A Comparative Study of Dynamic Multi Zone Dispatching Model in Truckload Trucking Management

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Abstract

In a decision regarding a conventional Multi Zone Dispatching (MZD), random traveling to over the roads between adjacent areas leads to different levels of load-imbalance. The MZD with minimal imbalance scenario can be modified as a Dynamic Multi Zone Dispatching (DMZD). In this problem, the rearrangement penalty will be added to the conventional model if there is a difference of the area arrangement in each zone within consecutive time periods. The objectives are to examine configurations of dispatching alternatives in each period for use in trucking operations and to eliminate empty repositioning movements between loads to maintain a high level of equipment utilisation. The dispatching alternatives with rearrangement penalty over a series of discrete time periods with the total minimal imbalance are determined via the constrained genetic (CGPS) and dynamic programming (DPS) strategies. From the experimental results, the DPS is practical merely for small problems. The results illustrate that minimising imbalance while controlling (minimising) runtime rely upon the problem parameters, number of zones, areas and consecutive time periods, used. The CGPS seems to be preferable on the tested data from Thai local transportation companies. The CGPS algorithm did not seem sensitive to the parameter choices, within reasonable limits. However, recommendations are made for the values of the parameters, although these values depend on the selected performance measure.

Keywords: Dynamic Multi Zone Dispatching, Imbalance, Constrained Genetic and Dynamic Programming Strategies

1. Introduction

Presently, transportation systems have a significant role toward business systems and organisations; especially in the companies that operate a transportation business. They may not only operate it by themselves, but also need support from other transportation companies. This support with a proper management system could reduce cost for business organisations abundantly [1]. Besides, most big companies use specific operators to liberate the burden of transportation cost. Meanwhile, it is important to have further research for this matter in order to generate a procedure to bring about great efficiency in transportation and the objective of business, to gain profits [2].

The prior transportation system uses a general approach which is a single zone transportation approach from point to point. The single zone approach is found to spend more time with the long distance part of each journey and has lots of available space to travel back. Later on, Taylor and Meinert [3] conducted research to increase the efficiency of transportation. They mentioned the Zone Dispatching or Zone Expedition approach that will be easier to manage and control. Furthermore, Taylor and teams [4] proposed a Multi Zone Dispatching (MZD) approach endeavoring to enhance the efficiency of the transportation system by adjusting the same point of products in and out to find the proper point of transportation to minimise the imbalance scenario.

The objective of this paper is to investigate the performance of the algorithmic approaches on the dynamic nature of the MZD model. A simulation study is based on the data from Thai local transportation firms. It aims to enhance the efficiency of transportation and pay more attention to the harmonious balance between cost and quantity. The algorithms to be applied to these problems could respond to the complication of a change of internal structure. Conclusions are drawn, and practical recommendations are made.

2. Dynamic Multi Zone Dispatching (DMZD)

Multi Zone Dispatching (MZD) management consists of 2 main principles in transportation management, i.e. area and zone. Taylor and teams [5] propose the notion called *Minimal Imbalance Scenario* approach in terms of load which contains 2 parts in each area: in-bound goods and out-bound goods, in each area within each zone, to find out the harmonious balance between inbound goods and outbound goods. However, business conditions are constantly changing. The need of a dynamic nature of the multi zone dispatching problems (new quantity of orders, new product lines, and technological advance) is proposed. There are a series of data in a static problem with its own "in-bound and out-bound freight" matrix for given finite discrete time periods. A period can be given in terms of months, quarters, or years. An additional rearrangement penalty in the objective function ties the static problems together whenever any area moves to the different zone in a consecutive time period.

The conventional multi zone dispatching model can be extended to the dynamic nature of this problem with the following mathematical integer programming:

Minimise:

$$\sum_{t=1}^{T}\sum_{j=1}^{Fit} ZP_{jt} - \sum_{t=1}^{T}\sum_{j=1}^{Fit} ZN_{jt} + \sum_{i=1}^{Fjt}\sum_{j=1}^{Fit}\sum_{k=1}^{Fit}\sum_{t=1}^{T-1} R_{ijkt}.X_{ijt}.X_{ik(t+1)} \qquad (1)$$

Subject to:

$$: \sum_{i\in F_{jt}} I_{it}X_{ijt} + I_{jt} - ZP_{jt} - ZN_{jt} = 0 \qquad \forall_{j,t} \qquad (2)$$

$$: \sum_{j\in F_{it}} X_{ijt} = 1 \qquad \forall_{j,t} \qquad (3)$$

$$: ZP_{jt} \geq 0 \qquad \forall_{j,t} \qquad (4)$$

$$: ZN_{jt} \leq 0 \qquad \forall_{j,t} \qquad (5)$$

$$: ZP_{jt}, ZN_{jt} = \text{integer} \qquad \forall_{j,t} \qquad (6)$$

$$: X_{ijt} = \text{binary}(0,1)\ \text{integer} \qquad \forall_{i,j,t} \qquad (7)$$

$:R_{ijkt}$ = the rearrangement penalty for area i moved from zone j to k in consecutive time.

In each time (t) period the equations above are used to find out the number of *Minimal Imbalance* from the sum of the remainder between ZP_{jt} and ZN_{jt} in each zone with an additional rearrangement penalty in consecutive time periods. ZP_{jt} in each zone is the positive valued imbalance (in loads) if the sum of in-bound goods in each zone is greater than the sum of out-bound freight. ZN_{jt} in each zone and time period is the negative valued imbalance if the sum of out-bound goods in that zone is greater than the sum of in-bound goods in that zone. ZN_{jt} equals zero when in-bound goods in that zone equal the sum of out-bound goods in that zone. Besides, I_{it} is an imbalance value of area i which comes from in-bound goods of area i to subtract with out-bound goods of area i. I_{jt} is an imbalance value of zone j that comes from in-bound goods of zone j minus out-bound goods of zone j. F_{it} is a set of feasible zones for area i. F_{jt} is a set of feasible areas for zone j. Finally, x_{ijt} is an integer that has 2 values: 1 and 0. The result comes to 1 when area i is in zone j and it equals 0 when area i is not in zone j.

Bring data in each period of time (t) continuously; the alteration of zone will reflect *Minimal Imbalance* as seen in the previous testimony [5]. A method for the DMZD model is a method for solving problems of statistical multi zone dispatching. Firstly, consider the imbalance proposed in a form of statistical multi zone dispatching at an interval and then consider a rearrangement penalty generated from time alteration in such period by finding a series of any solutions through all intervals. The objective of this approach is to minimise an imbalance with some penalty in zone dispatching planning over all the periods of time.

3 Related Method

3.1 Dynamic Programming Strategy, DPS

This strategy could tackle the complicated decisions by transforming them to one step of decision making which has 1-2 decisive variables to calculate. Each minor decision could provide many answers; the procedure needs to consider the previous reflection for the best answer. A Dynamic Programming Strategy is different from other strategies. It could alter the decisive problem with n variables to be n-

minor problems. Each of them will have one decisive variable. Each stage consists of a stage variable to connect each stage from the first to the last problem stages. In the study of transportation operations, Dynamic Programming Strategy is used as a tool in tackling problems by creating a model via computer simulation. The DPS is also used for many engineering matters such as a Cost Reduction Strategy for a signal controlling system in industry and Raw Material Management which is insufficient in Goods Collection [6]. The problem in use of the DPS could be separated to minor problems, which could arrange each area to each zone harmoniously.

3.2. Constrained Genetic Programming Strategy, CGPS

Holland [7] introduced the genetic programming strategy for finding the global optimum on various problems. The genetic programming strategy (GPS) is a set of rules for searching large solution spaces in a manner that mimics natural selection in biological evolution. Solutions with desirable characteristics are given a higher probability of being parents for the next generation and will cross their components to offspring, with a possible chance of mutation. The essential parameters are: the number of points tried initially (population size); the mutation and crossover operators; the probability of crossover; and the probability of mutation or other parameters. There is no single choice of parameters that has been found to be the best for all problems. Goldberg [8] used a high crossover probability, a low mutation probability, and a moderate population size for a five-function suite of problems following the work of De Jong [9]. In contrast, various levels of population size and probabilities of crossover and mutation were successfully applied to an optimisation problem in the textile industry by Backhouse et al. [10], and the dynamic plant layout problems (DPLP) by Balakrishnan et al. [11].

In the proposed CGPS, each of *NC* design points (population) consists of the dispatching alternatives for B_A-area and B_Z-zone of the T consecutive time periods. The dispatching alternative for each time period is coded in binary using B_AB_Z bits. Therefore a design point has B_AB_ZT associated bits and this sequence of bits is called a chromosome or string [12 and 13]. Table 1 illustrates binary coding for the 2-period-6-Area-2-Zone DMZD problem with 8 initial solutions [14].

It is common to start the algorithm with all the bits being assigned 0 or 1 with equal probability. The process is run at each of the *NC* design points or chromosomes. After these *NC* runs, parents are selected for the next generation or the reproduction process (*RP*). Schemes for selecting parents for mating consist of roulette wheel and binary tournament selections. The probability of using a particular chromosome is proportional to the corresponding process yield, or more generally, yield above some threshold, referred to as its fitness. Sampling is with replacement. The first two chromosomes to be selected may be mated by applying a crossover operation (*XO*). The probability of this crossover is some preset probability, P_c. If crossover is to be applied, a location along the chromosome is chosen at random and the bits beyond this location are swapped over to create two new chromosomes. Crossover processes in this study are position crossover [15] and union crossover [16]. If crossover does not occur, the parents are copied to the new generations without alteration. The process is repeated until *NC*/2 pairs of chromosomes have been considered, and hence the new generation maintains the population size at *NC*. Finally, there is a mutation operator to change, independently, the value at each position on the chromosome from one to zero or vice versa with some preset probability, P_m. Schemes for mutation (*MU*) consist of standard mutation, 2 operation adjacent swap mutation [17] and inversion mutation. Also we tried a form of elitism (*EL*), i.e. the best so far is retained, without mutation, in the next generation [18]. However, in this study there is a limitation of constraint (equation number 3). The mutation adjustment (*CT*) is then proposed for 2 cases, and adjusted after all CGPS processes and after only mutation processes. The details for these operators are as follows.

3.2.1 Reproduction

3.2.1.1 Roulette wheel selection

This selection is the easiest to be implemented in an algorithmic form. The procedure is to find the total fitness value of overall strings or chromosomes and calculate the expected value or percentage of population total fitness above as a weighted roulette wheel. A random number (RN) which follows a uniform distribution (0,1) is then generated to reproduce members in a mating pool. In this way more highly fit strings have a higher number of offspring in the succeeding generation. The previous steps are repeated until the number of strings is equal to the number of parents.

3.2.1.2 Binary Tournament Selection

The procedure starts to assign numbers from 1 to *NC* for all strings. The next step is to generate two random numbers from 1 to *NC* and prepare strings corresponding to numbers assigned above. A comparison of fitness values is made. Then, the highest valued parent in the mating pool is selected. The algorithm repeats until the number of strings is equal to the number of parents.

3.2.2 Crossover

3.2.2.1 Position Crossover

This operator starts to match each pair of parents and generates a random number which follows a uniform distribution (0,1) to compare with the percentage of crossover (P_c). If the RN is larger than P_c, a location along the chromosome is chosen at random (a uniform distribution) and the bits beyond this location are swapped over to create two new chromosomes. Otherwise, there is no crossover and the process is repeated until the number of strings is met.

3.2.2.2 Union crossover

The algorithm starts to match strings or chromosomes and change bits to Greek letters or numbers as in Table 5. The next step is to select a Sub-Chromosome from P2 and assign it to P1 and bring the remaining bits from P2 and assign them to S2 (order as appeared on P1). The process randomly selects S1or S2 to create new strings (Table 6). Transformation of letter strings to bits is then applied (Table 7). The process repeats until it covers all remaining bits.

Select: A D B C J H from P2

S1: A D B C J H

S2: I K G F L E

3.2.3 Mutation

3.2.3.1 Standard Mutation

This operator generates a random number which follows a uniform distribution (0,1) to reproduce members in each bit to compare with P_m. If the RN is less than P_m, there is a mutation operator to change independently. The value at each position on the chromosome is changed from one to zero or vice versa. Otherwise, there is no mutation.

3.2.3.2 Two Operation Adjacent Swap

The process is to generate a random number which follows a uniform distribution (0,1) to compare with P_m. If the RN is less than P_m, there is a mutation operator to change, independently. The value at each position on the chromosome is changed from one to zero or vice versa. Otherwise there is no mutation. The next step is to randomly generate two adjacent positions and swap their positions.

3.2.3.3 Inversion Mutation

The process is to generate a random number which follows a uniform distribution (0,1) to compare with P_m. If the RN is less than P_m, there is a mutation operator to change, independently. The value at each position on the chromosome is changed from one to zero or vice versa. Otherwise, there is no mutation. The next step is to randomly select positions and length of bits to invert.

4. Results

For finding the suitable solution(s) of the dynamic multi zone dispatching planning problem by the DPS and CGPS, a program written in Java has been developed to evaluate the results. All simulations were done on a Pentium-III machine with CPU speed of 1 GHz. A great deal of information is needed to support this research. We make use of a large quantity of historical freight data transformed from Thai local transportation firms because of the need to examine dynamic multi-zone implementation in a nearly-realistic setting. The simulation problem can be divided into two categories as follows. The problems considered are composed of small problems. Solutions are less than 10^7 possible combinations and the remaining are considered the big problems. The proposed CGPS approach requires many settings and operations as shown in Table 11. The CGPS parameters are varied to cover the range of values commonly found in the literature [10]. The tested problem consists of 11 areas, 6 zones and only one time period. The appropriate parameter choice is applied for the CGPS throughout, to compare with the DPS. The comparisons were made with consideration of the following performance measures.

4.1 Taguchi's measure of performance (Y_{F1})

Taguchi and Wu [19] proposed '*the smaller the better*' measure:

$$Y_{F1} = -10 \log \left(\sum_{i=1}^{n} y_i^2/n\right),$$

in which y_i represents the lowest imbalance at the end of trial i, and n is the number of trials, in this case there are five trials.

4.2 Minimise-the-Maximum performance measure (Y_{F2})

Another measure of the performance of the CGPS is the maximum of the lowest imbalances at the end of the trials. In the case of five trials, for example,

$$Y_{F2} = \mathrm{Max}\,(y_1, y_2, \ldots, y_5).$$

We wish to minimise Y_{F2}.

On the early phase of the parameter study, the seven parameters, P_m, P_c, *NC, RP, XO, MU* and *CT* are only varied between high and low levels in a 2^7 design. The low and high levels of P_m, P_c, *NC, RP, XO, MU* and *CT* were selected to cover the range of values commonly found in the literature: [0.01, 0.1], [0.6, 0.9], [100, 200], [0, 1], [0, 1] and [0, 1] for P_m, P_c, *NC, RP, XO, MU* and *CT*, respectively. We will begin the analysis of this data by constructing a normal probability plot of effect estimates. On this study, the results are given in Figure 1 via the statistics software Minitab. The important effects, with respect to two performance measures or responses, that emerge from this analysis of both performance measures, are the main effects of P_c, *NC*, *RP*, *XO* and the P_c* *NC*, P_c* *XO*, *NC***XO* interactions, where * denotes interaction. All of the other effects that lie along the line are negligible.

From the general full factorial design on the second phase, the analysis of variance for Y_{F1} is shown in Table 12, respectively. The main effect plots for only Y_{F1} are illustrated on Figure 2. The main finding was that the probability of crossover, number of chromosome, reproduction and crossover operators for $Y_{F1}$and Y_{F2} are low (0.60), 200, roulette wheel and union, respectively. This leads to lower average and a lower level of variance of imbalance values. No other statistically significant results were found at the 99% confidence interval. Results are included in which the ANOVA p-values, for main effects and interaction, are less than 0.01 in Table 13. Actually from the literature, if the size of searching area is identical, specifying the ratio of the population size and the number of generations not larger than 100 percent allows a better solution than specifying the number of generations larger than that of the population size. Moreover, if the searching area has been enlarged, the chance to achieve a better solution will also be considerably increased. While specifying the parameters of P_c and P_m in each calculation loop and problem size for different suitable numbers, it is found that P_m is high and P_c is low in contrast. This leads to finding a better feasible solution and it needs fewer runs, on average for evaluation, to converge to the optimum.

Results for small problems

In practice, the nature of the DMZD model is unlikely to be known and previous suggestions for the CGPS parameters are applied throughout this comparison. From the experimental results it can be concluded that the CPGS gives zone dispatching imbalance values equal to the optimal DPS solutions shown in Table 14. However, the CGPS gives higher performance, especially in terms of speed of convergence.

Combining other techniques to achieve better quality was researched. In the case of beginning with the tabu-search method and then bringing such solution to be the initial solution for the CGPS, this version of the CGPS has an ability to find a better solution than the original CGPS in some experiments and some problem sizes. Rosenblatt's sub-procedure with DPS to calculate the compensation value of imbalance of zone alteration in continuous time was also applied to find the better outcomes. The procedure is shown in the following equation [20]. $L_{tm}^* = \mathrm{Min}\,\{L_{t-1,k}^* + R_{km}\} + F_{tm}$ where,

L_{tm}^* = Minimal imbalance of the arrangement m at time t

R_{km} = Rearrangement penalty for arrangement k to arrangement m

F_{tm} = Imbalance of the arrangement m in time period t

k = Arrangement (states) for each time period

It is found that this version of the DPS is able to obtain better quality on the tested cases in the consideration of speed of convergence.

Results for big problems

It is found that the CGPS is able to obtain good solutions (Table 15) for the tested cases when compared with the DPS with Rosenblatt's sub-procedure, especially the speed of convergence. Moreover, the CGPS produces various possible combinations of zone dispatching alternatives for an implementation. In the case of various modifications, the CGPS with tabu-search, leads to better solutions in some problem sizes though the DPS is applied with Rosenblatt's sub-procedure. Also we tried a form of elitism (*EL*) to the CGPS with tabu-search. In the case of controlling the evaluation run time, the CGPS with the elitism and tabu-search operators is able to obtain a better solution than the pure strategy of the CGPS. However, convergence to the global optimum is not substantially rapid.

5. Conclusions

From the research of dynamic multi zone dispatching by the DPS and CGPS to find optimal solutions, it is found that in any small problems and big problems both with and without Rosenblatt's procedures in evaluation, the DPS is able to give an optimal solution, though it consumes very much time, especially on big problems. However, for combining Rosenblatt's procedures, optimum search speed can be increased. For big problems, the DPS is not able to give an optimal solution within a reasonable time. For any big problems which the evaluation time is limited, it was found that the CGPS is able to find a better solution than the DPS.

Finally, the CGPS seems to be preferable on the tested data from Thai local transportation companies. It is known that problems in planning of dynamic multi zone dispatching are seemingly huge and complex. To find out the best solution within a limited time, is obviously difficult. There are various modifications to overcome in the research. However, convergence to the global optimum is not substantially rapid. Recommendations are made for the values of the parameters, although these values depend on the selected performance measure. Other heuristic procedures such as Simulated Annealing, Tabu-search and Ant colony optimisation methods could be applied to this problem. The first one is the process of classical statistical mechanics. The second is a process for getting a solution developed from memory of the learning process of the convergent solution. The final one [21] is used for solving combinatorial optimisation problems such as dynamic facility layout problems [22]. These heuristic approaches may enhance the performance to achieve the target, especially in terms of speed of convergence or the quality of solutions.

6. References

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Table 1 Strings in the DMZD model

String	Period 1												Period 2												Constraint
	Zone 1						Zone 2						Zone 1						Zone 2						
1	1	1	0	1	0	0	0	0	1	0	1	1	1	1	0	0	0	1	0	0	1	1	1	0	✓
2	1	0	1	1	1	1	0	1	0	0	0	0	1	0	1	1	1	0	0	1	0	0	0	1	✓
3	0	0	1	0	1	0	1	1	0	1	0	1	0	1	0	1	0	1	1	0	1	0	1	0	✓
.			.						.						.						.				
.			.						.						.						.				
.			.						.						.						.				
.			.						.						.						.				
8	0	1	1	0	1	1	1	0	0	1	0	0	1	1	0	1	0	0	0	0	1	0	1	1	✓

Table 2 Constrained roulette wheel selection

String	Initial Population: Zone 1	Initial Population: Zone 2	Constraint	Imbalance (I)	p(I)	P(I)	RN	Mating Pool
1	0 1 0 0 1 0	0 0 1 1 0 1	☒					
	0 1 0 0 1 0	1 0 1 1 0 1	✓	220	0.200	0.200	0.081	0 1 0 0 1 0 1 0 1 1 0 1
2	1 1 0 0 1 1	0 0 1 1 0 0	✓	180	0.164	0.364	0.432	0 1 1 1 1 0 1 0 0 0 0 1
3	0 1 1 1 1 0	1 0 0 0 0 1	✓	256	0.233	0.597	0.701	1 1 0 0 0 0 0 0 1 1 1 1
4	1 0 1 0 1 1	0 1 0 1 0 0	✓	89	0.081	0.677	0.345	1 1 0 0 1 1 0 0 1 1 0 0
5	1 1 0 0 0 0	0 0 1 1 1 1	✓	72	0.066	0.747	0.225	1 1 0 0 1 1 0 0 1 1 0 0
6	0 0 1 0 1 0	1 1 0 1 0 1	✓	135	0.123	0.870	0.905	0 1 1 0 0 1 1 0 0 1 1 0
7	0 1 1 0 0 1	1 0 0 1 1 0	✓	78	0.071	0.940	0.287	1 1 0 0 1 1 0 0 1 1 0 0
8	1 1 1 0 0 1	0 0 0 1 1 0	✓	69	0.063	1.000	0.455	0 1 1 1 1 0 1 0 0 0 0 1

Table 3 Constrained binary tournament selection

String	Initial Population: Zone 1	Initial Population: Zone 2	Constraint	Imbalance (I)	RN1	RN2	Selected String	Mating Pool: Zone 1	Mating Pool: Zone 2
1	0 1 0 0 1 0	0 0 1 1 0 1	☒						
	0 1 0 0 1 0	1 0 1 1 0 1	✓	220	7	8	8	1 1 1 0 0 1	0 0 0 1 1 0
2	1 1 0 0 1 1	0 0 1 1 0 0	✓	180	6	2	6	0 0 1 0 1 0	1 1 0 1 0 1
3	0 1 1 1 1 0	1 0 0 0 0 1	✓	256	3	8	8	1 1 1 0 0 1	0 0 0 1 1 0
4	1 0 1 0 1 1	0 1 0 1 0 0	✓	89	1	1	1	0 1 0 0 1 0	1 0 1 1 0 1
5	1 1 0 0 0 0	0 0 1 1 1 1	✓	72	4	2	4	1 0 1 0 1 1	0 1 0 1 0 0
6	0 0 1 0 1 0	1 1 0 1 0 1	✓	135	4	5	5	1 1 0 0 0 0	0 0 1 1 1 1
7	0 1 1 0 0 1	1 0 0 1 1 0	✓	78	2	5	5	1 1 0 0 0 0	0 0 1 1 1 1
8	1 1 1 0 0 1	0 0 0 1 1 0	✓	69	6	1	6	0 0 1 0 1 0	1 1 0 1 0 1

Table 4 Constrained position crossover

String	Mating Pool: Zone 1	Mating Pool: Zone 2	RN	% Crossover	Position	Mating Pool: Zone 1	Mating Pool: Zone 2	Constraint
1	1 1 1 0 0 1	0 0 0 1 1 0				1 1 1 0 0 1	0 0 0 1 1 0	✓
2	0 0 1 0 1 0	1 1 0 1 0 1	0.54	0.6	N/A	0 0 1 0 1 0	1 1 0 1 1 1	✓
3	1 1 1 0 0 1	0 0 0 1 1 0				1 1 1 0 0 1	0 0 1 1 0 1	☒
						1 1 1 0 0 1	0 0 0 1 1 0	✓
4	0 1 0 0 1 0	1 0 1 1 0 1	0.78	0.6	5	0 1 0 0 1 0	1 0 0 1 0 0	☒
						0 1 0 0 1 0	1 0 1 1 0 1	✓
5	1 0 1 0 1 1	0 1 0 1 0 0				1 0 1 0 0 0	0 0 1 1 1 1	☒
						1 0 1 0 0 0	0 1 0 1 1 1	✓
6	1 1 0 0 0 0	0 0 1 1 1 1	0.92	0.6	8	1 1 0 0 1 1	0 1 0 1 0 0	☒
						1 1 0 0 1 1	0 0 1 1 0 0	✓
7	1 1 0 0 0 0	0 0 1 1 1 1				1 1 0 0 0 0	0 0 1 1 0 1	☒
						1 1 0 0 0 0	0 0 1 1 1 1	✓
8	0 0 1 0 1 0	1 1 0 1 0 1	0.66	0.6	3	0 0 1 0 1 0	1 1 0 1 1 1	☒
						0 0 1 0 1 0	1 1 0 1 0 1	✓

Table 5 Constrained union Crossover – Chromosome Matching

Order	Mating Pool: Zone 1						Mating Pool: Zone 2					
P1	0	1	0	0	0	0	0	0	0	0	0	0
P2	0	0	0	1	1	1	1	1	0	1	1	1

Order	Mating Pool: Zone 1						Mating Pool: Zone 2					
P1	A	J	B	I	H	D	K	C	G	F	L	E
P2	E	L	A	D	B	C	J	H	F	G	I	K

Table 6 Constrained union crossover – New chromosome settings

New chromosome settings	Randomly Select	S1	S2
A	S1	D B C J H	I K G F L E
A D	S1	B C J H	I K G F L E
A D I	S2	B C J H	K G F L E
A D I B	S1	C J H	K G F L E
A D I B K	S2	C J H	G F L E
A D I B K G	S2	C J H	F L E
A D I B K G F	S2	C J H	E
A D I B K G F L	S1	C J H	E
A D I B K G F L C	S1	J H	E
A D I B K G F L C J	S1	H	E
A D I B K G F L C J H	S2		E
A D I B K G F L C J H E			

Table 7 Constrained union crossover – Transformation

Zone 1						Zone 2						Constraint
A	D	I	B	K	G	F	L	C	J	H	E	
0	1	1	1	1	1	0	0	1	1	1	0	☒
0	1	1	1	1	1	1	0	0	0	0	0	✓

Table 8 Constrained standard mutation, Preset value of $P_m = 0.1$

Operator	Mating Pool												Constraint
	Zone 1						Zone 2						
Chromosome - Before	0	1	1	1	1	0	1	0	0	0	0	1	✓
RN	0.01	0.24	0.79	0.78	0.09	0.61	0.32	0.75	0.06	0.14	0.57	0.25	
Chromosome – After	1	1	1	1	0	0	1	0	1	0	0	0	☒
	1	1	1	1	0	0	0	0	0	0	1	1	✓

Table 9 Constrained standard mutation

Mating Pool												Constraint
Zone 1						Zone 2						
1	1	1	0	1	1	0	0	0	1	0	0	✓
1	1	1	0	1	0	1	0	0	1	0	0	☒
1	1	1	0	1	0	0	0	0	1	0	1	✓

Table 10 Constrained inversion mutation

Zone 1						Zone 2						Constraint
0	1	1	1	1	1	1	0	0	0	0	0	✓
0	1	0	1	1	1	1	1	0	0	0	0	☒
0	1	0	1	1	1	1	0	1	0	0	0	✓

Table 11 Summary of the parameter choices and levels for the proposed CGPS

Parameters	Levels (Coded Levels)
Probability of Mutation, P_m	0.01 – 0.10
Probability of Crossover, P_c	0.60 – 0.90
No. of Chromosomes, NC	50, 100, 150, 200
Reproduction Operator, RP	Roulette Wheel (0), Binary Tournament (1)
Crossover Operator, XO	Position (0), Union (1)
Mutation Operator, MU	Standard (0), 2 Operation Adjacent Swap (1), Inversion (2)
Constrained Adjusted Bits, CT	After all processes (0), After mutation process (1)

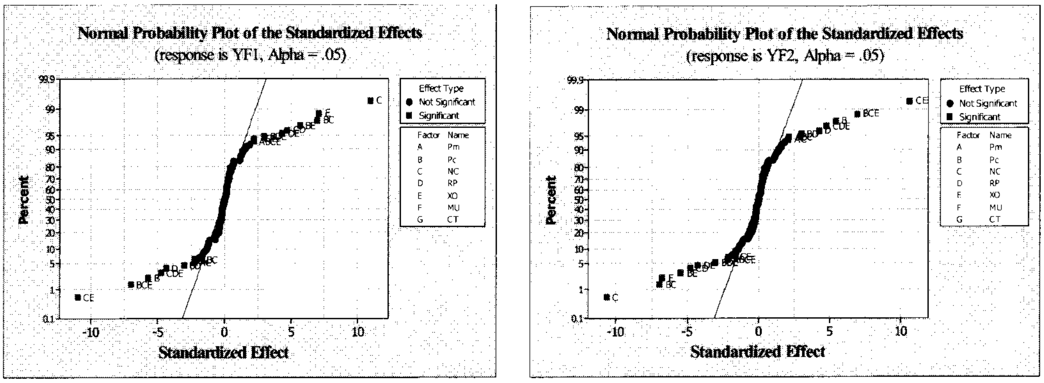

Figure 1 Normal probability plot of the estimates of effects on the early phase

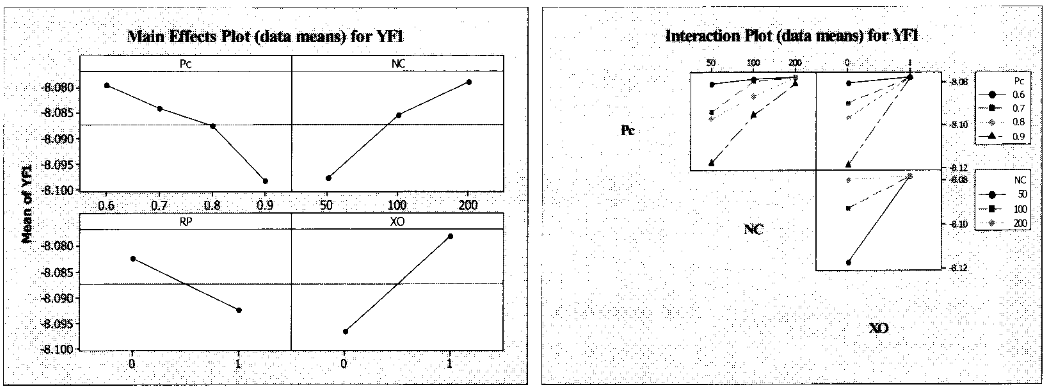

Figure 2 Main and Interaction Effect Plots for Y_{F1} on the second phase

Table12 ANOVA for Y_{F1} on the second phase

Source of Variation	Seq SS	DF	Adj SS	Adj MS	F	p-value
Main Effects	1.2317	7	0.5721	0.0817278	32.07	0.000
2-Way Interaction	1.0175	21	0.6754	0.0321608	12.62	0.000
3-Way Interactions	0.3323	35	0.2708	0.0077366	3.04	0.000
4-Way Interactions	0.0700	35	0.0560	0.0015999	0.63	0.957
5-Way Interactions	0.0208	21	0.0187	0.0008927	0.35	0.997
6-Way Interactions	0.0036	7	0.0025	0.0003635	0.14	0.995
7-Way Interactions	0.0010	1	0.0010	0.0009789	0.38	0.535
Residual Error	14.3524	5632	14.3524	0.0025484		
Lack of Fit	9.4841	2752	9.4841	0.0034462	2.04	0.000
Pure Error	4.8683	2880	4.8683	0.0016904		
Total	17.0292	5759	0.5721	0.0817278	32.07	0.000

Table 13 The Preferred Levels of the Parameters of the CGPS

Parameters	Preferred Levels	Over all F-significant and p-Value	
		Y_{F1}	Y_{F2}
Probability of Crossover, P_c	0.60	0.000	0.007
No. of Chromosomes, NC	200	0.002	0.002
Reproduction Operator, RP	Roulette Wheel	0.040	0.000
Crossover Operator, XO	Union	0.000	0.000

Table 14 The results of small problems

No. of Areas	No. of Zones	No. of Time Periods	Minimal Total Imbalance	
			CGPS	DPS
3	4	1	656,476	656,476
4	5	1	1,947,802	1,947,802
5	6	1	2,162,372	2,162,372
6	7	1	2,157,914	2,157,914
7	8	1	3,430,900	3,430,900
8	9	1	3,611,868	3,611,868
9	10	1	4,738,044	4,738,044
10	11	1	5,010,636	5,010,636

Table 15 The results of big problems

No. of Areas	No. of Zones	No. of Time Periods	Total Imbalance	
			CGPS	DPS
3	6	3	3,270,916	3,270,916
3	7	3	4,674,592	4,674,592
3	8	3	6,970,852	6,970,852
3	9	2	6,587,558	6,587,558
3	10	2	7,669,890	7,669,890