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Adaptive Genetic Algorithm for the Manufacturing/Distribution Chain Planning

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Abstract - In this research, we consider an integrated manufacturing/distribution planning problem in supply chain (SC) which has non-integer time lags. We focus on a capacitated manufacturing planning and capacity allocation problem for the system. We develop a mixed binary integer linear programming (MBLP) model and propose an efficient heuristic procedure using an adaptive genetic algorithm, which is composed of a regeneration procedure for evaluating infeasible chromosomes and the reduced costs from the LP-relaxation of the original model. The proposed an adaptive genetic algorithm was tested in terms of the solution accuracy and algorithm speed during numerical experiments. We found that our algorithm can generate the optimal solution within a reasonable computational time.

I. Introduction

In the areas of manufacturing/distribution planning, many researchers and practitioners have developed and evaluated the deterministic models to coordinate important and interrelated logistic decisions such as capacity management, inventory allocation, and vehicle routing. They initially have investigated the various process of SC separately and later become more interested in such problems encompassing the whole SC system.

Hackman and Leachman [12], Erengüç et al. [10], Escudero et al. [6], Jayaraman and Pirkul [13], and Syarif et al. [2] proposed integrated manufacturing/distribution planning models.

However, the research results are difficult to apply to real world problems due to some unrealistic assumptions. One such assumption is that processes occur instantaneously. It is not realistic for the operations with significant post processing lags or with significant processing times. To alleviate the difficulty, we introduce here a model for a SC system with non-integer manufacturing/distribution lags. Our model is the first realistic implementation of the general framework proposed by Hackman and Leachman [12]. In their paper, they focus on a general framework for a manufacturing system and did not cover implementation issues of the developed models explicitly. In contrast, we developed, in this paper, an integer programming model to represent the system with non-integer time lags and proposed a heuristic solution procedure based on adaptive genetic algorithm (AGA). The algorithm utilizes the reduced costs obtained from the LP-relaxation of the original model. Note that the general framework appeared in Leachman and Hackman [12] is not a main theme of this paper and therefore we do not attempt to explain the framework exhaustively.

Ⅱ. Mathematical Model

The notations are as follows:

Indices

i : product

k : distribution center (DC)

l : customer

t : time period

L_k : customer zone received the product from DC k

Variables

X_{it} : manufacturing rate of product i in time t

I_{it} : inventory level of product i in time t

I_{ikt}^{k} : inventory level of product i from DC k in time t

q_{ikt} : transportation quantity of product i from plant to DC k in time t

q_{iklt}^{k} : transportation quantity of product i from DC k to customer zone l

$U_i = 1$ if manufacturing is setup for product i. Otherwise 0

$V_k = 1$ if DC k is opened. Otherwise 0

Parameters

h_{it} : inventory cost of product i in time t

$\widetilde{h}_{ikt}$: inventory cost of product i at DC k in time t

p_{it} : manufacturing cost of product i in time t

c_{ikt} : transportation cost of product i from plant to DC k in time t

$\widetilde{c}_{iklt}$: transportation cost of product i from DC k to customer zone l

d_{iklt} : final demand for product i of customer l to DC k in time t

C_{it} : manufacturing capacity of product i in time t

$\widetilde{C}_{ikt}$: stocking capacity of DC k for product i in time t

LA_i : output/transfer lag

LB_i : input lag

LC_k : transportation lag

The system we are concerned is composed of a single manufacturing facility with multiple products, multiple distribution centers and customer zones. For the system, we consider an integrated manufacturing/distribution planning and capacity allocation problem. We assume that lead times exist in manufacturing and in transportation between plant and DC and they are not integer multiples of unit time period. The setup times and costs are negligible, and the demand rates for final products may vary from one period to the next, but is constant during a time period. There are no lags between DC and customer because it may be included in the transportation lags. The objective function is composed of three major cost components: linear manufacturing costs, inventory costs and transportation costs.

We are now ready to introduce the model. For simplicity of exposition, we first define two complex variables to be included inside model, $\overline{X}_{it}$ and $\overline{q}_{ikt}$.

$$\bar{X}_{it} = \begin{cases} (t)X_{i(-(LA_i+LB_i))^+} & \text{if } t-(LA_i+LB_i) < (-(LA_i+LB_i))^+ \\ \left[(-(LA_i+LB_i))^+ + (LA_i+LB_i)\right]X_{i(-(LA_i+LB_i))^+} + \sum\limits_{(-(LA_i+LB_i))^+ < \tau \le (t-(LA_i+LB_i))^-}^{T} X_{i\tau} & \text{otherwise} \\ +\left[(t-(LA_i+LB_i)) - (t-(LA_i+LB_i))^-\right]X_{i(t-(LA_i+LB_i))^+} & \end{cases} \quad (1)$$

$$\bar{q}_{ikt} = \begin{cases} (t)q_{ik(-LC_k)^+} & \text{if } t-LC_k < (-LC_k)^+ \\ \left[(-LC_k)^+ + LC_k\right]q_{ik(-LC_k)^+} + \sum\limits_{(-LC_k)^+ < \tau \le (t-LC_k)^-}^{T} q_{ik\tau} & \text{otherwise} \\ +\left[(t-LC_k) - (t-LC_k)^-\right]q_{ik(t-LC_k)^+} & \end{cases} \quad (2)$$

The main model is as follows:

MBLP:

$$Min \ \sum_{i,t}(h_{it}I_{it} + p_{it}X_{it}) + \sum_{i,k,t}(\tilde{h}_{ikt}I^k_{ikt} + c_{ikt}q_{ikt}) + \sum_{i,k,l,t}\tilde{c}_{iklt}q^k_{iklt}$$

subject to

$$I_{i0} - I_{it} + \bar{X}_{it} = \sum_{k,\tau}^{t^-} q_{ik\tau}, \quad \forall i,t \quad (3)$$

$$I^k_{ik0} - I^k_{ikt} + \bar{q}_{ikt} = \sum_{l \in L_k,\tau}^{t^-} q^k_{ikl\tau}, \quad \forall i,k,t \quad (4)$$

$$q^k_{iklt} = d_{iklt}, \quad \forall i,k,l,t \quad (5)$$

$$X_{it} \le C_{it}U_i, \quad \forall i,t \quad (6)$$

$$q_{ikt} \le \tilde{C}_{ikt}V_k, \quad \forall i,k,t \quad (7)$$

$$X_{it} \ge 0, \quad \forall i,t \quad (8)$$

$$I_{it} \ge 0, \quad \forall i,t \quad (9)$$

$$q_{ikt} \ge 0, \quad \forall i,k,t \quad (10)$$

$$q^k_{iklt} \ge 0, \quad \forall i,k,l,t \quad (11)$$

$$U_i \in \{0,1\} \quad \forall i \quad (12)$$

$$V_k \in \{0,1\} \quad \forall k \quad (13)$$

Constraints (3) are the inventory balance equations among quantities of manufacturing, inventory of plant, and products transferred to DC. Another balance equations among quantities of products received from plant and transferred to customer, inventories of DC are established by constraints (4) considering transportation lags.

Constraints (5) make equality between quantities received from DC and total demand. Constraints (6), (7) are used to force the binary setup variable of each product and binary allocation variables of DC respectively with being related to capacity. The technological constraints on the decision variables are given in constraints (8)-(13).

The objective function is to minimize the sum of the different cost factors, i.e. the costs for manufacturing, inventory of plant and DC, transportation between plant and DC. We can express both of an integer time lags and non-integer time lags using these expressions. This formulation is not only accurate but also requires significantly fewer constraints than the model using a time grid fine enough to make all time lags integer.

Ⅲ. AGA Approach

Despite the success of applying GA to solve many real-life problems, the identification of the correct settings of genetic parameters for the problems is not a simple task. If poor settings are used, a GA performance can be severely impacted. In order to mitigate this weakness, AGA is introduced. It involves some rules to adjust adaptively the crossover and mutation rates according to the performance of the genetic operators.

3.1. Representations and initialization

Let V_m denote m_th chromosome in a population as follows:

$$V_m = [v_{mit}^{(X)} v_{mikt}^{(q)} v_{mit}^{(I)} v_{mikt}^{(I^k)}], m = 1,2,..., pop\_size, \forall i,k,t$$

where

$$v_{mit}^{(X)} = [X_{11} ... X_{1t} X_{21} ... X_{2t} ... X_{it}],$$

$$v_{mikt}^{(q)} = [q_{111} q_{112} \cdots q_{11t} q_{121} q_{122} \cdots q_{1jt} q_{211} q_{212} \cdots q_{ikt}],$$

$$v_{mit}^{(I)} = [I_{11} ... I_{1t} I_{21} ... I_{2t} ... I_{it}],$$

$$v_{mikt}^{(I^k)} = [I_{111}^k I_{112}^k ... I_{11t}^k I_{121}^k I_{122}^k ... I_{11kt}^k I_{211}^k I_{212}^k ... I_{ikt}^k],$$

and *pop_size* means population size. For solving proposed model, it is convenient to represent strings as solution vectors [14]. We insert only needed decision variables which will be calculated actually into V_m.

3.2. Crossover and mutation

We use the basic concept of Srinivas and Patnaik [11] and revised it. we modify α_1 and α_2 to improve the individuals efficiently by reflecting the characteristics of reduced costs. We firstly solve the LP relaxation of the original problem, then derive the reduced costs of variables, calculate the average of the reduced costs, and take the ratio of set smaller than it as α_1 and α_2. We expect that this modified operator has a good performance, because it is apt to make crossover and mutation happen having tight ratio for searching better direction. The procedure of modifying α_1 and α_2 is as follows.

Procedure: Specification of α_1 and α_2

Step 1: Solve LP relaxation of the proposed problem:

Relax the proposed problem by ignoring binary variables of constraints (9) and (10).

Step 2: Derive the reduced costs of variables and calculate the average of them.

Step 3: Count number smaller than average of the reduced costs and divide it by total number of variables.

Step 4: Insert the ratio obtained from Step 3 into α_1 and α_2 respectively.

3.3 Algorithm

Step 1: Set initial and the parameters: Set population size *pop_size*, maximum generation *max_gen*, and calculate crossover rate P_C and mutation rate P_M.

Step 2: Generate initial population: Generate initial chromosome from initialization process procedure.

Step 3: Evaluation : Calculate eval(V_m) for each chromosome.

Step 4: Genetic operators: Crossover and mutation.

Step 5: Selection: Roulette wheel approach.

Step 6: Terminating condition

Increase generation number. If it is less than *max_gen*, go to Step 3.

Step 7: Output the solution.

Ⅳ. Conclusions

In this paper, we proposed the model for the integrated manufacturing/distribution planning in SC using the dynamic manufacturing function considering the non-integer time lags. We also developed an efficient AGA heuristic procedure, which utilizes the reduced costs obtained from the LP-relaxation of the original model. From the results of numerical experiments, we found that the proposed AGA can get the optimum rapidly. These results also coincided with our expectation that our method could solve large-scale problems within a reasonable computational time.

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