Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Cooperator selection and industry assignment in supply chain network with line balancing technology

Zhen-Guo Che^a, Z.H. Che^{b,*}, T.A. Hsu^c

^a Institute of Information Management, National Chiao Tung University, 1001, University Rd., Hsinchu 300, Taiwan, ROC ^b Department of Industrial Engineering and Management, National Taipei University of Technology, 1, Sec. 3, Chung-Hsiao E. Rd., Taipei 106, Taiwan, ROC ^c Department of Management Information System, Chung Yuan Christian University, 200, Chung-Pei Rd., Jhongli City, Taoyuan County 32023, Taiwan, ROC

ARTICLE INFO

Keywords: Cooperator selection Industry assignment Supply chain network Line balancing Genetic algorithm

ABSTRACT

Losses from cooperator delivery delay may greatly undermine the supply chain network performance leading to losses in the increased business cost. This paper mainly discusses and explores how to create the optimized cooperators and industry sets intelligently in the supply chain network. A mathematical model and a genetic algorithm solving model for cooperator selection and industry assignment in supply chain network are presented to minimize the total delivery delay loss. The mathematical model based on the line balancing technology since the supply chain network can be treated as the extension of assembly production line can be used as a foundation for further practical development in the design of supply chain network. The genetic algorithm solving model is adopted to get a satisfactory near-optimal solution with great speed. The application results in real cases show that the solving model presented by this research can quickly and effectively plan the most suitable type of the cooperators and industry sets in supply chain network.

© 2009 Elsevier Ltd. All rights reserved.

1. Introduction

Most enterprises took the independent operation business mode in the past. However, such businesses could not deal with the challenges they are faced with independently in the changing competition environment. Hence, businesses gradually integrated individual resources in cooperation to lower operation costs, raise profits and market shares, creating the upstream and downstream supply chain cooperation pattern, and then the cooperator selection became an important issue for constructing the supply chain network. Jagdev and Browne (1998), Mikhailov (2002), Papazoglou, Ribbers, and Tsalgatidou (2000), Sha and Che (2005) and Talluri, Baker, and Sarkis (1999) claimed that the key issue in forming a virtual enterprise was to select agile, competent, and compatible partners. Davis and O'Sullivan (1999) and Korhonen, Huttunen, and Eloranta (1998) stated the partner selection process as an important function for the information management systems of extended virtual enterprises. Sha and Che (2004, 2006) indicate that selective partnerships involve in determining appropriate upstream suppliers/vendors and downstream manufacturers/distributors for specific enterprises. There are a number of potential options that must be assessed. More recently, Yan, Chen, Huang, and Mi (2008), Yang, Yang, and Abdel-Malek (2007), Wang (2007, 2008) and Wang, Yu, and Xue (2007) indicate that partners/suppliers selection problem in supply chains is an important issue for decision makers who face numerous challenges particularly in today's globally competitive environment.

In the supply chain network cooperation, these cooperators may locate at different geographical locations and the commodities are delivered among these cooperators. The operation performance of supply chain is impacted by the delivery performance of the commodities. If the delivery delay is increased, the cooperative operation will be unsmooth to complete the commodity production/distribution causing a decrease in the utility rates of cooperators. Based on the above discussion, the operation mechanism of supply chain is similar to the assembly production line. The line balancing technology had been utilized effectively to assign the tasks to workstations to save time in the assembly production line; that is to say, the utility rates of workstations should be enhanced. Hence, this paper attempts to adopt the line balancing technology to complete the cooperator selection and industry assignment for cooperation mechanism with the lower delivery delay loss of the supply chain network.

Assembly production line balancing problems are NP-hard (Gutjahr & Nemhauser, 1964; Lapierre, Ruiz, & Soriano, 2006). The concepts of the task assignment are shown in Figs. 1 and 2. In this paper, we consider the supply chain network with multiechelon and multiple cooperators of each industry. The main objective of this research is to find suitable cooperator in each





^{*} Corresponding author. Tel.: +886 2 2771 2171x2346; fax: +886 2 7317168. *E-mail address:* zhche@ntut.edu.tw (Z.H. Che).



Fig. 1. Precedence diagram.



Fig. 2. Workflow diagram.

industry and to assign the industries to the adequate industry sets. Thus, the problem becomes even more difficult in our case.

Simaria and Vilarinho (2004) pointed out that the genetic algorithm could be employed to solve combinatorial optimization problems effectively. Genetic algorithms have also been used for the assembly line balancing problem (Brown & Sumichrast, 2005; Ji, Sze, & Lee, 2001; Kim, Kim, & Cho, 1998; Kim, Kim, & Kim, 2000; Mcgovern & Gupta, 2007; Ponnambalam, Aravindan, & Naidu, 2000; Rekiek, DeLit, & Delchambre, 2000). Therefore, this paper aims to construct the optimized cooperator selection and industry assignment model by using the features of heuristic genetic algorithms.

The purposes of this paper are twofold: (1) to present a mathematical model for cooperator selection and industry assignment in supply chain network with the objective of minimizing the total delivery delay loss proportion for a given cycle, and (2) to apply a genetic algorithm approach to efficiently solve the mathematical model. To the best of our knowledge, no mathematical model for cooperator selection problems by considering the delivery delay loss proportion has been presented yet. In this paper, we emphasize the suitability of adopting a genetic algorithm to find the solution of the mathematical model. Comparisons with other heuristic algorithms are not presented for the time being due to this problem has been presented in this paper first of all, is not solved by other heuristic algorithms.

The rest of the paper is organized as follows. The problem description and a mathematical model for this problem are presented in Section 2. Section 3 proposes a genetic algorithm solving model for dealing with the mathematical model. In Section 4, an illustrative example is presented and the results are discussed. Section 5 concludes the paper.

2. Assumptions and mathematical model development

This paper is to apply line balancing in dealing with the relationships of supply chain members to work out the optimized cooperator set at the minimum total delivery delay loss proportion. First, the precedence diagram determines that the supply chain network should be worked out. Second, after the successful representation of precedence diagram, the related parameters and assumptions would be set for mathematical construction to produce the illustration of the optimized cooperator. Since the mathematical model constructed in this paper covers the topic of the whole supply chain, the following assumptions are proposed with illustration: (1) replace workstations with industry set (*IS*); (2) industry cycle time refers to the total time limits of delivery within IS; (3) the set *IS* process is continuous and non-stop; (4) *IS* procedure sequential order should not be in conflict with the supply chain procedure; (5) a cooperator can be selected in each industry at the same time; (6) cooperator of each industry belongs to one *IS* only; and (7) the operation and delivery time of each cooperator in the supply chain are known.

The following notations are used in the mathematical model:

DOT	daily operation time
ER	expected ratio of the center manufacturer
ICT	industry cycle time (<i>ICT = DOT/ER</i>)
TDDLP	total delivery delay loss proportion
i, l	index of industry, $i = 1,, I$, $l = 1,, L$
I, L	total number of industries
j	index of cooperator, $j = 1,, J_i$
Ji	total number of cooperators in the industry <i>i</i>
IS_k	index of IS, $k = 1, \dots, K$
IS_n	number of <i>ISs</i> , $n = 1,, N$
IS_N	total number of ISs
IS_N′	integer value of <i>n</i> by eliminating the decimal
ot _{i.j}	operation time for cooperator <i>j</i> of industry <i>i</i>
ot _{k.i.j}	operation time for cooperator j of industry i in IS_k
Wi	IS_k to which industry <i>i</i> belong
$W_{i,l}$	IS_k to which industry l after industry i belong
dt _{i.j}	delivery time of cooperator <i>j</i> of industry <i>i</i>
dt _{k.i.j}	delivery time of cooperator j of industry i in IS_k
$tt'_{i,i}$	total process time of cooperator j of industry i
$tt'_{k,i,j}$	total process time of cooperator j of industry i in IS_{j}
$x_{i,j} = \begin{cases} 1 \\ 0 \end{cases}$	if cooperator <i>j</i> is selected from industry <i>i</i> otherwise
$x_{k.i.j} = \begin{cases} 1 \\ 0 \end{cases}$	if cooperator <i>j</i> is selected from industry <i>i</i> in <i>IS_k</i> otherwise

This paper aims to find out the most suitable *IS* number by line balancing method. With the most suitable *IS* number, balancing indicators are calculated to minimize the total delivery delay loss by evaluating whether the cooperators and industry sets in the whole supply chain has reached optimization to be an indicator for appraisal of cooperators' sequence. In order to set up mathematical functions better in accordance with the whole supply chain network model, the operation time of cooperators has been added for consideration in addition to their delivery time. Namely, the total process time of cooperators are considered as well. The related parameters are defined as follows:

$$tt'_{ii} = dt_{ii} + ot_{ii} \tag{1}$$

$$tt'_{k,ij} = dt_{k,ij} + ot_{k,ij}.$$
(2)

In terms of the above notation, the problem can be formulated as in the following steps.

Step 1: Industry set number

$$IS_n = \frac{\sum_{i=1}^{l} \sum_{j=1}^{l_i} tt'_{ij} x_{ij}}{ICT}$$
(3)

$$IS_N' = \|IS_n\|. \tag{4}$$

Step 2: Total delivery delay loss proportion (Objective function)

$$Min \ TDDLP = \frac{\sum_{k=1}^{K} \left(ICT - \sum_{i=1}^{I} \sum_{j=1}^{J_i} tt'_{k,i,j} \times x_{k,i,j} \right)}{IS_{-}N' \times ICT} \times 100\%$$
(5)

The following limiting conditions listed must be satisfied in the calculation process to achieve the minimized supply chain total delivery delay loss in objective function:

$$w_i \leq w_{i,l}, \quad \forall i,l \tag{6}$$
$$x_{k,i,j}, x_{i,j} \in \{0,1\} \tag{7}$$

1 represents that all the cooperators of industry *i* are selected while 0 represents that all the cooperators of industry *i* are not selected.

$$\sum_{i=1}^{j_i} x_{ij} = 1, \forall i \tag{8}$$

Only one cooperator can be selected in the same industry *i*.

$$\sum_{j=1}^{J_i} x_{k,i,j} = 1, \forall k, i \tag{9}$$

Cooperators of the same industry *i* belong to one IS.

3. Genetic algorithm solving model for cooperator selection and industry assignment

In order to solve the problem described in Section 1, we propose a genetic algorithm solving procedure with the following steps:

Step I: Coding pattern

In general, the initial groups of chromosome character strings in genetic algorithms are produced randomly. Similarly, this paper produces the initial groups. The lengths of the chromosome character strings in genetic algorithms are determined by the number of industries *i* and the number of cooperators *j*. Coding begins from the farthest satellite cooperator to the nearest one in the genetic chromosome character strings sequencing. The makeup of character strings includes the following two points: (1) the most suitable total *IS* number of the search (*IS_N''*). *IS_N''* is set at the interval (*IS_N' - 2*, *IS_N' + 2*). (2) 1 represents the cooperator being selected while 0 represents the status of being not selected (x_{ij}).

As to the chromosome for selecting the optimized set of cooperators in this study, variables of IS_N'' , x_{ij} , and w_i are mainly concerned with other variables being related to their interrelationships and relevant limiting conditions. The coding pattern of real mode number of the whole chromosome is shown in Fig. 3.

Step II: Production of fitness function

Only the fitness function is involved in the calculation process of genetic algorithms. Hence, the quality of fitness function has a fundamental influence on the solution to the problem. The design of fitness function (Eq. (10)) of this study is to minimize the total delivery delay loss of the supply chain network, i.e. to find out the optimized cooperators and industry sets in the supply chain network

$$Min \ TDDLP = \frac{\sum_{k=1}^{K} (ICT - \sum_{i=1}^{I} \sum_{j=1}^{J_i} tt'_{k,ij} \mathbf{x}_{k,ij})}{IS N'' \times ICT} \times 100\%.$$
(10)

Minimum total delivery delay represents the highest supply network integration efficiency with the best fitness of the chromosome set. The preservative offspring of the chromosome with the best fitness will be put into the mating pool for repeated execution of evolution steps to produce the offspring with highest fitness. Thus, the quality cooperators and industry sets will be found out.



Fig. 3. Real number coding illustration.

Step III: Performance and evaluation of Algorithms

Step 1: Produce random initial sets of chromosomes for evaluating calculations to ensure same occurrences each time when the system begins to search.

Step 2: Judge whether the limiting conditions are satisfied or not.

Sub-Step 2.1: Decide the total *IS* number of this chromosome group and produce randomly the cooperator being selected. Sub-Step 2.2: Assign the selected cooperators to *IS*.

Sub-Step 2.3: Judge whether the *IS* sequence is in conflict with the supply chain network process. If not, keep it or delete it.

Sub-Step 2.4: Judge whether the business to which the selected cooperator belongs appears only in one *IS* in this chromosome group, if so keep it, if not delete it.

Sub-Step 2.5: Judge whether only one cooperator has been selected in each industry in this chromosome group. If more than one cooperator has been selected, delete the chromosome group, if not keep it.

Sub-Step 2.6: Chromosomes satisfying Sub-Steps 2.3–2.5 conditions concurrently are qualified for evolution mathematical calculation.

Step 3: Preserve the chromosome with comparatively higher fitness for reproduction.

Step 4: Perform the crossover and mutation operators.

Step 5: Judge whether the ending conditions are satisfied. If yes, go to Step 6, else go to Step 2.

Step 6: Produce the acceptable solutions.

4. Model application and result analysis

This section is to explain how to use genetic algorithms in constructing the mathematical model for supply chain network partners and in verifying the feasibility and practicability of the model by parameters setting and experiments. The programming language Power Builder 9.0 and database Microsoft SQL Server 2000 are used in development. It is an important and much concerned topic for the center manufacturer to select excellent cooperators to cooperate with and to meet the customers' demands with timely delivery, making highest profits. However, these are often made on the basis of the experiences and impressions of the major decision makers for the cooperator selection judgments. Thus, this paper proposes to apply line balancing technology with genetic algorithms in considering the operation time and delivery time at the same time to work out for the least delivery delay loss based on the cooperators sequence leading to the best cooperator set in hope that information technology can help the center manufacturer raise accuracy in selection by avoiding the possible loss from human errors.

The line balancing problems with 6, 7, 8, or 9 tasks were separately discussed in the literature (Bautista & Pereira, 2007; Boysen & Fliedner, 2008; Boysen et al., 2007a, 2007b; Gökçen, Agpak, & Benzer, 2006; Mcgovern & Gupta, 2007). In order to explain the classic example, we suppose there are altogether seven industries (as tasks) in the whole supply chain and each industry has five cooperators. The illustrative case of supply chain network structure which is constructed according to semiconductor industry is shown in Fig. 4 and the related data of time for the case is listed in Table 1. In this paper, we select only one cooperator of each industry to participate in the supply chain network with 30 min of the initial cycle time in *IS*, with operation time and delivery time of each cooperator known. Mathematical calculations can be conducted after the setting is completed.



Fig. 4. Supply chain network for illustrative case.

Table 1	
Related data of time for all cooperators.	

Co.	Time	Co.	Time	Co.	Time	Co.	Time	Co.	Time	Co.	Time	Co.	Time
Operatio	on time												
S _{1.1}	13	S _{2.1}	10	S _{3.1}	14	S _{4.1}	10	S _{5.1}	8	S _{6.1}	22	S _{7.1}	25
S _{1.2}	9	S _{2.2}	4	S _{3.2}	9	S _{4.2}	11	S _{5.2}	1	S _{6.2}	21	S _{7.2}	15
S _{1.3}	5	S _{2.3}	14	S _{3.3}	3	S _{4.3}	3	S _{5.3}	12	S _{6.3}	19	S _{7.3}	16
S _{1.4}	10	S _{2.4}	11	S _{3.4}	3	S _{4.4}	8	S _{5.4}	3	S _{6.4}	2	S _{7.4}	20
S _{1.5}	3	S _{2.5}	2	S _{3.5}	11	S _{4.5}	17	S _{5.5}	14	S _{6.5}	14	S _{7.5}	27
Delivery	' time												
S _{1.1}	3	S _{2.1}	5	S _{3.1}	2	S _{4.1}	2	S _{5.1}	1	S _{6.1}	5	S _{7.1}	5
S _{1.2}	2	S _{2.2}	1	S _{3.2}	3	S _{4.2}	4	S _{5.2}	2	S _{6.2}	4	S _{7.2}	3
S _{1.3}	2	S _{2.3}	6	S _{3.3}	2	S _{4.3}	1	S _{5.3}	4	S _{6.3}	6	S _{7.3}	3
S _{1.4}	4	S _{2.4}	5	S _{3.4}	1	S _{4.4}	3	S _{5.4}	2	S _{6.4}	1	S _{7.4}	2
S _{1.5}	2	S _{2.5}	4	S _{3.5}	2	S _{4.5}	5	S _{5.5}	4	S _{6.5}	2	S _{7.5}	1

Co.: Cooperator.

To reach the greatest efficiency of the proposed approach, experimental design should be implemented on each parameter by obtaining a set of optimal parameter combination and making the approach solve cooperator selection problems effectively and efficiently. Wu and Cao (1997) set the crossover rate from 0.6 to 0.98, and mutation rate from 0.01 to 0.2, in the parameters setting of stochastically optimized genetic algorithm. Rojas et al. (2002) set the crossover rate with five grades - 0.4, 0.5, 0.6, 0.7 and 0.8, and mutation rate with five grades - 0.05, 0.1, 0.15, 0.2 and 0.25 while analyzing the parameters setting of genetic algorithm using a statistical method. Sha and Che (2006) performed the experiments under different combinations using three population sizes (5, 15, and 50), three generation sizes (500, 1000, and 1500), three crossover rates (0.5, 0.8, and 1.0) and three mutation rates (0.05, 0.2, and 0.3). Wang (2008) conducted the genetic calculation with different parameter values with a total of 16 combinations of tests. Parameters of tests were set as: population size (10 and 40), generation number (300 and 500), crossover rate (0.6 and 0.8) and mutation rate (0.03 and 0.05). Wang and Che (2007) set different genetic parameters as the generation number: 200 and 500, population size: 10 and 50, crossover rate: 0.3 and 0.6, and mutation rate: 0.03 and 0.05. According to the researches mentioned above, there are no specific rules on determining the genetic algorithm parameters. Therefore, the research set the population number at 10 and 50, crossover rates at 0.3 and 0.6, mutation rates at 0.03 and 0.05, and generation number at 100 and 500.

In addition, this research is to take single point crossover with points being produced randomly and to take one-point mutation to produce new chromosomes comparatively different from the original one with mutation points being produced randomly. The crossover and mutation concepts are illustrated in Figs. 5 and 6. In Fig. 6, the cooperator 2.1 is selected to perform mutation operation and $x_{2.1}$ from 0 becomes 1. For satisfying the constraint Eq. (8), accordingly, the original selected cooperator 2.2 will be



Fig. 5. Crossover mechanism.



Fig. 6. Mutation mechanism.

weeded out and $x_{2,2}$ becomes 0 to 1. Computation was carried out using Intel Pentium III CPU 1.0 GHz with a 256 MB RAM.

In order to increase the robustness of the proposed model and to solve the problem, each experiment is performed for 30 times, and the average values of objective function and execution time are obtained. Experimental results can be achieved by following the aforementioned steps as shown in Table 2. The Z-tests are

Table 2Experiment results of all combinations.

Population number (I	PN)	10		50	
Generation size (GS)		100	500	100	500
Crossover rate (CR)	Mutation rate (MR)				
0.3	0.03	(A) 3.677 ^a 29.26 ^b	(E) 3.502 28.10	(I) 3.677 26.81	(M) 3.703 27.43
	0.05	(B) 3.766 29.69	(F) 3.640 29.07	(J) 3.677 28.35	(N) 3.566 28.17
0.6	0.03	(C) 3.677 28.32	(G) 3.703 28.00	(K) 3.529 28.42	(0) 3.529 28.07
	0.05	(D) 3.825 27.29	(H) 3.566 29.16	(L) 3.677 27.79	(P) 3.566 28.98

^a Average fitness value (%).

^b Average execution time (s).

performed on the fitness values and execution times of different parameters to determine the significant difference in the efficiency for these parameters, as shown in Table 3. According to the test results, only the interaction of population number and crossover rate may influence the execution time to find the results. For the fitness value, the analysis of the experimental results shows that different parameters have no significant difference in solving effect, and the genetic algorithm solving model proposed in this study has robust solving ability.

Combination E has the best calculation results, with the average least total delivery delay loss (3.502%) after the systematic mathematical calculation. The best value of the least total delivery delay

 Table 3

 Compared results for different genetic algorithm parameters.

•	• •	-		
Source	Dependent variable	Mean square	F	Sig.
PN	FV	.092	.108	.742
	ET	44.044	3.082	.080
GS	FV	1.027	1.204	.273
	ET	2.080	.146	.703
CR	FV	.010	.012	.913
	ET	1.281	.090	.765
MR	FV	.164	.193	.661
	ET	31.416	2.198	.139
PN * GS	FV	.041	.048	.826
	ET	4.408	.308	.579
PN * CR	FV	.503	.590	.443
	ET	64.827	4.536	.034*
GS * CR	FV	.041	.048	.826
	ET	25.669	1.796	.181
PN * GS * CR	FV	.164	.193	.661
	ET	15.769	1.103	.294
PN * MR	FV	.000	.000	1.000
	ET	1.925	.135	.714
GS * MR	FV	.010	.012	.913
	ET	22.794	1.595	.207
PN * GS * MR	FV	.092	.108	.742
	ET	7.450	.521	.471
CR * MR	FV	.164	.193	.661
	ET	20.090	1.406	.236
PN * CR * MR	FV	.041	.048	.826
	ET	1.180	.083	.774
GS * CR * MR	FV	.503	.590	.443
	ET	30.000	2.099	.148
PN * GS * CR * MR	FV	.257	.301	.584
	ET	.833	.058	.809
Error	FV	.853		
	ET	14.292		

FV: Fitness value; ET: Execution time.

* P value < 0.05.



Fig. 7. Evolution process of the best result of combination E.



Fig. 8. Industry sets of the best result of combination E.

losses of all combinations is 3.333%. The relationship between evolution generation and fitness function of the best result of combination E is shown in Fig. 7. The best cooperator sequence in the supply chain network, [**IS**₁: S_{1.2}, S_{2.5}, S_{3.2}; **IS**₂: S_{4.5}, S_{5.2}, S_{6.4}; **IS**₃: S_{7.1}], is shown in Fig. 8. With the help of this model, the center manufacturer can apply it to cases of making decision in ultra short time (e.g. unexpected big order or timely delivery requirements) for best solutions in addition to the selection of optimized upriver and downriver cooperator sets. At the same time, the production of flow sequence from minimum total delivery delay loss will reduce the time for decision-making and occurrence of human errors for raising the global decision-making quality.

This study mainly proposes a method to apply line balancing technology with a genetic algorithm to construct a mathematical model to find out the optimal cooperators and industry sets within the shortest time, making a whole process of minimum delivery delay loss. In addition to the method proposed in this study, the following traditional rules are commonly applied for assembly line balancing problems in general production management (William, 1999):

Rule 1: Selection starts from the task of longest operation time and assign the tasks to suitable workstation on the basis of precedence diagram.

Rule 2: Selection starts from the maximum sequential tasks and then assign them each by each to a suitable workstation.

Rule 3: Selection starts from the task at the very beginning and then assigns each by each to a suitable workstation.

Rule 4: Define the positional weight of each task as the summation of the operation time of the task and all the sequential tasks. Then assign to the workstation from the task with highest positional weight to the lowest. To verify the practicality of the solving model constructed in this study, the best cooperator set (*GS*) obtained by the model under the same limiting conditions will be calculated in four traditional rules for the comparative study for differences. Owing to the innate calculating procedures, the traditional rules could only deal with the assignments of industries to industry sets could not perform the suitable cooperators selection in each industry in this problem. Thereby, verification is performed by traditional rules under the specific cooperator which is selected in each industry by the proposed genetic algorithm solving model. For the conciseness of this paper, detailed processes for calculating the results in accordance with these four rules are not presented. Hence, for 30 min of cycle time, seven solutions (RS_1-RS_7) are found out according to four rules as shown in Table 4.

By following the above steps, we can get the total delivery delay loss proportion of the supply chain network with the traditional rules as shown in Table 5. The comparative results of the loss proportions of total time between the assignment solutions with the proposed method and each traditional rule are also listed in Table 5. The average delay loss proportion (3.502%) of *GS* is greater than the solution *RS*₂'s delay loss of 3.333%, but that is 84.393% better than other solution responses (27.50%). The best delay loss proportion of *GS* is equal to the solution *RS*₂'s, but that is 87.880% better than the other solution responses. Thus, we find that the benefits of assignments by traditional rules of industries are much less than those of the model proposed in this paper.

The calculation procedure of each traditional rule resembles the enumerative algorithm that would spend a lot of time to find all feasible combinations. In addition, each industry has a number of cooperators in the supply chain network. The network design problem with the characteristic of the number of cooperators cannot be conducted by the traditional rules, namely, the traditional rules are only to find the feasible combinations of industry sets, but that cannot perform the selection mechanism to find the proper cooperator in each industry.

Table 4

Solution sets of proposed method and traditional rules.

	IS ₁	IS_2	IS ₃	IS_4
GS	S _{1.2} , S _{2.5} , S _{3.2}	S _{4.5} , S _{5.2} , S _{6.4}	S _{7.1}	-
RS_1	S _{4.5}	S _{3.2} , S _{1.2} , S _{2.5}	S _{6.4} , S _{5.2}	S _{7.1}
RS_2	S _{1.2} , S _{2.5} , S _{3.2}	S _{4.5} , S _{5.2} , S _{6.4}	S _{7.1}	-
RS ₃	S _{6.4} , S _{5.2}	S _{4.5} , S _{2.5}	S _{3.2} , S _{5.2} , S _{6.4}	S _{7.1}
RS ₄	S _{1.2} , S _{3.2} , S _{6.4}	S _{4.5} , S _{2.5}	S _{5.2}	S _{7.1}
RS ₅	S _{4.5} , S _{6.4}	S _{1.2} , S _{2.5} , S _{3.2}	S _{5.2}	S _{7.1}
RS ₆	S _{4.5}	S _{1.2} , S _{2.5} , S _{6.4}	S _{3.2} , S _{5.2}	S _{7.1}
RS ₇	S _{4.5}	S _{1.2} , S _{3.2} , S _{6.4}	S _{2.5} , S _{5.2}	S _{7.1}

Table 5

Comparisons between each traditiona	I rule and proposed method.
-------------------------------------	-----------------------------

	Industry set				Time loss	Percentage	Percentage		
		IS ₁	IS_2	IS_3	IS ₄	proportion (%)	improve ^a	improve	
Process time	GS	29	28	30	-	Best: 3.333 Average: 3.502	-	-	
	RS_1	22	29	6	30	27.500	87.880	84.393	
	RS_2	29	28	30	-	3.333	0	-5.070	
	RS_3	11	28	18	30	27.500	87.880	84.393	
	RS_4	26	28	3	30	27.500	87.880	84.393	
	RS_5	25	29	3	30	27.500	87.880	84.393	
	RS_6	22	20	15	30	27.500	87.891	84.393	
	RS_7	22	26	9	30	27.500	87.891	84.393	

^a The percentage improve of the best value of proposed method and results of traditional rules.

^b The percentage improve of the average value of proposed method and results of traditional rules.

This is mainly due to the fact that each center industry has several numbers of cooperators in the supply chain network. It is time consuming, taxing and energy wasting job to find out the optimal cooperators and industry sets manually among these cooperators. And the job is very prone to human error. Hence, this study provides an automatic mathematical calculation mechanism to produce many cooperators to avoid the aforementioned disadvantages automatically. It makes it possible for the center manufacturer to find out the best decision of cooperators and industry sets with least delivery delay loss proportion within the ultra short time period. The advantages of this model will be outstanding, especially, when the cooperators of the center manufacturer are in large number.

5. Conclusions

This research is to discuss the problem of optimized cooperators selection and industries assignment in the supply chain network. Firstly, a mathematical model based on the line balancing technology has been presented for raising the overall performance. The proposed mathematical model considers the cooperator operation time and the delivery time in multi-echelon supply chain network to achieve the goal of least losses due to delivery delay and find out the optimized cooperators and industry set sequences at the same time. Secondly, to solve the optimal mathematical model, the genetic algorithm based approach was developed. This approach is capable of dealing with the cooperator selection and industry assignment problems with various cooperators, as shown in the illustrative example. Although, the use of a genetic algorithm may not get the near-optimal solution, the proposed model efficiently obtained the best solution from a huge solution area. Further research should be concerned to employ other heuristic algorithms such as particle swarm optimization and simulated annealing for solving this problem. We also thought about extending this developed approach to more complex problems such as this problem involving the resource constraints.

References

- Bautista, J., & Pereira, J. (2007). Ant algorithms for a time and space constrained assembly line balancing problem. *European Journal of Operational Research*, 177(3), 2016–2032.
- Boysen, N., & Fliedner, M. (2008). A versatile algorithm for assembly line balancing. European Journal of Operational Research, 184(1), 39–56.
- Boysen, N., Fliedner, M., & Scholl, A. (2007a). A classification of assembly line balancing problems. European Journal of Operational Research, 183(2), 674–693.
- Boysen, N., Fliedner, M., & Scholl, A. (2007). Assembly line balancing: Which model to use when? International Journal of Production Economics (in press, corrected proof).
- Brown, E. C., & Sumichrast, R. T. (2005). Evaluating performance advantages of grouping genetic algorithms. *Engineering Applications of Artificial Intelligence*, 18(1), 1–12.
- Davis, M., & O'Sullivan, D. (1999). Systems design framework for the extended enterprise. Production Planning and Control, 10, 3–18.
- Gökçen, H., Ağpak, K., & Benzer, R. (2006). Balancing of parallel assembly lines. International Journal of Production Economics, 103(2), 600–609.
- Gutjahr, A. L., & Nemhauser, G. L. (1964). An algorithm for the line balancing problem. *Management Science*, 11, 308–315.
- Jagdev, H., & Browne, J. (1998). The extended enterprise a context for manufacturing. Production Planning and Control, 9, 216–229.
- Ji, P., Sze, M. T., & Lee, W. B. (2001). A genetic algorithm of determining cycle time for printed circuit board assembly lines. *European Journal of Operational Research*, 128, 175–184.
- Kim, Y. J., Kim, Y. K., & Cho, Y. (1998). A heuristic-based genetic algorithm for workload smoothing in assembly lines. *Computers and Operations Research*, 25(2), 99–111.
- Kim, Y. K., Kim, J. Y., & Kim, Y. (2000). A coevolutionary algorithm for balancing and sequencing in mixed model assembly lines. Applied Intelligence, 13, 247–258.
- Korhonen, P., Huttunen, K., & Eloranta, E. (1998). Demand chain management in global enterprise – information management view. *Production Planning and Control*, 9, 526–531.
- Lapierre, D. L., Ruiz, A., & Soriano, P. (2006). Balancing assembly lines with tabu search. European Journal of Operational Research, 168(3), 826–837.

- McGovern, S. M., & Gupta, S. M. (2007). A balancing method and genetic algorithm for disassembly line balancing. *European Journal of Operational Research*, 179(3), 692–708.
- Mikhailov, L. (2002). Fuzzy analytical approach to partnership selection in formation of virtual enterprises. *Omega*, *30*, 393–401.
- Papazoglou, M., Ribbers, P., & Tsalgatidou, A. (2000). Integrated value chains and their applications from a business and technology standpoint. *Decision Support System*, 29, 323–342.
- Ponnambalam, S. G., Aravindan, P., & Naidu, G. M. (2000). A multiobjective genetic algorithm for solving assembly line balancing problems. *International Journal of Advanced Manufacturing Technology*, 16, 297–302.
- Rekiek, B., DeLit, P., & Delchambre, A. (2000). Designing mixed-product assembly lines. *IEEE Transactions on Robotics and Automation*, 16(3), 268– 280.
- Rojas, I., Gonzalez, J., Pomares, H., Merelo, J. J., Castillo, P. A., & Romero, G. (2002). Statistical analysis of the main parameters involved in the design of a genetic algorithm systems, man, and cybernetics, Part C: Applications and reviews. *IEEE Transactions*, 32(1), 31–37.
- Sha, D. Y., & Che, Z. H. (2004). A multi-criterion analysis approach for capacitated multi-echelon production-distribution network modeling. *Journal of Management*, 21(3), 331–343.
- Sha, D. Y., & Che, Z. H. (2005). Virtual integration with a multi-criteria partner selection model for the multi-echelon manufacturing system. *International Journal of Advanced Manufacturing Technology*, 25(7–8), 739–802.
- Sha, D. Y., & Che, Z. H. (2006). Supply chain network design: Partner selection and production/distribution planning using a systematic model. *Journal of the Operational Research Society*, 57(1), 52–62.

- Simaria, A. S., & Vilarinho, P. M. (2004). A genetic algorithm based approach to the mixed-model assembly line balancing problem of type II. *Computers & Industrial Engineering*, 47(4), 391–407.
- Talluri, S., Baker, R., & Sarkis, J. (1999). A framework for designing efficient value chain networks. International Journal of Production Economics, 62, 133–144.
- Wang, H. S. (2007). A two-phase ant colony algorithm for multi-echelon defective supply chain network design. European Journal of Operational Research, doi:10.1016/j.ejor.2007.08.037.
- Wang, H. S. (2008). Configuration change assessment: Genetic optimization approach with fuzzy multiple criteria for part supplier selection decisions. *Expert Systems with Applications*, 34(2), 1541–1555.
- Wang, H. S., & Che, Z. H. (2007). An integrated model for supplier selection decisions in configuration changes. *Expert Systems with Applications*, 32(4), 1132–1140.
- Wang, Y., Yu, X., & Xue, X. (2007). An application of the method of combined radix determination for selecting construction supply chain partners. *International Journal of Project Management*, 25(2), 128–133.
- William, J. S. (1999). Production/operation management (6th ed.). New York: McGraw-Hill.
- Wu, Q. H., & Cao, Y. J. (1997). Stochastic optimization of control parameters in genetic algorithms. *IEEE International Conference on Evolutionary Computation*, 13(16), 77–80.
- Yan, W., Chen, C. H., Huang, Y., & Mi, W. (2008). An integration of bidding-oriented product conceptualization and supply chain formation. *Computers in Industry*, 59, 128–144.
- Yang, S., Yang, J., & Abdel-Malek, L. (2007). Sourcing with random yields and stochastic demand: A newsvendor approach. *Computers & Operations Research*, 34(12), 3682–3690.