

Multi-Echelon Multi-Period Supply Chain Network Design for Agile Manufacturing using Tabu Search Algorithm

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Abstract

An efficient Supply Chain Network Design (SCND) can substantially improve the performance of an organizational structure. This research explores the designing of a supply chain network for agile organizations with several echelons over several periods. It is assumed the problem involves multiple customers with high-quantity demands. The problem is modeled to integrate decision variables regarding the selection of companies to be involved at each echelon and the volumes of production, inventory, and transportation for each company with the objective of minimizing total operating costs across the entire supply chain. Given that the problem is NP-Hard, Tabu Search (TS) is used to solve the developed model. The results are compared with the results of the Lagrangian method employed by one of the recent work in the literature. This comparison shows that TS algorithm outperforms the Lagrangian algorithm in obtaining optimal solutions.

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1. Introduction

Companies operating in competitive markets are in constant struggle to overcome challenges like how to cope with diverse and shifting customer needs and demands. It is important for these companies to be able to quickly design, produce, and distribute products and at the same time improve their production performance and operating costs. One way to deal with these problems is to adopt an approach known as agile manufacturing. In an agile supply chain, product design, production, and distribution are progressively configured to exploit market opportunities and maintain flexibility against environmental changes and market uncertainties (Pan and Nagi, 2013).

One of the factors determining the structure, costs, and performance of a supply chain is Supply Chain Network Design (SCND). In today's competitive and dynamic markets, the goal of SCND is to provide an efficient structure for re-engineering and value improvement across the entire supply chain (Farahani et al., 2014)(Ahmadi, Azadani, 2018). SCND has significant long-term impacts on the supply chain performance and is a subject of interest to businesses facing increased competition (Pham and Yenradee, 2017)(Najjartabar et al., 2016) .

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In this paper, a multi-echelon supply chain network is designed for agile manufacturing setting using Tabu Search (TS) algorithm. The second section of this paper describes the concepts of agile manufacturing and multi-echelon supply chain and reviews the previous works that have utilized TS algorithm. The third section presents the problem description and discusses the modeling approach. The fourth section explains the steps taken in TS algorithm to solve the problem. In the fifth section, an instance of the discussed multi-echelon supply chain problem is solved by TS algorithm. And finally, the sixth section presents the results and some suggestions for future research.

2. Research background

In the context of management, the term “agility” refers to an organization’s ability to properly respond to unpredictable environmental changes and use these changes to advance its interests (Agarwal et al., 2007). Agile manufacturing is a relatively new model developed for eliminating the vulnerabilities of lean manufacturing (Adeleye and Yusuf, 2006). Hence, agile manufacturing can be seen as a flexible combination of lean manufacturing and operational adaptability. This is why agile manufacturers are said to be flexible manufacturers that they can deliver high-quality products at relatively low prices and in relatively shorter times (Jain and Jain, 2001). In a study done by Hosseini-Motlagh et al. (2016), a robust optimization model was presented for designing blood supply chain networks with emergency transmission routes between blood centers. Zahedi et al. (2015) proposed the use of fuzzy set theory in the design of integrated closed loop supply chain networks. The logistics model proposed by these researchers had three forward echelons and three echelons in reverse direction. Varsei and Polyakovskiy (2017) investigated a multi-objective integer programming model to design a general model for sustainable supply chain networks with economic, environmental and social objectives. In a study by Rahmani and Mahoodian (2017), they designed a supply chain model for reducing carbon footprint. This model was designed based on the Benders decomposition algorithm (e.g. see Makui et al., 2016) with the purpose of dealing with uncertain parameters. In a study carried out by Vinodh et al. (2013), they stated that with access to computers, organizations need to evolve products more efficiently and respond more quickly to the needs of their customers and then designed a model with agile supply chain characteristics based on fuzzy logic to accommodate this need. Subulan et al. (2015) employed a mixed integer programming to design a multi-objective closed-loop supply chain network capable of accounting for several uncertainty and risk factors, including the “variability index”, “downside risk” and “conditional value at risk”. Hasani and Khosrojerdi (2016) implemented a nonlinear model based on Taguchi algorithm to design a supply chain network.

Lemmens et al. (2016) argue that since every supply chain needs a stable network, it is imperative to consider the key indicators of economic performance and technology and interests and values of stakeholder in the design of supply chain models. In a study by Badri et al. (2013), they developed a mathematical model for multi-echelon supply chain networks with the help of Lagrange relaxation. This model was shown capable of considering tactical and strategic decisions in different time frames. Najjartabar et al. (2018) examined the role of third parties in the supply chain design in order to improve the understanding of uncertainties regarding this matter. They introduced a nonlinear model for optimizing closed-loop supply

chains and solved the model by the imperialist competitive algorithm and the particle swarm optimization.

In the present work, TS algorithm is used to design a multi-echelon supply chain for agile manufacturing. After designing and validating the model in GAMS, a numerical example of the problem is solved by CPLEX, and finally, the solutions are compared with the results of the Lagrange method.

3. Problem statement and modeling

In this study, it is assumed that the supply chain has to meet stochastic demand from several customers and backlog is not allowed. The model is designed for multiple time periods (T) and there cannot be any violation in the production and transportation capacities of any company at any period. In order to satisfy customers' demand, it is possible to choose one or more companies at each echelon at any period. The order of operations in the supply chain is defined by the variable φ , which represents the number of echelons in the supply chain. At each echelon, there are several candidate companies for performing operations of that echelon. The main goal is to choose a number of companies at each echelon so as to form an optimal supply chain network. Depending on the production and transportation capacity and costs, a company may be able to perform multiple operations at multiple echelons. The set E_α is the set of factories that can perform operation α ($\alpha = 1, 2, \dots, \varphi$). Also, the virtual echelon $\varphi + 1$ is defined to represent the final customer. The set of edges is defined such that there are no edges in the set of nodes X and direct edges extend from the set E_α to one or more other groups in the set $E_{\alpha+1}$ ($\alpha = 1, 2, \dots, \varphi$). Also, $E_\alpha \neq \Phi$ for $\forall \alpha \in P$, meaning that no echelon can be empty of operations. In this model, it is assumed the final product is delivered to the end customer through only one output (E_φ), and that other echelons E_α ($\alpha = 1, 2, \dots, \varphi - 1$) are not allowed to give the unfinished products to the customer. The product (output) of the echelon $\alpha - 1$ is used as the raw material (input) of the echelon α .

The duration of each operation is the time needed for production and transportation. Different companies may have different production and transportation capacities in a given time horizon. These capacities may also vary with the time period. The model assumes that there exists zero inventory at the beginning of the first period. Hence, the output of the first echelon will reach the second echelon at the end of the first period, and the second echelon operations can start at the beginning of the second period. By the same token, the final product will not be delivered to the customer before the beginning of the period $t = \varphi + 1$. This assumption means that it will take exactly a single period for the product to arrive at the next echelon. Since the product delivery time at each echelon is always constant (a single period), there is no need to consider the transport method and cost-time tradeoff in the transportation system. In this problem, it is assumed that there is only one transportation method, which has a limited capacity.

3.1. Model parameters

The notation and description of parameters used for problem modeling are presented in Table 1.

Table 1. Parameters used in problem modeling.

Parameter	Description
P	The order of the operations (echelons) required to manufacture the product $P = \{1, 2, \dots, \varphi\}$
N_α	The number of eligible companies at the echelon α
T	The number of periods in the planning horizon
$F_{i(\alpha)j(\alpha+1)}$	The fixed cost of a link between the company i at the echelon α with the company j at the echelon $\alpha + 1$
$C_{i(\alpha)j(\alpha+1)}$	The unit transportation cost from the company i at the echelon α to the company j at the echelon $\alpha + 1$ in the period t
$H_{i(\alpha)t}^f$	The unit final product inventory cost in the company i at the echelon α in the period t for
$H_{i(\alpha)t}^r$	The unit raw material inventory cost in the company i at the echelon α in the period t for
$U_{i(\alpha)t}$	The unit production cost for the company i at the echelon α in the period t
$\Phi_{i(\alpha)t}$	Available production capacity in the company i at the echelon α in the period t
$\Psi_{i(\alpha)j(\alpha+1)t}$	The transportation capacity of the company i at the echelon α for transport to the company j at the echelon $\alpha + 1$ in the period t
θ_α	The number of units of raw material needed from the echelon $\alpha + 1$ to produce a unit of product at the echelon α
D_{jt}	Demand of the customer j in the period t

For all parameters, t can take an integer value in the acceptable range and not refers to the entire time horizon.

3.2. Decision variables

The decision variables used in problem modeling are listed in Table 2.

Table 2. Decision variables used in problem modeling.

Parameter	Description
$z_{i(\alpha)t}$	The amount of product produced in the company i at the echelon α in the period t
$x_{i(\alpha)j(\alpha+1)t}$	The amount of product transported from the company i at the echelon α to the company j at the echelon $\alpha + 1$ in the period t (if $\alpha = \varphi$, then the product is delivered to the end customer j).
$h_{i(\alpha)t}^f$	The final product inventory in the company i at the echelon α in the period t ($\alpha = 1, 2, \dots, \varphi$)
$h_{i(\alpha)t}^r$	The raw material inventory in the company i at the echelon α in the period t ($\alpha = 1, 2, \dots, \varphi$)
$W_{i(\alpha)}$	$\begin{cases} 1 & \text{If the company } i \text{ at the echelon } \alpha \text{ participates in the network,} \\ 0 & \text{Otherwise.} \end{cases}$
$Y_{i(\alpha)j(\alpha+1)t}$	$\begin{cases} 1 & \text{If there is a link between the company } i \text{ at the echelon } \alpha \text{ and the company } j \\ & \text{at the echelon } \alpha + 1, \\ 0 & \text{Otherwise.} \end{cases}$

3.3. Mathematical model

The objective function of the model consists of all operating costs, fixed costs, and production-related costs. Fixed cost is the cost of a link between two companies at two adjacent echelons. Production cost comprises the production cost, the transportation cost, and the inventory holding cost for raw materials and final products. The proposed problem model is presented as follows:

$$\begin{aligned}
& \text{Min} \sum_{\alpha=1}^{\varphi-1} \sum_{i=1}^{N_{\alpha}} \sum_{j=1}^{N_{\alpha+1}} F_{i(\alpha)j(\alpha+1)} Y_{i(\alpha)j(\alpha+1)} \\
& + \sum_{\alpha=1}^{\varphi} \sum_{i=1}^{N_{\alpha}} \sum_{t=\alpha}^{T-\varphi-\alpha} U_{i(\alpha)t} Z_{i(\alpha)t} \\
& + \sum_{\alpha=1}^{\varphi} \sum_{i=1}^{N_{\alpha}} \sum_{j=1}^{N_{\alpha+1}} \sum_{t=\alpha}^{T-\varphi+\alpha} C_{i(\alpha)j(\alpha+1)t} X_{i(\alpha)j(\alpha+1)t} \\
& + \sum_{\alpha=1}^{\varphi} \sum_{i=1}^{N_{\alpha}} \sum_{t=\alpha}^{T-\varphi+\alpha} H_{i(\alpha)t}^f h_{i(\alpha)t}^f \\
& + \sum_{\alpha=2}^{\varphi} \sum_{i=1}^{N_{\alpha}} \sum_{t=\alpha}^{T-\varphi+\alpha} H_{i(\alpha)t}^f h_{i(\alpha)t}^r
\end{aligned} \tag{1}$$

subject to

$$\begin{aligned}
Y_{i(\alpha)j(\alpha+1)} & \leq W_{i(\alpha)} \\
i & = 1, \dots, N_{\alpha}; j = 1, \dots, N_{\alpha+1}; \\
\alpha & = 1, \dots, \varphi - 1
\end{aligned} \tag{2}$$

$$\begin{aligned}
Y_{i(\alpha)j(\alpha+1)} & \leq W_{j(\alpha+1)} \\
i & = 1, \dots, N_{\alpha}; j = 1, \dots, N_{\alpha+1}; \\
\alpha & = 1, \dots, \varphi - 1
\end{aligned} \tag{3}$$

$$\begin{aligned}
\sum_{j=1}^{N_{\alpha+1}} Y_{i(\alpha)j(\alpha+1)} & \geq W_{i(\alpha)} \\
i & = 1, \dots, N_{\alpha}; \alpha = 1, \dots, \varphi - 1
\end{aligned} \tag{4}$$

$$\begin{aligned}
\sum_{i=1}^{N_{\alpha}} Y_{i(\alpha)j(\alpha+1)} & \geq W_{j(\alpha+1)} \\
j & = 1, \dots, N_{\alpha+1}; \alpha = 1, \dots, \varphi - 1
\end{aligned} \tag{5}$$

$$\begin{aligned}
Z_{i(\alpha)t} & \leq \Phi_{i(\alpha)t} W_{i(\alpha)} \\
i & = 1, \dots, N_{\alpha}; \alpha = 1, \dots, \varphi; t \\
& = \alpha, \dots, T - \varphi + \alpha
\end{aligned} \tag{6}$$

$$\begin{aligned}
X_{i(\alpha)j(\alpha+1)t} & \leq \Psi_{i(\alpha)j(\alpha+1)t} Y_{i(\alpha)j(\alpha+1)} \\
i & = 1, \dots, N_{\alpha}; j = 1, \dots, N_{\alpha+1}; \alpha = 1, \dots, \varphi - 1; t \\
& = \alpha, \dots, T - \varphi + \alpha
\end{aligned} \tag{7}$$

$$\begin{aligned}
h_{i(\alpha)t}^f & = h_{i(\alpha)t-1}^f + Z_{i(\alpha)t} - \sum_{j=1}^{N_{\alpha+1}} X_{i(\alpha)j(\alpha+1)t} \\
i & = 1, \dots, N_{\alpha}; \alpha = 1, \dots, \varphi; t \\
& = \alpha, \dots, T - \varphi + \alpha
\end{aligned} \tag{8}$$

$$h_{i(\alpha)t}^r = h_{i(\alpha)t-1}^r - \theta_{\alpha} Z_{i(\alpha)t} + \sum_{j=1}^{N_{\alpha-1}} X_{j(\alpha-1)i(\alpha)t-1}$$

$$\begin{aligned} i &= 1, \dots, N_\alpha; \alpha = 2, \dots, \varphi; t \\ &= \alpha, \dots, T - \varphi + \alpha \end{aligned} \quad (9)$$

$$\sum_{i=1}^{N_\varphi} X_{i(\varphi)j(\varphi+1)t} = D_{jt} \quad (10)$$

$$j = 1, \dots, N_{\varphi+1}; t = \varphi, \dots, T$$

$$\begin{aligned} h_{i(\alpha)t-1}^f &= 0 \\ t &= \alpha; i = 1, \dots, N_\alpha; \alpha = 1, \dots, \varphi \end{aligned} \quad (11)$$

$$\begin{aligned} h_{i(\alpha)t-1}^r &= 0 \\ t &= \alpha; i = 1, \dots, N_\alpha; \alpha = 2, \dots, \varphi \end{aligned} \quad (12)$$

$$\begin{aligned} Z_{i(\alpha)t} &\geq 0 \\ i &= 1, \dots, N_\alpha; \alpha = 1, \dots, \varphi; t = \alpha, \dots, T - \varphi + \alpha \end{aligned} \quad (13)$$

$$\begin{aligned} X_{i(\alpha)j(\alpha+1)t} &\geq 0 \\ \forall (i, j) \in A; \alpha &= 1, \dots, \varphi; t = \alpha, \dots, T - \varphi + \alpha \end{aligned} \quad (14)$$

$$\begin{aligned} h_{i(\alpha)t}^f &= 0 \\ i &= 1, \dots, N_\alpha; \alpha = 1, \dots, \varphi; t = \alpha, \dots, T - \varphi + \alpha \end{aligned} \quad (15)$$

$$\begin{aligned} h_{i(\alpha)t}^r &= 0 \\ i &= 1, \dots, N_\alpha; \alpha = 1, \dots, \varphi; t = \alpha, \dots, T - \varphi + \alpha \end{aligned} \quad (16)$$

$$Y_{i(\alpha)j(\alpha+1)} \in \{0,1\} \quad \forall (i, j) \in A \quad (17)$$

$$\begin{aligned} W_{i(\alpha)} &\in \{0,1\} \\ i &= 1, \dots, N_\alpha; \alpha = 1, \dots, \varphi \end{aligned} \quad (18)$$

Eqns. (2) to (5) are formulated to ensure that two companies can be linked only if both of them are selected to participate in the network. Also, when the solution does not include any link to a certain company, that company will not be part of the solution. Constraint (6) makes sure that production happens only in selected companies. Constraint (7) asserts that transportation can happen only if the two companies are linked. Constraints (8) and (8) are formulated to ensure that the balance equation between final products and raw materials is established. Constraint (9) guarantees that the entire amount of raw material needed at each echelon is obtained from the previous echelon. Constraint (10) makes sure that the demands of all customers are satisfied. Constraints (11) and (12) determine the amount of inventory that should be held by the company to satisfy the demand. And finally, Constraints (13) to (18) specify binary variables and non-zero variables of the problem.

4. Tabu Search algorithm

Tabu Search (TS) algorithm is a meta-heuristic method for solving nonlinear and combinatorial optimization problems based on an iterative neighborhood search approach (Altıparmak and Karaoglan, 2008). This algorithm starts with finding an acceptable solution and proceeds by searching the neighborhood of this solution for better solutions until finally reaching the optimal or near optimal solution (Silva and Cunha, 2017).

TS algorithm consists of the following steps:

Step 1: TS algorithm starts with an initial solution, which in many cases, is selected at random. The algorithm sets the objective function value of this initial solution as the currently best value.

Step 2: The algorithm searches the neighborhood of the selected solution according to the introduced neighborhood structure.

Step 3: The algorithm determines and selects the best neighborhood among the available options.

Step 4: The algorithm checks the tabu list to determine whether it is allowed to move to that neighborhood. If this move is prohibited, the algorithm proceeds to step 5 and otherwise it proceeds to step 6.

Step 5: The algorithm checks whether the prohibited move satisfies the criteria called the aspiration criteria. If the aspiration criteria are met, the algorithm carries out the move, otherwise, it returns to step 3 to select the next best solution.

Step 6: The algorithm moves from the current solution to the new solution and sets this new solution as the current solution.

Step 7: The algorithm stores the best solution found during the above processes. At first, it considers the initial solution as the best solution. But after each move, it compares the new solution with the currently best solution and updates it if necessary.

Step 8: After each move, the algorithm checks the stopping condition and terminate the operation if this condition is met; otherwise it proceeds to the next step.

Step 9: After each move, the algorithm adds the move to the tabu list and updates the list. The duration that a move stays in the tabu list and the way the list is updated should be defined from the beginning. The customary updating rule is to remove one (or more) of the oldest moves whenever a move is added to the list. After updating the tabu list, the algorithm returns to step 2 and starts searching the neighborhoods around the new solution. As mentioned, TS algorithm is an efficient metaheuristic method for solving combinatorial optimization problems. The features that make this algorithm attractive are the flexibility and the ability to obtain optimal and near-optimal solutions without getting trapped in local optima (Sun, 2006). Figure 1 illustrates how this algorithm optimizes the value of the objective function (S) in a typical optimization problem.

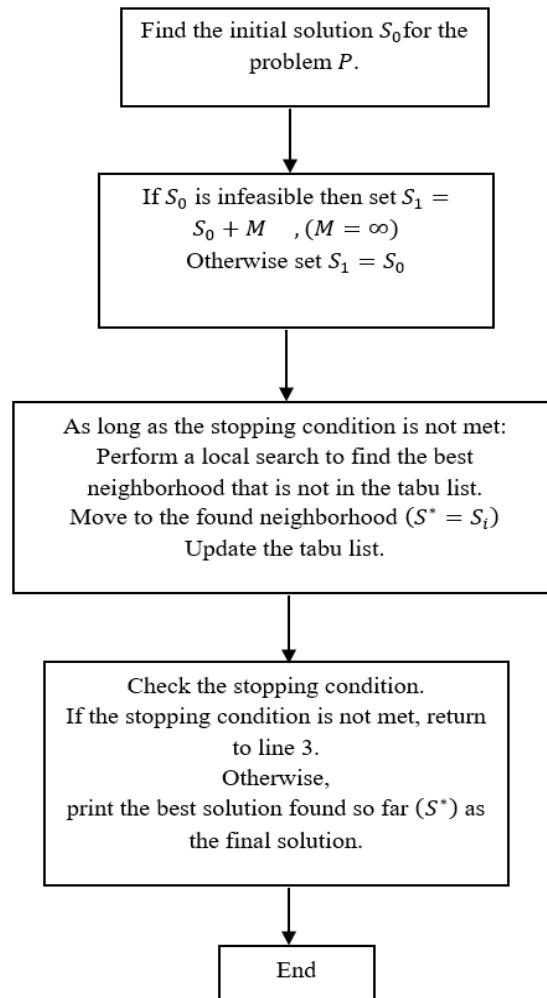


Fig. 1. Flowchart of TS algorithm.

The results are categorized into two classes: small and medium problems and large sized problems. In Tables 4 and 5, the optimal solutions are compared with the results of the proposed formulation and the results of Pan and Nagi (2013).

Table 4. Comparison of computational results for small and medium problems.

Deviation from the optimal solution		Optimal solution (CPLEX 12.1)	Lower bound of the solution of Pan and Nagi (2013)	Upper bound of the solution of Pan and Nagi (2013)	Solution of TS	Number of iterations	Number of customers	Number of Periods	Problem structure
Pan and Nagi (2013)	TS algorithm								
0.05 %	0.03%	1517633	1505348	1518451	1518088	500	1	18	2, 5, 3
0.44 %	0.50%	243583	236338	244652	244801	500	1	3	3, 3, 3, 3
0.05 %	0.04%	600007	586990	600321	600247	500	1	8	3, 3, 3, 3
0.51 %	0.53%	770798	754419	774786	774883	500	1	6	6, 4, 8, 5, 6
0.83 %	0.54%	1554292	1527067	1567272	1562685	500	2	7	13, 5, 6, 6

1.10 %	0.67%	1297202	1273138	1311590	1305893	500	1	10	6, 4, 5, 8, 5, 6
0.65 %	0.55%	1035990	1014444	1042789	1041688	500	2	6	10, 5, 21, 5, 4
0.64 %	0.58%	1516694	1485196	1526419	1525491	500	2	6	5, 5, 5, 5, 5, 5
0.16 %	0.03%	4652696	4597004	4660344	4654092	500	2	11	3, 3, 3, 3, 3, 3, 3, 3, 3, 3
1.70 %	0.83%	577366	563730	587338	582158	500	1	7	21, 29, 20, 10

Table 5. Comparison of computational results for large problems.

Difference between the solutions of TS and Pan and Nagi (2013)	Lower bound of the solution of Pan and Nagi (2013)	Upper bound of the solution of Pan and Nagi (2013)	Solution of TS	Number of iterations	Number of customers	Number of Periods	Problem structure
0.94%	2744036	2817443	2761872	500	1	20	6, 5, 6, 10, 3, 3
1.20%	4132184	4236887	4144666	500	2	14	8, 6, 5, 9, 10, 3, 4
1.23%	2706498	2788743	2721948	500	2	10	6, 6, 8, 5, 6, 10
4.45%	2492277	2568494	2425066	100	5	4	10, 10, 10, 10, 10
4.68%	4082134	4272226	3999808	100	5	4	20, 20, 20, 20, 20, 20, 20, 20, 20, 20

According to the results presented in Table 4, the optimality gap for small and medium-sized problems is about 1%. The Lagrangian method used by Pan and Nagi (2013) produces two results, which are the upper and lower bounds of the solution. As shown in Table (4), the solutions obtained with TS method are closer to the optimal solutions produced by CPLEX than the solutions obtained by Pan and Nagi (2013) using the Lagrangian method. The results presented in Table 5 show that the optimality gap for large problems is less than 5%. It can be seen that the higher is the number of iterations, the lower is the difference between the solutions of TS algorithm and the Lagrangian method employed by Pan and Nagi (2013), indicating that the two methods will produce more similar solutions for larger problems.

5. Conclusions and future research directions

Considering the variety of existing supply chain structures and models and the ways that they can be expanded, in this study, a model developed for agile supply chains with several customers and high-quantity demand based on specific conditions and assumptions. Given the high quantity of demand and production and transportation capacity constraints, in order to prevent demand loss, the supply chain network was formed by choosing several companies at each echelon. After examining and theoretical analysis of the model, the following results were inferred.

In the presence of dynamic demand, the agility of the supply chain was dependent upon production flexibility. Production, warehousing, and transportation plans of the selected companies were integrated into the supply chain network in order to form a virtual organization. Given the NP-hardness of the problem, an effective solution approach was developed based on TS algorithm to track acceptable solutions with the help of strategic oscillation. The proposed model minimizes the cost of the link between the companies at two adjacent echelons. After executing the model with the data contained in the research of Pan and Nagi (2013), the results showed that TS algorithm used in this study outperforms the Lagrangian algorithm used by Pan and Nagi (2013), as it has a higher convergence rate and performs especially better for larger problems.

To expand this work, it is suggested to develop exact solution methods for larger variants of the problem. The use of convergence acceleration methods to increase the algorithm's convergence rate for large-scale problems can also be an interesting approach. Also, some of the parameters embedded in this model are associated with uncertainties that can be modeled through approaches such as fuzzy programming.

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