of particle which equals to $\boldsymbol{K \times R \times P}$; $\boldsymbol{VarMin\ and\ VarMax}$ represent lower and upper bound respectively. The function $\boldsymbol{randint}$ generates random integer with size of $\boldsymbol{N_{pop} \times N_{var}}$ and the number must be member of interval ($\boldsymbol{VarMin\ \ VarMax}$) Zhan et al. (2009).

In general, the lower bound for all variables is equal to zero, while the upper bound takes different values. The pseudo code of determined upper bound may be written as follows.

```
Procedures of determined upper bound
s=0;
for k=1:K
    for r=1:R
        if UR(k,r) ≠0
for p=1:P
   VarMax(s)=ceil(GR(k,p)/BS(k,p))*BS(k,p);
   s=s+1;
end
```

```
      else
         VarMax(s:s+P-1)=0;
         s=s+P;
      end
   end
end
```

E. Particles Movement :

Moving a particle involves updating its speed and position at each iteration. The importance of this stage cannot be overstated because it provides the algorithm with the power to optimize. It is necessary to update the velocity of each particle in the swarm by applying the following equation:

$$V_i^{n+1} = round\left(\frac{w*V_i^n + c_1*r_1(P_i^n - x_i^n) + c_2*r_2(P_g - x_i^n)}{BS}\right) * BS \quad (15)$$

in which c1 and c2 are both positive constant integers, which are referred to as the cognition and social coefficients respectively r1 and r2 are random number vectors in the range (0, 1); w is a coefficient of inertia that decreases or increases in proportion to the speed of the particle. P i(n+1) is the velocity of particle I at iteration n+1; V i(n) is the velocity of particle I at iteration n; x i(n) is the position of particle I at iteration n; P i(n+1) is the best position the particle has passed through in its history (stored in memory); P g is the best particle in the entire universe (stored in memory). Finally, the new position of particle I denoted by the symbol x i(n+1), is computed using the equation (16).

$$x_i^{n+1} = x_i^n + V_i^{n+1} \quad (16)$$

Some parameters can be adjusted to improve the solutions. The linear reduction of the coefficient of inertia w. This strategy consists of gradually reducing the coefficient of inertia as the iterations progress. In the first iterations, the particles have a great capacity for exploration and, as the process progresses, their speed decreases favoring convergence. This effect can be achieved with the equation(17) as well as the constant c1 and c2 by function (18) and (19).

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \quad (17)$$

$$c_1 = c_{1max} - \frac{c1_{max} - c_{1min}}{iter_{max}} \times iter \quad (18)$$

$$c_2 = c_{2max} - \frac{c_{2max} - c_{2min}}{iter_{max}} \times iter \quad (19)$$

F. Mutation Operator :

The mutation operator is important to add diversity to the process and prevent the algorithm from falling to local minima because all particles are too similar from one generation to another, Goldberg (1989). Following the movement of particles in the evolutionary progression of (HPSO), a mutation operator is applied, which includes adding or deleting one manufacturing batch size from a specific variable in the particle as part of the evolutionary progression. The particles are chosen based on the probability of mutation (pm). When a mutation results in a poor particle, we revert to the particle that existed before to the mutation in this procedure. Maurya et al.(2019)

G. Stopping criteria :

Different conditions, such as completing the maximum amount of iterations or achieving marginal progress in the goal function, can be used as termination criteria. The following table summarizes the HPSO's pseudo-code:

Procedures of HPSO

Step 1: Initializing parameters of HPSO algorithm and set iter=0;

Step 2:

2.1: Define the parameters of FMOMPS problem;

2.2: Generate some particles using eqn.(14) and initialize velocities of all particles;

Step 3: iteration loop iter=iter+1

Step 4:

4.1: Evaluate each particle fitness value;

4.2: Each particle velocity should be updated;

4.3: Apply Mutation operator

4.4: Update P_i^n and P_g;

Step 5: Stopping Criterion Control; until a stopping criterion is satisfied, repeat steps 3-5.

4. Industrial Case

This section discusses a real-world problem involving the master production schedule. The textile plant in Mosul was founded in 1956 as a medium-sized operation and now produces a diverse range of items, including fabrics, clothing, and towels. We develop a fuzzy master production schedule for a towels plant in this article. Towels Project is one of the investment projects, which came as a result of the development in meeting the needs of this change and to engage in market competition, production capacity of this project is nearly 144,000 towels annually.

A. Calculate the MPS Parameters.

To generate the MPS problem in the towels facility, the MPS settings in Table 1 must be used in conjunction with the towels facility. Before estimating availability, it is necessary to look at the production rates in Table 2.

Table 1. MPS's input parameters

Parameters	Value
K	5(T88,T89,T90,T91,T92)
R	4(DTL1,DTL2,EJTL1,EJTL2)
P	6 weeks (3rd contain day off)
BS_{kp}	12 units are required for all goods and all time slots
UR_{rp}	Table 2.
OH_k	Zero for all products
SS_{kp}	240 units are required for all goods and all time slots
AC_{rp}	40 hours/ resource
OL_{max}	5 hours/ resource

B. Determine Gross Requirements :

The production activity aims to provide the necessary products and services to consumers (Gross Requirements). Therefore, the demand forecasting process is the main guide of the productive activity in all projects. There is a wide variety of statistical methods developed to generate forecasts. The main drawback is that these methods are based on assumptions about data trends, generally having to use a different model for different demand behaviors. Ribas(2003). Prediction methods based on artificial neural networks (ANN) have contributed to improving the accuracy of forecasts in business situations Zhang(2003). They are methods that learn from the data, that is, they do not have predetermined equations based on assumptions about the behavior of the data. Therefore, BP artificial neural networks were used for predicting the MPS gross requirements

	DLT1	DLT2	EJTL1	EJTL2
T88	20	20	20	20
T89	24	24	24	24
T90	0	0	8	8
T91	56	56	56	56
T92	148	148	148	148

Table 2. The primary Production rates (unit/hour)

For each product, we used weekly demand statistics. The sample data collection period was from 31 December 2014 to 1 January 2020 and included a total of 261 observations. A multi-layer feed forward neural network with one hidden layer, one output node were used. The data were classified into two groups training and testing set for the purpose of conducting experiments to determine number of input nodes and number of hidden nodes for the network to choose the best construction for the network. The input nodes were chosen with a variation from 1-10 of the nodes while the hidden nodes varying from 2-10 with an increments of 2. So, a total of 50 neural network models were tested for each series of product demand before reaching the final structure of the neural network model.

In this study, the Levenberg Marquardt algorithm that was designed to approach second-order training speed without calculate Hessian matrix has been used. It has been proved that this algorithm provides faster convergence of feed forward neural network with moderately sized. Zhang (2003). Table 3 illustrates the optimal neural network structure and the total requirements for each product.

Table 3. The best ANN structures and gross requirements

Prod.	Str.	Weeks					
		1st	2nd	3rd	4th	5th	6th
T88	5,6,1	1058	811	1146	790	1195	857
T89	6,8,1	420	210	252	126	288	340
T90	9,4,1	294	525	542	227	619	238
T91	5,4,1	378	378	208	302	238	306
T92	7,8,1	1260	181	1260	378	1440	1020

C. Calculate Production Rates:

To calculate production rates, the failures occurring for a period of three months in the period preceding the period of master production schedule are modelled using a probabilistic distribution. The simulation scenario entails the implementation of failures on workstations. Four failure controllers STO 1, STO 2, STO 3, and STO 4 are configured to initiate random failures in workstations DLT1, DLT2, EJTL1, and EJTL2. In this study, we apply the Geometric Process (GP) model with lognormal distribution to analyze four data sets, each one belongs to type of failure. The reason of using GP instead of renewal process is the mean time to failures MTTF is increasing with time and the mean time between failures MTBF is decreasing with time Lam (2007). By using Least squares method Yeh and Chan (1998), we estimate the GP model parameter values for all failures. which are presented in Table 3. Table14 shows the availability values according to estimated parameters.

Fail.	Res.	MTTF			MTBF		
		a	μ	σ	a	μ	σ
STO_1	DLT1	0.971	1.34	0.35	1.039	38.76	12.1
STO_2	DLT2	0.983	1.08	0.33	1.027	38.82	7.55
STO_3	EJTL1	0.994	1.041	0.18	1.006	38.97	6.30
STO_4	EJTL2	0.987	1.046	0.22	1.023	38.97	7.56

Table 4. The parameter values of GP model for all failures

Res.	Weeks					
	1st	2nd	3rd	4th	5th	6th
DLT1	96.658	96.433	96.192	95.937	95.664	95.375
DLT2	97.293	97.175	97.053	96.925	96.792	96.653
EJTL1	97.398	97.368	97.337	97.305	97.274	97.242
EJTL2	97.386	97.294	97.198	97.098	96.996	96.890

Table 5. The availability values for resources

D. Create Fuzzy Model :

The FMOMPS model will be used for evaluation. Most significantly, the maximum and lower bounds for target level should be set for all objectives. Table 6 contains the values of Z i1 and Z i0. For practical solutions, it is recommended that the objective level must be reasonable. For overtime goal (a and b), the tolerable violation parameters are set to 5 and 4 hours, respectively.

Objective	Z_i^1	Z_i^0
Ending Inventory Z_1	3500	100
Requirement not met Z_2	1200	0
Inventory below safety stock Z_3	1000	50
Overtime Z_4	5	9

Table 6. The upper and lower bound of goal level

Equation 1 has been substituted with the parameter values. The following steps are taken to acquire a model of the fuzzy multi-objective MPS problem:

$$max \quad 0.25\mu_{z1}(x) + 0.25\mu_{z2}(x) + 0.25\mu_{z3}(x) + 0.25\mu_{z4}(x)$$

$$s.t.$$

$$\mu_{z1}(x) \leq \frac{3500 - Z_1(x)}{3400}$$

$$\mu_{z2}(x) \leq \frac{1200 - Z_2(x)}{1200}$$

$$\mu_{z3}(x) \leq \frac{1000 - Z_3(x)}{950}$$

$$\mu_{z4}(x) \leq 1 - \frac{5 - Z_4(x)}{5}$$

$$\mu_{z4}(x) \leq 1 - \frac{Z_4(x) - 5}{4}$$

$$CUH_{rp} - AC_{rp} \leq 5$$

$\mu_{zi} \in [0,1]$;i=1,2,3,4

$$x_{krp} \geq 0\,; k = 1 \dots 5; r = 1 \dots 4; p = 1 \dots 6 \qquad (20)$$

E. Fuzzy Solution :

Using the HPSO method to solve the FMOMPS model yields the following satisfaction and completion levels for the goals of the optimal solution.

$\boldsymbol{\mu_{z1}(x) = 0.742\,, \mu_{z2}(x) = 0.911\,, \mu_{z3}(x) = 0.8, \mu_{z4}(x) = 1}$

$\boldsymbol{Z_1 = 977\,, Z_2 = 105.8\,, Z_3 = 239.5, Z_4 = 0}$

Table 7 shows the best solution of FMOMPS model. The value "zero" indicates that there are no items available for manufacture in the resource and time period specified.

	Res.	Week					
		1st	2nd	3rd	4th	5th	6th
T88	DLT1	384	312	480	144	480	372
	DLT2	432	168	372	264	516	120
	EJTL1	300	156	240	168	60	324
	EJTL2	180	180	48	216	132	48
	Total	1296	816	1140	792	1188	864
T89	DLT1	204	0	36	108	72	60
	DLT2	144	144	60	12	60	48
	EJTL1	96	12	48	0	60	96
	EJTL2	204	108	60	24	84	132
	Total	648	264	204	144	276	336
T90	DLT1	0	0	0	0	0	0
	DLT2	0	0	0	0	0	0
	EJTL1	96	192	96	192	204	108
	EJTL2	108	168	156	168	192	180
	Total	204	360	252	360	396	288
T91	DLT1	192	36	24	132	108	36
	DLT2	96	264	48	72	12	144
	EJTL1	36	156	72	60	72	0
	EJTL2	168	48	60	60	24	132
	Total	492	504	204	324	216	312
T92	DLT1	216	96	252	72	372	432
	DLT2	408	24	528	96	432	108
	EJTL1	576	36	132	168	480	216
	EJTL2	300	24	348	60	132	276
	Total	1500	180	1260	396	1416	1032

Table 7. The best MPS solution found

5. Comparison Between HPSO And GA

To tackle the identical MPS problem, Soares et al. and Supriyanto employed genetic algorithms, whereas Sadiq et al. used memetic algorithms. To facilitate comparison, the outcome of Soares' study will be referred to as the non-fuzzy solution whilst the outcome of Supriyanto's study will be referred to as the fuzzy solution of GA. Sadiq et al(2020) alresult .'s will be referred to as the non-fuzzy solution, and we applied the same approach to obtain the fuzzy solution. Vieira et al. (2007), Soares and Vieira(2008)and Supriyanto(2011). The HPSO algorithm's parameters are as follows: w max equals 1.4, w min equals 0.4, c 1max and c 2max equal 2.5, and c 1min and c 2min equal 1. The population size is 500, and the maximum number of iterations is 600 without any modifications.

Table 8 showed the comparison results between GA and HPSO for non-fuzzy and fuzzy solutions for the production scenario of Soares.

Alg.	Solution	EI	RNM	BSS	OC
GA	Fuzzy	4943	842	821	3
	Non Fuzzy	5228.5	985.7	585.7	4.33
MA	Fuzzy	4401.6	894.6	510.9	0
	Non Fuzzy	4428.5	942.8	528.5	0.3
HPSO	Fuzzy	4364.8	708.1	382.6	0
	Non Fuzzy	4428.5	942.8	528.5	0.3

Table 8. The comparison among GA, MA and HPSO

The non-fuzzy GA solution achieves high levels of all targets whereas the non-fuzzy HPSO method achieves lower levels of inventory, fewer unmet requirements, fewer inventory levels below safety stock, and fewer overtime hours Singh et al.(2020).

In comparison to HPSO's fuzzy solution, GA's fuzzy solution achieves the highest levels of all objectives. It appears as though the GA is not prepared to distribute overtime adequately ("where and when" is not well-defined explicitly). Adding overtime to the right resources at the right moment can possibly lower inventory levels. It is also possible to answer questions such as when more capacity is needed, how much more space it will take up, and where it will be introduced, although HPSO is superior than MA in obtaining the ideal fuzzy solution. Mohmmad et al.(2018)

6. **Conclusions**

The optimization of master production schedule is extremely complex due to the fact that it works with conflicting objectives such as, maximizing the service levels, minimizing inventory levels, minimizing overtimes and minimizing inventory below safety stock. In addition, production characteristics such as capacity and quantity of resources, unstable demand, unsteady preparation times and a planning horizon composed of several periods with varying duration must also be considered. The research proposes a hybrid particle swarm optimization technique for solving MPS issues. The HPSO can solve efficiently the fuzzy model of MPS. It has capability to control and distribute additional capacities (overtimes) and the inventory levels can be minimized without influencing service level, especially in fuzzy solutions.

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