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Simultaneous Solution of Material Procurement Scheduling And Material Allocation to Warehouse Using Simulated Annealing

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ABSTRACT

One of the classes of the project schedule is the Material Procurement Scheduling (MPS) problem, which is considered besides the material allocation to warehouse (MAW) problem recently. In the literature, the Simultaneous Solution of MPS-MAW is investigated by considering one warehouse and unlimited capacity of the warehouses most of the times. In this paper, we propose the propositional and mathematical model of the simultaneous MPS-MAW with multiple warehouses and the limited capacity at the whole of the horizon planning for each warehouse. The proposed model aims to obtain the best ordering point, selection of the best suppliers, the best activity start, and the fair material distribution to the warehouses as possible by the given objective function. The proposed model is NP-hard, so a metaheuristic namely simulated annealing is proposed to reach the acceptable but not optimal solutions in a short time. Also, to overcome the complexity of the model, the encoding of the decision variables have been done by adding the auxiliary variable. Comparing the solutions of the small problems with the exact methods shows the validation of the proposed SA. Also, the design of experiments shows the significance of the model and each SA parameters. Finally, by the optimum values of the SA parameters, the large problems have been solved at acceptable times.

1. Introduction

Project scheduling is about the determination of the starting time of the activities. In addition to activities, the material ordering, delivering time are important factors in every project. These three variables including activities start time, ordering, and delivering time of materials are considered in the Project Logistic Problem (PLP). In fact, PLP is critical because of its role in the project-planning phase when the activities start time is affected by the time of material delivery. In other words, in the real world, there is no any project in which when its activities want to start, all of its required materials are already prepared. However, PLP is not enough to schedule the project correctly. For example, consider the project in which the activities are done by labors that have to move between each activity and where the materials are gathered (warehouses). These trips between the places each activity is done and the warehouses make the project scheduling more complex.

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In each project, in addition to the Material Procurement Scheduling (MPS), the Material Allocation to the Warehouse (MAW) must be considered. In fact, if we only consider MPS, the solution to the problem will be a local minimum. On the other hand, if we just solve MAW, the solution will be a local minimum one, because, in MAW, the allocation and material transportation costs are considered which are insufficient to model the objective function of the real projects. Therefore, the consideration of both MPS and MAW is necessary in order to reach the global optimum solution through the modeling with more reality. In this paper, we aim to solve MPS and MAW simultaneously, so that the cost of material ordering from different suppliers and costs related to MAW are minimized by the optimum determination of the material ordering, delivering and activities start times and the quantities of the materials allocation to the warehouses.

2. Literature Review

PLP has been investigated by many researchers. One of the papers which have solved PLP with integrating the procurement and construction processes is [1] in which the ordering time and quantity of the materials were determined by considering the stochastic construction process. Also, the optimum ordering and activities start times were obtained by considering the lag between the ordering time and delivering time of the materials through the progress curve of the delivery and construction process in order to avoid lateness. The lag between the ordering time and material delivery time was considered as a stochastic parameter. Finally, by determination of the sufficient stock of materials through the mathematical formulas, the project is protected from being late by the optimum scheduling of the ordering time and construction process start time.

The article [2] investigated the construction resource planning and scheduling by simulation and analytical techniques. In other words, the near-optimum distribution of the different resources such as manpower, equipment, space, and material in the life cycle of the project is the main purpose of this paper. To solve the problem, an intelligent scheduling system (ISS) was proposed in which the duration, cost and Net Present Value (NPV) of the project had been minimized. Although the distribution of resources is the important factor, material allocation is not considered in this paper.

By [3], the procurement scheduling for complex projects had been investigated with the fuzzy environment. The activities duration and lead times are fuzzy. Their fuzzy mathematical programming is able to determine the optimum ordering time with considering the shortage and holding costs. While the ordering point is important, but the activities start time must be considered in the model.

In the paper [4], two separated problems – MPS and Project Scheduling Problem (PSP)–are integrated under the different suppliers. For this integrated problem, they proposed the mixed-integer programming model with holding, ordering, purchasing and activities related costs as an objective function without consideration of the capacity of the warehouses. Their solution technique was an enhanced Genetic Algorithm (GA), which was able to solve the problem when its size was going to arise in a reasonable time.

The [5] Investigated the previous problem by adding the second objective function in a robust environment. The second objective is the schedule robustness maximization. The uncertainty is considered of the activities duration time and execution costs. In order to solve the bi-objective model, the NSGA-II is used and by considering the total slack and free slack, the robustness of the schedule is measured. In the proposed model, although the resource availability constraint is considered, the warehouse's capacity is not mentioned, while this is an important factor when the warehouse space is limited like the real projects.

In the paper [6], the MPS and PSP are solved simultaneously by the hybrid SA and GA. Their proposed model has two costs of ordering and holding. The decision variables are the start time of the activities, the ordering time and quantity, and the inventory level for only one warehouse. Also, the project duration is limited by the deadline and there is no supplier in the model. The results show that the proposed hybrid SA-GA is more efficient than the exact methods when the problem size is rising.

The previous article had been developed by the paper [7] with consideration of the multi-mode activities and quantity discount policy. Their mixed integer programming model consists of three objective functions called the project duration minimization, maximization of the robustness of the project and minimization of the total costs including ordering, holding, procurement, and resources employment. The project is constrained by deadline and resource availability, while the capacity of the warehouse is not considered. Then, the proposed model is solved by multi-objective problems solution methods like NSGAII, SPEAII, MOPSO, and MOEAD. The results show that the NSGAII is better than the other method in most of the metrics.

The paper [8] has investigated the integrated planning of project scheduling and material procurement with consideration of the environmental impacts. The proposed mixed integer model aims to determine the optimum value of the activity start time, ordering time, and quantity while considering the constraints of the resources availability, ordering quantity and environmental impacts with two objective functions. The solution techniques are NSGA-II and MOMBO. The results show the better efficiency of the MOMBO when the instances are getting larger. Moreover, by [9] the Project Scheduling and Material Ordering (PSMO) problem had been solved by two multi-objective metaheuristic algorithms called NSGA-II and MOPSO. Their contributions were considering the economic, environmental, and social concerns in the objective functions and using the data of the real case study in Iran.

As the papers related to our topic have been reviewed, it can be seen that the papers modeled the MPS and PSP by just one warehouse, so that not considering the multiple warehouses is a gap in the literature. Also, the above-mentioned articles just consider the one related cost to warehouses or inventories as a holding cost of the resources ; this is the second gap. In fact, the costs related to the warehouses can be developed by determination of which materials allocate to which warehouse in order to minimize the material travel distance on the project site, because when the materials come to the work site, at first, they are assigned to the proper warehouses and then, they are used by the related activities; this is the third gap. In addition, by considering multiple warehouses, in addition to their capacities, which is less considered in the literature even for one warehouse, the fair distribution of the materials to the warehouses can be added to the objective function. Therefore, the contributions of this paper can be listed below:

- Considering the multiple warehouses on the project site.
- Considering the material allocation to warehouses problem besides the MPS.
- Considering the fair distribution of the materials to the warehouses.
- Considering the maximum capacity of the warehouses.

In the next Section, the problem is stated in which the MPS and MAW are investigated with more details and the details of the decision variables, and objective functions are mentioned too. In the third part, the propositional and the mathematical models are proposed. In the fourth part, the solution technique is introduced and its functions are explained. In the fifth part, we have the results and discussions about the outputs. Finally, in the last part, the conclusions and recommendations for future studies are proposed.

3. Problem Statement

The problem of this paper can be seen as two separated parts called before delivery and after delivery. In the first part, before the materials deliver to the activities, the ordering and delivering time and also, selection of the supplier are determined. After that, in the second part, when the materials reach the site, the selection of the warehouses which the materials allocate to them and the activities start time are determined. In other words, not only the activities schedule is affected by the ordering and delivering times, but also the material allocation to the warehouses is determined by the activities location. So, the project costs are not limited to ordering or holding costs. In fact, the material transportation costs are included too by the solution of MAW. In the following, the assumptions or the propositional model and mathematical model are proposed.

3.2 Problem Modeling

In this section, the propositional model or the structured assumptions are proposed. This propositional model is the structured form of the assumptions which we can understand the whole problem and see its strong points or weak points by them.

3.1.1 The propositional model

- In the site modeling, the location of each warehouse is predetermined and dimensionless.
- The shape of each material is dimensionless.
- Each material for each activity is ordered only one time with the predetermined quantity.
- The material transportation cost per unit is predetermined.
- The quantity of material transportation is equal to the material ordering quantity.
- The lead time for each material by each supplier is deterministic.
- The unit of time is discrete.
- The activity start time must be bigger than the delivering time of the materials.
- Each material must be ordered from only one supplier.
- Each warehouse has a limited capacity.
- Each activity location is predetermined.
- The distance between each activity location and each warehouse is predetermined.
- Each material for each activity must be allocated to only one warehouse.
- The requirement material for each activity is deterministic and predetermined.
- There is no discounted ordering.
- Each activity can be started between its earliest start time and latest start time.
- The material can leave the warehouse when its related activity wants to start, otherwise, the material will stay in the warehouse.
- The activities are finish-to-start with zero lag, non-preemptive, deterministic duration, with one mode and without cash flow.
- There is no deadline for the project completion.

– There is a penalty when the materials distribution to the warehouses is not fair.

Now by the above-mentioned propositional model, the mathematical model is available.

3.1.2 The mathematical model

The notations, indices, sets, parameters, and decision variables are defined below:

– Indices

j=1,…,N	Index of activities.
m=1,…,M	Index of materials.
s=1,…,S	Index of suppliers.
t=0,…,H	Index of time.
l=1,…,L	Index of warehouses.

– Sets

J_t	The set of activities, which can be started at *t*.
O_t	The set of activities, which their requirement material can be ordered at *t*.
B_j	The set of activities preceding *j*.

– Parameters

N	Number of activities.
M	Number of materials.
L	Number of warehouses.
S	Number of suppliers.
H	The horizon of planning.
G_{ms}	The cost of ordering material m form supplier *s*.
h_m	The holding cost of material m in each warehouse.
R_{jm}	The requirement material m for activity *j*.
L_m	Lead time of material m for each supplier.
F_l	The maximum capacity of the warehouse *l*.
d_j	The duration of activity *j*.
e_j	The earliest start time of the activity *j*.
l_j	The latest start time of the activity *j*.
C_m	The transportation cost per unit of the material *m*.
D_{lj}	The distance between the warehouse *l* and the location of the activity *j*.
P	The amount of the penalty of the unfair material distribution per unit.

– Decision variables

I_l	The total inventory of the warehouse *l* of the cycle time of the project.
X_{jt}	Equals to 1 if the activity *j* starts at time *t* and 0, otherwise.

γ_{mjst}	Equals to 1 if the material *m* is ordered from supplier *s* for the activity *j* at the time *t* and 0, otherwise.
y_{mjlt}	Equals to 1 if the material *m* that is ordered for activity *j* is allocated to warehouse *l* at the time *t* and 0, otherwise.
$\bar{I}$	The mean of the amounts of I_l.

In the following, the mathematical model is proposed below:

$$Min\ Z = (\sum_{l=1}^{L}(I_l - \bar{I})^2)/(L-1) \times P,$$

$$+\sum_{m=1}^{M}\sum_{j=1}^{N}\sum_{s=1}^{S}\sum_{t=0}^{e_j - L_m} G_{ms} \times \gamma_{mjst}, \quad (1)$$

$$+\sum_{m=1}^{M}\sum_{j=1}^{N}\sum_{l=1}^{L}\sum_{t=L_m}^{H-1} R_{jm} \times D_{lj} \times C_m \times y_{mjlt},$$

$$s.t. \quad \sum_{t=e_i}^{l_i} t * X_{it} + d_i \le \sum_{t=e_j}^{l_j} t * X_{jt}, \quad i \in B_j,\ j = 1,2,\dots,N \quad (2)$$

$$X_{10} = 1, \quad (3)$$

$$\sum_{t=e_j}^{l_j} X_{jt} = 1, \quad j = 1,2,\dots,N \quad (4)$$

$$I_l = \sum_{m=1}^{M}\sum_{j=1}^{N}\sum_{t=L_m}^{e_j} y_{mjlt} * R_{jm}, \quad l = 1,2,\dots,L \quad (5)$$

$$I_l \le F_l, \quad l = 1,2,\dots,L \quad (6)$$

$$\sum_{s=1}^{S}\sum_{t=0}^{e_j - L_m} \gamma_{mjst} = 1, \quad m = 1,2,\dots,M,\ j = 1,2,\dots,N \quad (7)$$

$$\sum_{l=1}^{L}\sum_{t=L_m}^{e_j} y_{mjlt} = 1, \quad m = 1,2,\dots,M,\ j = 1,2,\dots,N \quad (8)$$

$$\sum_{s=1}^{S}\sum_{t=0}^{e_j - L_m} t * \gamma_{mjst} = \sum_{l=1}^{L}\sum_{t=L_m}^{e_j} t * y_{mjlt} - L_m, \quad m = 1,2,\dots,M,\ j = 1,2,\dots,N \quad (9)$$

$$\sum_{s=1}^{S}\sum_{t=0}^{e_j - L_m} t * \gamma_{mjst} \le \sum_{t=e_j}^{l_j} t * x_{jt} - L_m, \quad m = 1,2,\dots,M,\ j = 1,2,\dots,N \quad (10)$$

$$\bar{I} = (\sum_{l=1}^{L} I_l)/L, \quad (11)$$

$$X_{jt}\{0,1\},\ y_{mjlt}\{0,1\}, \gamma_{mjst}\{0,1\},\ I_l \ge 0\ Integer. \quad m = 1,2,\dots,M,\ l = 1,2,\dots,L,\ j = 1,2,\dots,N,\ t = 0,1,\dots,H \quad (12)$$

The Eq. (1) defines the objective function, which is the sum of the total costs including cost of the unfair material distribution, ordering cost, and material transportation cost respectively. Cost of the unfair material distribution is calculated by the formula of variance so that its larger value indicates the more unfair distribution. Constraint (2) controls the precedence relations of the activities. By constraint (3), the start time of the first activity is determined at 0. By constraint (4), each activity starts between its earliest and latest start time. Constraint (5) calculates the overall inventory of each warehouse of the cycle time of the project. Constraint (6) limits the overall inventory of each warehouse with the aim of controlling the fair material distribution. By constraint (7), each material of each activity must be ordered at interval time between 0 and its activity earliest start time (e_j) minus its material lead time (L_m) just one time and from one supplier. By constraint (8), each material of each activity must be allocated to only one warehouse at interval time between (L_m) and its activity earliest start time (e_j) just one time. By constraint (9), after L_m time unit, ordered material must be delivered to its related activities. By constraint (10), after L_m time unit, ordered material can be allocated to its related activities. Constraint (11) calculated the mean of the amounts of I_l. At last, by constraint (12), the type of the decision variables of the model is determined. From the complexity theory viewpoint, the above-mentioned mathematical model is in the class of NP-hard problems.

- Proof
  - Premise: Based on the literature the Multi-Dimensional Travel Salesman Problem (MTSP) is in the class of NP-complete problems.
  - Argument: If in the above-mentioned model the material allocation section is removed, the MPS remains. Furthermore, by MTSP, we want to find a path with the minimum sum of the distances that each salesman meets every city just one time and returns to its first city. If in MTSP instead of the cities, we consider the project operations such as ordering, delivering, allocating, and processing, and also, we consider each material as each salesman, MTSP can be reducible to MPS problem. So, MPS problem is at least as hard as MTSP.
  - Conclusion: By the premise (i) and argument (ii), therefore, MPS problem or our mathematical model is in the class of NP-hard problems.
  - Our proposed mathematical model is NP-hard. As a result, we cannot reach the optimal solution if the size of the problem increases. So, in the following, a metaheuristic algorithm is proposed to reach an acceptable but not optimal solution when the problem size rises.

4. Simulated Annealing for MPS-MAW

In this section, a simulated annealing optimization algorithm is proposed. Our SA is not modified basically, but its functions of generating the neighborhood solution are adapted to the decision variables of the problem, which it is described in the following. SA was introduced by [10] for the first time. Its function is influenced by the natural phenomenon in which the molecular structure of the metals is getting organized when it gets cold gradually. Three references [11-13] are sufficient to understand the concept and how to implement the SA. SA is a single-solution based algorithm basically. Hence, SA improves only one solution at its iterations. This makes the SA fast; however, its performance of finding a global solution is weakened. Totally, the performance of SA of solving the combinatorial optimization problems has been proved in the literature, and this is our reason to select it as a solution technique.

The pseudo code of the proposed SA is presented below that is coded by C++ programming.

a) Inputs
b) Cooling starts

```
Generate an initial solution (s = s_0);
Set initial temperature (T_0 = T_max);
i=0;
While (T_i > T_min) do
{
    t=0;
    While (t < N_ex) do
```

```
{
Generate the neighborhood solution by function M (ś);
Calculate the (ΔE = f(s) − f(ś));
If ((ΔE ≤ 0) then s = ś
Else
        {
        ran =a random number between 0 and 1;
        If (ran ≥ e^(−ΔE/T_i)) then s = ś
        Else continue;
        }
t++;
}
Update the temperature (T_{i+1} = α ∗ T_i);
i++;
}
```

c) Display the best solution.

In this pseudo code, at first step, inputs are inserted. These inputs consist of the problem parameters and SA parameters. SA parameters are described with their notation in Table 1. The notation s_0 is the initial solution, which is an important factor because of its impact on the solution quality. The initial solution can be determined randomly or greedy. In this paper, we do not investigate the impact of the initial solution. The notation T_i denotes the temperature of the iteration i. This temperature is cooled by the equation $T_{i+1} = \alpha * T_i$ in which α is the cooling rate. Also, if α is valued between 0.8 and 0.99, the cooling plan will be slow and efficient [14]. The notation $f(s)$ is the objective function or fitness function of the problem. Function *M* generates the neighborhood solution, which is similar to mutation function of GA.

Table 1. *Definition of SA parameters.*

Parameter	Notation	Definition
Maximum temperature	T_{max}	Initial temperature.
Minimum temperature	T_{min}	The final temperature that the algorithm stops when the T_i reaches T_{min}.
Maximum iteration in each temperature	N_{ex}	The temperature of the algorithm is cooled when the t reaches N_{ex}.
Cooling rate	α	The ratio which the temperature is cooled by it.

4.1 Solution Representation

The encoding of the decision variables of the problem is shown in Table 2. The problem is coded by the C++ programming and all of the decision variables are encoded by 2-dimension matrices. In order to encode the decision variables y_{mjlt} and γ_{mjst} which have the four indices, we use the auxiliary variable called A_{mjt}. In other words, the representation of the decision variable with four indices increases the computational complexity. To overcome this problem, we introduce A_{mjt}. At first, for each material of each activity, the ordering time is determined by the variable A_{mjt}. Now, for γ_{mjst} we just need to determine its index of supplier, because the index t is common between $A_{mjt}$and γ_{mjst}that is obtained before. Also, the index t of y_{mjlt} is calculated by adding amount of $L_m$to the index t of γ_{mjst}. Hence, the variable y_{mjlt} can be encoded by a 2-dimension matric in which the value of index l

is determined. Variable X_{jt} is encoded by the 1-dimension matric in which each array is valued by the discrete numbers indicate the start time of the activities.

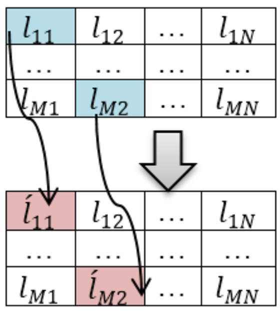
Table 2. *Solution representation by C++ programming.*

Decision variables	Solution representation				
A_{mjt}		j_1	j_2	$\dots$	j_N
	m_1	t_{11}	t_{12}	$\dots$	t_{1N}
	$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
	m_M	t_{M1}	t_{M2}	$\dots$	t_{MN}
γ_{mjst}		j_1	j_2	$\dots$	j_N
	m_1	s_{11}	s_{12}	$\dots$	s_{1N}
	$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
	m_M	s_{M1}	s_{M2}	$\dots$	s_{MN}
y_{mjlt}		j_1	j_2	$\dots$	j_N
	m_1	l_{11}	l_{12}	$\dots$	l_{1N}
	$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
	m_M	l_{M1}	l_{M2}	$\dots$	l_{MN}
X_{jt}	j_1	j_2	$\dots$	$\dots$	j_N
	t_1	t_2	$\dots$	$\dots$	t_N

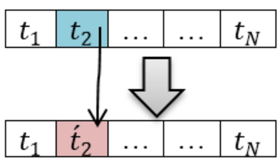
4.2 How to Generate Neighborhood Solutions

In this section, we define the process of function M. by function M, the code of solution is changed, as it is shown below. This function has one parameter called m_r which is determines the number of arrays which have to be changed or mutated. In this paper, we call m_r as mutation rate and include it in SA parameters.

For example, for the variable y_{mjlt} with $m_r = 2$, we have:



or for the variable X_{jt} with $m_r = 1$ we have:



Therefore, in this section, the proposed SA is introduced. Our SA is not modified basically, but the decision variables are encoded in a simple way to decrease the computational complexity of the problem and SA is able to move towards the new solution by the mutation function. In the following, by the proposed SA, we are going to solve the problem of small and large sizes to evaluate the performance of the algorithm.

5. Computational Results

In this section, at first, we validate the proposed SA of solving the small problem by comparing its performance with the exact solution techniques, which are proposed by GAMS software. Then, the Design of Experiments (DOE) is performed in order to obtain the optimum value of SA parameters. Based on literature, DOE has been accepted as an efficient tool to conduct and analyze the experiments [15]. Finally, by the optimum SA parameters, we solve the problem with large size by the proposed SA and also, the artificial intelligence of the solution algorithm is shown by the history of convergence.

5.1 Small Problem

In this part, a numerical example with the size of 6 activities, 2 materials, 4 suppliers, and 2 warehouses is solved. The project network of the example with activities durations and the required material of each activity are shown in Fig. 1. The inputs of the examples with small and large sizes are not shown in this paper but they can be given if they are requested.

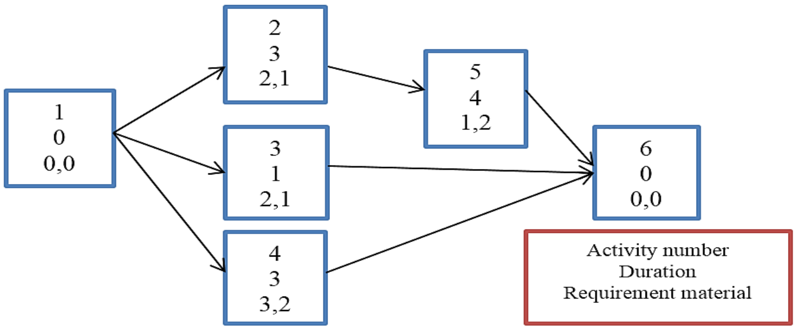


Fig 1. *The project network of the numerical example with the small size.*

The results of the solution of the numerical example with small size by the proposed SA and the exact solver of GAMS are shown in Table 3. The results show that the exact solver COUENNE is faster than the proposed metaheuristic when the problem size is small, while the other exact solver BONMIN is not as fast as our proposed SA and all of the solvers could reach the optimal solution. Also, SA is coded under the system with Core i3, 2.30 GHz and 2 GB of RAM. So, the results show that our proposed SA is valid to model the MPS-MAW problem in a correct way.

Table 3. *Comparison of the results obtained by the proposed SA and exact solvers of GAMS software of the problem with the small size.*

Solvers	Problem size	Best objective function	Worst computational time (in sec.)	Best computational time (in sec.)	Average of computational times (in sec.)
COUENNE (Full)	(6*2*4*2)	192	0.0160	0.0001	0.0064
BONMIN (Full)	(6*2*4*2)	192	13.1250	12.8030	13.0132
Proposed SA	(6*2*4*2)	192	0.1120	0.0700	0.0956

5.2 DOE

In this section, a DOE is organized to evaluate the relationship between each SA parameter and the computational time of the algorithm. DOE's method is Response Surface Methodology (RSM), which its outputs is calculated by Design Expert software. The experiments are done in order to investigate the 5 SA parameters. The range of changes of each SA parameter is given in Table 4. Moreover, the DOE's result is shown in Table 5, which shows the significance of each parameter and model. By Table 5, we can see that the parameters T_{max}, α, and N_{ex} are significant and in the other words, they have a direct impact on the computational time of the algorithm. Also, among the dual compositions, the composition of two parameters α, and N_{ex} is distinguished significant with high certainty at the level 0.05. The significance of the other parameters and other dual compositions are given in Table 5 too.

Finally, the DOE gives us the minimum value of the SA parameters in order to solve the problem in a short time as it is shown in Table 6.

Table 4. *The range of changes of SA parameters in the experiments.*

SA parameter	T_{max}	T_{min}	α	N_{ex}	m_r
Range of changes	[1,50,100]	[0.1,0.05,0.0001]	[0.9,0.94,0.98]	[5,8,10]	[1,2,3]

Now by the optimal values of SA parameters obtained by DOE process in the previous part, the large problems are getting solved in the next part that the performance of the proposed SA has been increased by the optimal values.

5.3 Large Problems

In this part, 36 examples which are available in the library of the project scheduling instances[1] (PSPLIB) with the size of 30 and 60 activities, 1 to 4 materials, 2 to 4 suppliers and 2 to 4 warehouses are solved. The problems with 30 activities had been executed 5 times and the results are given in Table 7. In this table, WCT is the worst computational times among the executions, BCT is the best computational time, ACT is the average of the computational times, WOF is the worst objective function, BOF is the best objective function, and finally AOF is the average of the objective functions obtained the proposed SA of each problem. The results of Table 7 show that by increasing the problem size, the computational time has been growing which was predictable. The convergence history of the objective functions values

[1] http://www.om-db.wi.tum.de/psplib/

of the problem number 36 is indicated in Fig. 2. Moreover, the results of Table 7 show that the total average of the computational times is 0/855, which is acceptable for the problems with the 30 activities.

Table 5. *Significance evaluation of the relationships between each SA parameters and the computational time.*

ANOVA for Response Surface Quadratic model						
Source	**Sum of Squares**	**df**	**Mean Square**	**F Value**	**p-value**	**significant**
Model	3.86	20	0.19	34.77	< 0.0001	YES
A-T_{max}	0.11	1	0.11	19.23	0.0011	YES
B-T_{min}	0.017	1	0.017	3.02	0.1103	NO
C-α	2.18	1	2.18	392.01	< 0.0001	YES
D-N_{ex}	0.54	1	0.54	96.69	< 0.0001	YES
E-m_r	4.325E-003	1	4.325E-003	0.78	0.3963	NO
AB	4.290E-003	1	4.290E-003	0.77	0.3981	NO
AC	0.046	1	0.046	8.21	0.0154	YES
AD	0.032	1	0.032	5.74	0.0355	YES
AE	7.482E-003	1	7.482E-003	1.35	0.2702	NO
BC	0.023	1	0.023	4.22	0.0646	NO
BD	1.156E-003	1	1.156E-003	0.21	0.6570	NO
BE	3.844E-003	1	3.844E-003	0.69	0.4230	NO
CD	0.25	1	0.25	44.68	< 0.0001	YES
CE	3.969E-003	1	3.969E-003	0.72	0.4158	NO
DE	2.250E-004	1	2.250E-004	0.041	0.8441	NO
A^2	0.012	1	0.012	2.15	0.1702	NO
B^2	2.087E-004	1	2.087E-004	0.038	0.8498	NO
C^2	0.11	1	0.11	19.98	0.0009	YES
D^2	2.409E-003	1	2.409E-003	0.43	0.5235	NO
E^2	0.042	1	0.042	7.58	0.0188	YES
Residual	0.061	11	5.550E-003			
Lack of Fit	0.022	6	3.616E-003	0.46	0.8144	not significant
Pure Error	0.039	5	7.871E-003			
Total	3.92	31				

Table 6. *Optimal values of SA parameters obtained by DOE.*

SA parameters	T_{max}	T_{min}	α	N_{ex}	m_r
Optimal values	15	0.07	0.92	8	2

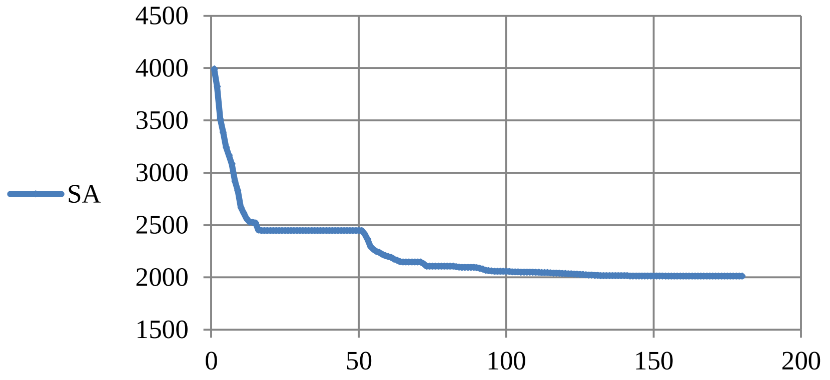


Fig 2. *The history of the convergence of the proposed SA of the solution of the problem j30 (Num. 36) (vertical axis: the value of the objective function, horizontal axis: number of iterations).*

Table 7. *Results of solution of 36 problems with 30 activities by the proposed SA.*

Pro. num.	**Size** j	**M**	**S**	**w**	**WCT**	**BCT**	**ACT**	**WOF**	**BOF**	**AOF**
1	30	1	2	2	0/433	0/306	0/386	2454	2451	2452
2	30	2	2	2	0/546	0/531	0/535	3117	3112	3114
3	30	3	2	2	0/779	0/425	0/578	4121	4107	4114
4	30	4	2	2	0/774	0/478	0/664	4333	4313	4326
5	30	1	3	2	0/355	0/267	0/308	2452	2451	2451
6	30	2	3	2	0/759	0/209	0/456	3110	3099	3103
7	30	3	3	2	0/469	0/367	0/364	4100	4098	4099
8	30	4	3	2	0/557	0/34	0/451	4311	4302	4307
9	30	1	4	2	0/498	0/369	0/424	2456	2451	2454
10	30	2	4	2	1/029	0/735	0/891	3085	3078	3082
11	30	3	4	2	1/238	0/455	0/787	4109	4090	4097
12	30	4	4	2	0/881	0/308	0/540	4274	4259	4266
13	30	1	2	3	0/892	0/852	0/878	1648	1647	1647
14	30	2	2	3	1/252	0/571	0/929	2051	2037	2044
15	30	3	2	3	0/93	0/884	0/779	2885	2851	2863
16	30	4	2	3	0/905	0/851	0/767	3041	3024	3031
17	30	1	3	3	0/986	0/954	0/922	1646	1644	1645
18	30	2	3	3	0/988	0/603	0/751	2046	2038	2042
19	30	3	3	3	1/462	0/928	1/144	2856	2844	2851
20	30	4	3	3	0/861	0/302	0/628	3030	3009	3019
21	30	1	4	3	1/154	0/99	0/957	1645	1644	1645
22	30	2	4	3	1/349	0/828	1/166	2034	2025	2029
23	30	3	4	3	1/632	1/347	1/219	2834	2828	2832
24	30	4	4	3	0/943	0/393	0/623	2998	2987	2993
25	30	1	2	4	1/294	1/045	1/161	1071	1066	1069
26	30	2	2	4	1/237	1/158	1/211	1401	1394	1397
27	30	3	2	4	2/674	1/359	1/816	1971	1961	1966
28	30	4	2	4	1/021	0/445	0/707	2211	2112	2154
29	30	1	3	4	1/313	0/998	1/199	1068	1065	1066
30	30	2	3	4	1/341	0/921	1/185	1399	1399	1399
31	30	3	3	4	1/275	1/09	1/113	1956	1951	1953
32	30	4	3	4	0/817	0/444	0/684	2117	2098	2108
33	30	1	4	4	1/703	1/165	1/449	1068	1065	1067
34	30	2	4	4	1/474	0/862	1/108	1387	1373	1380
35	30	3	4	4	1/531	1/143	1/388	1955	1941	1947
36	30	4	4	4	0/702	0/458	0/615	2095	2085	2090
Total	-	-	-	-	2/674	0/209	0/855	-	-	-

In the following, the problems with 60 activities had been solved with 5 execution of each problem. The results of the solution of j60 problems with 3 and 4 materials, 3 and 4 suppliers and 3 and 4 warehouses are shown in Table 8. The convergence history of the objective functions values of the j60 problems (number 37) is indicated in Fig. 3.

Table 8. *Results of solution of j60 problems by the proposed SA.*

Pro. num.	**Size J**	**M**	**S**	**w**	**WCT**	**BCT**	**ACT**	**WOF**	**BOF**	**AOF**
37	60	3	3	3	0/866	0/503	0/637	5751	5727	5735
38	60	4	3	3	0/704	0/482	0/498	5784	5753	5763
39	60	3	4	3	1/387	1/325	1/075	5737	5709	5720
40	60	4	4	3	0/866	0/27	0/637	5751	5727	5735
41	60	3	3	4	1/213	0/728	0/972	3953	3940	3945
42	60	4	3	4	0/276	0/115	0/172	4321	4291	4311
43	60	3	4	4	1/872	1/164	1/245	3953	3915	3936
44	60	4	4	4	0/267	0/069	0/191	4309	4261	4281
Total	-	-	-	-	1/872	0/069	0/678	-	-	-

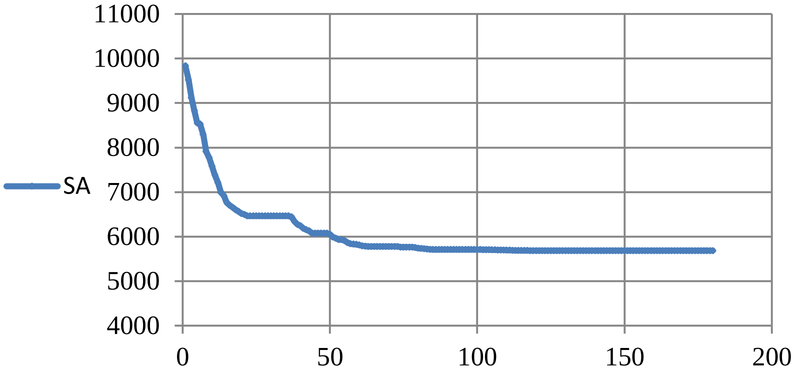


Fig 3. *The history of the convergence of the proposed SA of the solution of the problem j60 (Num. 37) (vertical axis: the value of the objective function, horizontal axis: number of iterations).*

As a result, our proposed SA was able to solve the problems with 30 and 60 activities in acceptable times. The convergence history shows the performance of the artificial intelligence of the algorithm in which the convergence rate is acceptable.

6. Conclusions

In this paper, the material allocation to the warehouse problem was modeled as a second problem besides the material procurement problem (MPS-MAW) which was not considered in the literature. In addition, the warehouse was considered as one place with the unlimited capacity in most of the papers, which is an unreal assumption in the real world. To overcome this issue, we developed MPS-MAW by considering multiple warehouses, which were unlimited at each period, however, these capacities were limited at the whole of the horizon planning with the objective function, which aims to consider the fair material distribution to the warehouses. By adding the new objective function besides the ordering and material transportation costs, not only the materials were allocated to the proper warehouses but also their assignments to the warehouses were leveled in order to maximize the utility of each warehouse. In order to solve this NP-hard problem, SA optimization algorithm was proposed in which the movement towards the neighborhood solution was improved by considering the mutation rate parameter, which was responsible to generate the solutions with high quality. Also, the encoding of the decision variables that was done by adding the auxiliary variable decreased the complexity of the modeling. Moreover, the solution of the small problem and comparing the results with the outputs of the exact method showed the validation of the proposed SA. Then, the outputs of DOE showed that the impact of each SA parameters on the computational results. Finally, by the optimum values of the SA parameters, the large problems with the size of 30 and 60 activities, 1 to 4 materials, 2 to 4 suppliers and 2 to 4 warehouses were solved in acceptable times. For future studies, the MPS-MAW with considering the capacity of each warehouse at each period is suggested that is very real. Another suggestion can be using the other metaheuristics in order to compare each performance with our proposed model. The advanced modeling of the warehouses can be considering them as a 2-dimensional or multi-dimensional shape that each material must satisfy the geometry-related constraints.

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