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Meta-Heuristics for Integrated Scheduling of Production and Air Transportation

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Abstract

The efficient integrated scheduling of production and distribution in a supply chain becomes a challenging problem as global companies move towards higher collaborative and competitive environments. The problem is to determine both production schedule and air transportation allocation in coordinated way. In order to solve the given problem, a genetic algorithm (GA) and a Differential evolution algorithm (DE) are developed. The two proposed algorithms have been examined and tested on randomly generated instances. The experimental results show that the effectiveness and robustness of the proposed DE algorithm are better than GA.

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INTRODUCTION

The recent market globalization and merging processes, the development of complex and tightly integrated plants, have encouraged companies to improve their efficiency and increase the planning and scheduling technology not only focused on a plant level, but extended to the optimization of the whole supply chain (SC). Production and transportation operations are the two most important operational functions in a SC. To achieve optimal operational performance in a SC, it is critical to coordinate these two functions and schedule them jointly in a coordinated way.

The coordinated production and transportation processes rely on inventory storing to buffer both activities from each other. However, inventory costs and the trend to operate in a just-in-time (JIT) manner are putting pressure on firms to reduce inventories in their transportation chain. Coordinating production and distribution activities requires the consideration of additional features. In our work, SC is illustrated in Fig. 1. Within this SC, products are hold in inventory. For delivery of customer's order finished products are transported to customers using air transportation to meet their due dates. Due to heavy cost of missing a shipment in a scheduled flight, coordination of production and air transportation activities is critical. The earliness costs of departure time may result from the need for holding the customer's order at the plant (warehouses, inventory cost) or waiting cost or penalties at the airport. Delivery earliness (resp. tardiness) penalty is incurred if an order is completed before its committed due date (resp. after its committed due date). The delivery earliness penalties could result from the need for warehouse in the retailer's stores. The delivery tardiness cost includes contract penalties, customer dissatisfaction, loss of sales and potential loss of customer goodwill due to late orders.

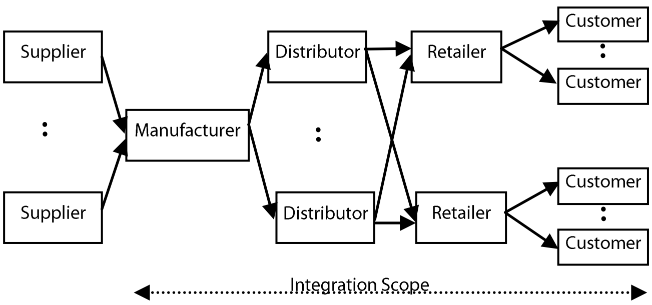

Fig 1. Supply chain stages Integration

Optimization of the trade-off between production, distribution, retailer's costs and customer service level is the goal of the decision maker of such systems. So the problem is to find a coordinated schedule that minimize supply chain total cost which includes transportation, plant, delivery earliness tardiness and departure time earliness tardiness costs. We investigate two policies and they are as such: first policy considers delivery tardiness

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and the second one assumes that no delivery tardiness is authorized.

There are considerable numbers of researches in production-distribution coordination. But all of them have only given consideration to the coordination of production scheduling and vehicle routing and no study has been conducted on the coordination of production scheduling and air transportation. Having reviewed the literature we came to realize that no study has been investigated in this field. Therefore, we were galvanized into presenting a pioneer consolidated model in this area. Also there are a few researches on synchronization of production scheduling and air transportation scheduling. In synchronization the overall problem is decomposed into two coordinated tasks such that the first task is to assign accepted orders to available flights' capacities to minimize the total transportation and delivery earliness tardiness costs. The allocation is restricted by plant such that it should be balanced with plant capacity. The second task is to determine orders sequence or completion time to minimize plant and departure time earliness tardiness costs.

Li et al. [7] studied the synchronization of single machine assembly and air transportation considering single destination. The overall problem is decomposed into air transportation problem and single machine assembly scheduling problem. They formulated two problems and then presented a backward heuristic algorithm for production of products in the single machine environment. Li et al. [9] developed their previous work to consider multiple destinations in the distribution activity. Li et al. [10] demonstrated the allocation of orders to flights have the structure of regular transportation problem, while the scheduling of single machine assembly problem is NP-hard. They also proposed a forward heuristic and a then backward heuristic for production scheduling [8]. Li et al. [11] developed their previous work by considering parallel machine assembly environment in production. The problem was modelled as a parallel machine assembly with only departure time earliness penalties or with no tardiness policy. They also demonstrated the scheduling of parallel machine assembly problem is NP-Complete and a simulated annealing algorithm was presented to determine the sequence of orders in parallel machine problem.

Zandieh and Molla-Alizadeh-Zavardehi [21] extended the proposed model by Li et al. [8] and proposed Synchronized scheduling models considering due window and two type flight capacities. Zandieh and Molla-Alizadeh-Zavardehi [22] extended their work considering various capacities with different transportation cost and also charter flights (commercial flights). Rostamian Delavar et al. [16] proposed a coordinated production and air transportation scheduling and two genetic algorithms are developed to solve the problem. Due to the dependency of most meta-heuristic algorithms on the correct choice of operators and parameters, a Taguchi experimental design method is applied to set and estimate the proper values of proposed algorithms parameters to improve their performance. In this paper, we extended the works by Zandieh and Molla-Alizadeh-Zavardehi [21] and [22] to coordination of these two task in a single optimization model that include various capacities, delivery tardiness, no delivery tardiness and due window.

Also many papers about of production scheduling and vehicle routing problem coordination in the case of road transportation can be seen in [1,2,3,4,5,12,13,17,20].

The remainder of this paper is organized as follows. The next section describes the problem's details and elaborates the mathematical formulation of our model. The proposed GA and DE are explained in Sections 3. Section 4, describes the computational results. Finally, in Section 5, conclusions are provided and some areas of further research are then presented.

MATERIAL AND METHODS

Mathematical model

The problem is modeled considering on the following assumptions;

- The allocation of air transportation and scheduling of production are for the accepted orders in the previous planning period.
- Order fulfillment is achieved when the order reaches the destination airport on time.
- There are several flights in the planning period with different departure and arrival time and other specifications such as capacity, cost, etc.
- Business processing cost and time, together with loading time and cost for flights are included in the transportation cost and transportation time.
- Local transportation transfers customer's orders from the production to the airport. Local transportation time is assumed to be included in production time.

The model allocates orders to the existing transportation capacities and determines the sequence and completion time for the allocated orders in production. This requires solving a scheduling problem to ensure that allocated orders catch their flights so that total cost of supply chain is minimized. The required notation to present the model is as follows:

i,i',j,j'	The order / job index, $i=1,2,...,N$;
f,f'	The flight index, $f=1,2,...,N$;
k	The destination index, $k=1,2,...,K$;
D_f	The departure time of flight *f* at the local airport;
A_f	The arrival time of flight *f* at the destination;
Q_i	The quantity of order i;
α_i	The delivery earliness penalty cost (/unit/h) of order i;
β_i	The delivery tardiness penalty cost (/unit/h) of order i;
d_i	The due date of order i;
Des_i	The order i's destination;
des_f	The flight f's destination;

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Cap_{tf}	The available tth type capacity of flight f that $t=1,\ldots,T$; $f=1,\ldots,F$;
Tc_{tf}	The transportation cost for per unit product when allocated to tth type capacity of flight f;
q_{tif}	The quantity of portion of order i allocated to type t capacity of flight f;
p_i	The processing time of order i;
c_i	The completion time of order / job i;
α'_i	The per hour earliness penalty of order / job i for production;
p, p'	The position or sequence of order i $p=1,\ldots,N$;
u_{ip}	1 if order i be in position p, 0 otherwise;
λ	The per hour plant costs (including machine cost, operator wages and other production variable costs which is completely related to the length of working hours;
I_i	The idle time before order i in the schedule;
$C_{\max}$	The maximum completion time of orders that is equal to shut down time of shop;
LN	A large positive number;
θ	A number between (0, 1);

Li et al. [8, 10] defined two type capacities in each flight with two different transportation cost. For extension of their work and generating more realistic schedule we assumed that in many industries, we may have only one or more than two type capacities in each flight. Therefore, we considered T type capacities by $Cap_{t,f}$ in the notation. Also if for a given flight f, we have h type capacities, $Cap_{t,f}$ that $t=h+1\ldots,T$ will be zero. The mathematical programming formulation of the model is shown as follow:

$$\min \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{f=1}^{F} TC_{tf}\, q_{tif} + \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{f=1}^{F} \alpha_i * \max(0, d_i - A_f) * q_{tif} + \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{f=1}^{F} \beta_i * \max(0, A_f - d_i) * q_{tif} + \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{f=1}^{F} \alpha_{1i} * (D_f - C_i) * q_{tif} + \lambda C_{\max} \quad (1)$$

s.t:

$$(\sum_{t=1}^{T} q_{tif}) * (Des_i - des_f) = 0 \quad i=1,\ldots,N;\ f=1,\ldots,F \quad (2)$$

$$\sum_{i=1}^{N} q_{tif} \le Cap_{tf} \quad t=1,\ldots,T;\ f=1,\ldots,F \quad (3)$$

$$\sum_{t=1}^{T}\sum_{f=1}^{F} q_{tif} = Q_i \quad i=1,\ldots,N \quad (4)$$

$$\sum_{p=1}^{N} u_{ip} = 1 \quad i=1,\ldots,N \quad (5)$$

$$\sum_{i=1}^{N} u_{ip} = 1 \quad p=1,\ldots,N \quad (6)$$

$$\sum_{p=1}^{N}\left(u_{ip}\left(p_i + I_i + \sum_{p'=1}^{p-1}\sum_{i'=1}^{N} u_{i'p'}(P_{i'} + I_{i'}) \right)\right) = c_i \quad i=1,\ldots,N \quad (7)$$

$$\sum_{i=1}^{N}\left(\frac{\max\left(0, \left(\sum_{t=1}^{T}\sum_{f'=1}^{f} q_{tif'}\right) - 0.5\right)}{\left(\sum_{t=1}^{T}\sum_{f'=1}^{f} q_{tif'}\right) - 0.5} \right) p_i \le D_f \quad f=1,2,\ldots,F \quad (8)$$

$$\sum_{i=1}^{N} u_{iN} c_i = C_{\max} \quad (9)$$

$$I_i \ge 0 \quad i=1,\ldots,N \quad (10)$$

$$u_{ip} \in \{0,1\} \quad i=1,\ldots,N;\ p=1,\ldots,N \quad (11)$$

$$q_{tif} = \textit{Non-negative integer variable} \quad (12)$$

The decision variables are $q_{tif}, c_i, I_i, u_{ip}$ and $C_{\max}$. The objective is to minimize total cost which consists of total transportation cost for the orders allocated to type 1 to T capacity, total delivery earliness tardiness penalties, total departure time earliness penalties of jobs and plant cost. Constraint sets (2) ensures that if order i and flight f have different destinations, order i cannot be allocated to flight f. Constraint sets (3) that the capacity 1 to T of flight f is not exceeded. Constraint set (4) ensures that order i is completely allocated. Constraint sets (5) and (6) state that each job has to be assigned to a position, and each position has to be covered by a job. Constraint set (7) calculates completion time of jobs, considering inserted idle times among jobs. Since all jobs must catch their scheduled flights, constraint set (8) ensures that order i catches all of its departure times or the completion time of q_{tif} has to be less than or equal to their related flight departure times allocated to q_{tif}.

Solution approach

Genetic Algorithm: Genetic Algorithm (GA) proposed by Holland in the early 1970s, as a stochastic global search method based on principles of evolution theory. Its original idea comes from Darwinian's evolution theory. It is based on the idea of "survival of the fittest," which repeats evaluation, selection, crossover, and mutation after initialization until a stopping criterion is satisfied [14].

In GA there are some chromosomes (The solution to a problem is called a chromosome) which play the role of a set of values for independent variables as a solution for the problem. In each iteration (called generation), there are three basic genetic operations, such as selection, mutation and crossover, then applied one after another to obtain a new generation of chromosomes in which the expected quality over all the chromosomes is better than that of the previous generation. This process is repeated until the termination criterion is met, and the best chromosome of the last generation is reported as the final solution [19].

Selection: In the model, we want to minimize the objective function. Because in Roulette-Wheel we give more chance to the solution which has greater fitness value, we consider the fitness value as follow:

$$\textit{Fitness Value} = 1/\textit{Objective Function}$$

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Considering inverse objective function as a fitness value, the greater fitness value a solution has, the more chance it has to be selected.

Genetic operators

Reproduction: With more probability, better parents can generate better offspring, so it would be necessary to transfer the best solutions of each generation to the next one. Therefore, the pr% of chromosomes with the better fitness values are copied to the next generation. This is called reproduction.

Crossover: The main purpose of crossover is to search the parameter space and hence is considered as the most important operator in GA. The crossover operator takes two chromosomes (parents) from the old population and exchanges the next generation of their structures to produced new offspring. There are wide varieties of proposed crossover operations. The commonly used crossover operators are one-point crossover, Two-point crossover, Uniform crossover and Arithmetic crossover.

Mutation: The mutation operator can be considered as a simple form of a local search. The main purpose of applying mutation is to avoid convergence to a local optimum and diversify the population. The used mutation operators in the literature are Swap Mutation, Big Swap Mutation, Inversion Mutation, Displacement Mutation and Perturbation mutation.

Differential evolution: Differential Evolution (DE) is a very simple population-based global optimization algorithm. This algorithm created by [18], whose main objective is functions optimization.

DE starts with a number of populations of *NP* candidate solutions, so-called individuals. The DE's main strategy is to generate new individuals by calculating vector differences between other randomly selected individuals of the population. The subsequent generations in DE are denoted by $G = 0,1,\ldots,G_{Max}$. It is usual to denote each individual as a D-dimensional vector $X_{i,G} = X^{1}_{i,G},\ldots,X^{D}_{i,G}, i = 1,2,\ldots,NP$ called a target vector. This algorithm uses four important parameters: population size, mutation, crossover and selection operators; there are different variants.

Initial population: Like other evolutionary algorithms, DE works with a population of individuals (candidate solutions) and this number never changes during the optimization process. Normally the initial population is randomly generated and the population will be improved by the algorithm iteratively, through the mutation, crossover and selection operators [15].

Mutation operator: According to the DE, after initialization, it employs the mutation operator. The mutation in DE is a distinct innovation. It is based on the difference of different individuals (Solutions), to produce a mutant vector $V_{i,G}$ with respect to each individual $X_{i,G}$, in the current population. This main operation is founded on the differences of randomly sampled pairs of solutions in the population. For each target vector $X_{i,G}, i = 1, 2,\ldots, NP$, a mutant vector $V_{i,G}$ can be made by the following mutation operators. In all types, the scale factor F is a positive control parameter for scaling the difference vector. The following mutation operator proposed by Storn and Price [18].

$$V_{i,G} = X_{r_1,G} + F(X_{r_2,G} - X_{r_3,G})$$

Crossover operator

In order to increase the diversity of the perturbed parameter vectors, crossover is introduced after the mutation operation. Crossover operation is employed to generate a temporary or trial vector by replacing certain parameters of the target vector by the corresponding parameters of a randomly generated donor vector. To get each individual's trial vector, $U_{i,G+1}$, crossover operation is performed between each individual and its corresponding mutant vector. The following crossover operator proposed by Storn and Price [18]:

$$U_{i,j,G+1} = \begin{cases} V_{i,j,G+1} & if\ Rand(j) \le CR \quad or \quad j = Rand(i) \\ X_{i,j,G+1} & if\ Rand(j) > CR\ or \quad j \ne Rand(i) \end{cases}$$

Where *rand(j)* is the *j*th evaluation of a random number uniformly distributed in the range of [0,1], and *rand(i)* is a randomly chosen index from the set {1, 2,…, N}. $CR \in [0,1]$ is a crossover constant rate that controls the diversity of the population. The more the value of CR, the less the influence of the parent will be.

Selection operator

To generate the new individual for the next generation, selection operation is performed between each individual and its corresponding trial vector by the following greedy selection criterion:

$$X_{i,G+1} = \begin{cases} U_{i,G+1} & if\ f(U_{i,G+1}) < f(X_{i,G}), \\ X_{i,G} & otherwise, \end{cases}$$

where *f* is the objective function, and $X_{i,G+1}$ is the individual of the new population.

Computational experiments

Instances

In order to evaluate the performance of the existing algorithm based on GA and DE developed in this research for solving the problem, a plan is utilized to generate test data. Table 1 shown the experimental design. The data required for the problem include the number of jobs, flights and destinations. The values of common parameters are used from Li et al [8]. The number of jobs *N* ranges from 20 to 100, the number of flights *F* ranges from 4 to 20, and the number of destinations *K* ranges from 2 to 5. The problem size is determined by the number of jobs, the corresponding number of flights, and the number of destinations. The value of *N* is set equal to 5*F* for each problem. The destination for each order and each ordinary flight is generated from uniform distribution between 1 to the number of destinations of the corresponding problem configuration. Nine different problem sizes are considered for experimental study.

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Departure time of each ordinary flight is generated from a uniform distribution subject to its destination. The total number of flights that have the same destination is denoted by TF_k. The corresponding flights are assigned to an ordinary flight number FN_f, which starts from 1 to TF_k. Each flight's departure time is then generated using uniform distribution from [24 * (FN_f -1)/TF_k, 24 * FN_f /TF_k]. Each flight's transportation time is given and set to be the value of its destination number. The planning period is set to 24 hours for the nine test problem sets. Orders due date is drawn from uniform distribution. The earliest delivery time of an order is the sum of processing time of the order and air transportation time. Therefore, the range for an order's due date is between $Qi*p_i + t_i$ and $6(Q_i*p_i + t_i)$, where Q_i*p_i is the order's processing time and t_i is the air transportation time to its destination. Initially, a number is specified to every unit of each order as processing time, using uniform [0.5, 1.5]. Due to 24 hours planning period, problem's size and orders quantity producing all of orders might be impossible because total processing time of entire orders must be less than 24 hours. Therefore the upcoming method is acquired to modify the initial processing times. Assuming that the plant is able to produce 1.2 to 2 times of the total orders quantity in the planning period [19], a random number between 1.2 and 2 is generated which indicates the plant's production capacity to produce orders totally. Then the processing time adjustment rate is calculated as:

$$\lambda = (\Sigma Q_i p'_i) \times \textit{uniform}\ [1.2,\ 2]/24.$$

At the end, each initial processing time (p'_i) is transformed to modified processing time (p_i) using λ.

Table 1. Random problems generation

Problem parameter	Values
Number of orders (N)	20, 30, 40, 50, 60, 70, 80, 90, 100
Number of flights (F)	4, 6, 8, 10, 12, 14, 16, 18, 20
Number of destinations (K)	2, 2, 3, 3, 3, 4, 4, 4, 5
Order quantity(Q_i)	Uniform [50,200]
Order due date(d_i)	Uniform [1,6]*(Q_i*p_i+t_i)
Order delivery earliness penalty cost (α_i)	Uniform [3,5]
Order departure time earliness penalty cost (α'_i)	Uniform [3,5]
Order delivery tardiness penalty cost (β_i)	Uniform [5,8]
Order destination (Des_i)	Uniform [1,K]
Ordinary flight destination (des_f)	Uniform [1,K]
Ordinary flight departure time (D_f)	Uniform [24*(FN_f-1)/TF_k, 24*FN_f/TF_k]
The available 1st type capacity of ordinary flight f (Cap_{1f})	Uniform [200,800]
The available 2nd type capacity of ordinary flight f (Cap_{2f})	Uniform [100,200]
Transportation cost of per unit product allocated to 1st type capacity of ordinary flight (Tc_{1f})	Uniform [60+20 des_f, 80+20 des_f]
Transportation cost of per unit product allocated to 2nd type capacity of ordinary flight (Tc_{2f})	Uniform [60+20 des_f, 80+20 des_f]
Transportation cost of per unit product allocated to its charter flight (β'_i)	Uniform [60+20 des_f, 80+20 des_f]
Ordinary flight arrival time(A_f)	$D_f + t_f$
Maximum departure time of charter flight for order i (MD_i)	$d_i - t_i$
(p'_i)	Uniform [0.5,1.5]
λ	λ=(ΣQ_ip'$_i$)* uniform [1.2,2]/24
The unit product processing time of order i(p_i)	p_i=p'$_i$/λ

RESULTS

We set searching time to be identical for both algorithms which is equal to 2.25 × (N + F + K) milliseconds. Hence, this criterion is affected by both *n* and *m*. We generated 20 instances for each nine problem type, summing to 9 × 20 = 180 instances which are different from the ones used for parameter setting to avoid bias in the results. Considering twenty instances for each of the twenty eight problem type, or eighty instances for each of the nine problem sizes, for both algorithms, the instances have been run five times. Hence, using the RPD we deal with 900 data for each algorithm in each problem size.

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Since, we are to evaluate the robustness of the proposed algorithms in different problem sizes; the effects of the problem sizes on the performance of both GA and DE are analyzed and compared. So, the averages of RPDs for each algorithm in each seven problem size are calculated. The interaction between the efficiency of them and the size of problems is showed in Fig. 1. As can be seen from the result figure, not only is the overall performance of DE better than GA, but it is more robust.

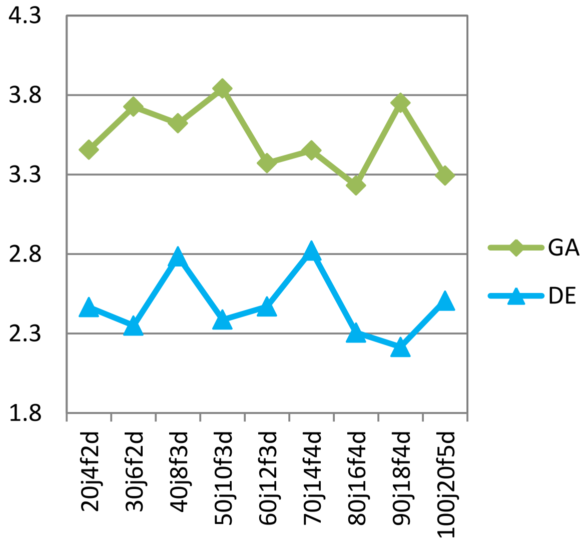

Fig 1. Interaction between proposed algorithms and problem size

CONCLUSION

This paper has considered both production schedule and air transportation allocation in coordinated way. In order to solve the given problem, two meta-heuristic algorithms, namely Genetic Algorithm (GA) and Differential Evolution (DE) algorithm, have been utilized. Because of the dependency of these proposed algorithms on the correct choice of parameters, various operators have been employed.

The computational results have shown the superiority of the DE algorithm in comparison with GA. There still exist rich opportunities for researchers to further the study in this area. For future research, it can be interesting to investigate and develop new algorithms based on other meta-heuristics and compare them with our algorithms. Furthermore, we can use the response surface methodology (RSM) for tuning the parameters of these algorithms.

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