Locating Input/ Output point in Facility Design

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Abstract: Input and output points location problem is an NP-Hard combinatorial problem with many applications. We consider location of input and output points on perimeter of shortest single loop path. In this paper, a genetic algorithm is developed to solve input and output points location problem. Parameter setting is one of the most important issues of research in Genetic Algorithms (GAs). An efficient experimental design method for parameter optimization in a genetic algorithm was carried out using the Taguchi method. Genetic parameters including the population size, the crossover rate, the mutation rate, gene mutation rate and the stopping condition are considered as design factors. We investigate effect of number of AGV vehicles and their capacity on total time of AGV systems in the uncertain environment. Using simulation based optimization, we determine a robust solution and numerical results show efficiency of our solutions comparing with the result of deterministic approach.
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1. Introduction

One of the oldest activities done by industrial engineers is facilities planning. The term facilities planning can be divided into two parts: facility location and facility layout. The latter is one of the foremost problems of modern manufacturing systems and has three sections: layout design, material handling system design and facility system design (Tompkins et al., 2003). Determining the most efficient arrangement of physical departments within a facility is defined as a Facility Layout Problem (FLP). Layout problems are known to be complex and are generally NP-Hard (Garey & Johnson, 1979). To solve industrial-sized cases, meta-heuristics and heuristics were developed.

Input/Output (I/O) points location problem is one of the principal design decision in the facility layout design problem. Potential I/O points location are considered as intersections of departments or on the perimeter of flow path. In the design of material flow path, AGV is one of the most common approaches in which a driverless vehicle is used for the transportation of material between departments. Maxwell and Muckstadt (1982) was first introduced the problem of AGV flow system. One of the common types of AGV system is single loop path that AGV vehicle moves on the perimeter of single loop to transport material flows. In real problem, production time of each department is uncertain and it makes some effect in working time of AGV system. In this paper, we consider multi vehicle with multi capacity AGV system. Due to complexity of problem, we develop a genetic algorithm (GA) and to solve uncertainty issue, we use simulation based optimization and design a robust solution based on simulations' scenarios.

The most difficult and time-intensive issue in the successful implementation of genetic algorithms is to find good parameter setting, one of the most popular subjects of current research in genetic algorithms. An efficient experimental design method for parameter optimization in a genetic algorithm was carried out using the Taguchi method. Genetic parameters including the population size, the crossover rate, the mutation rate, gene mutation rate and the stopping condition are considered as design factors. Taguchi's design of experiments has been widely used instead of trial and error method to set the best parameters. This method was used by Sukthomya and Tannock (2005) to determine the optimum setting of neural network parameters in a multilayer perceptron (MLP) network trained with the back propagation algorithm. Naderi et al. (2008) employed the Taguchi method to extensively tune different parameters and operators of simulated annealing algorithm which is used in the problem of scheduling hybrid flowshops introduced by them. This method is also used to determine an optimal process parameter setting which critically influences productivity, quality, and cost of production in the plastic injection molding (PIM) industry (Chen et al., 2009). The rest of paper is has the following structure. In section 2 problem is defined, section 3 contains GA algorithm, and computational results are given in section 4, conclusions are presented in section 5.

2. Problem Definition

I/O points location problem is a type of network queuing model in which material flows enter the queuing system from a department and exit from the system from another department. There are some assumptions:

- If an AGV vehicle is fully occupied, it cannot present a service for prepared goods and materials.
- Potential I/O points location are in intersection of departments on the perimeter of single loop path.
  Each vehicle can transport different material flows at the same time.

3. Genetic Algorithm

Genetic algorithms are based on biological evolution. They have been applied to many fields of optimization, and they have shown to be highly effective. Genetic algorithm is a population-based search approach. GA parameters are defined as follows.

- pop_size: initial population
- max_generation: maximum generations until stop
- gene_mut_rate: probability of mutation for each gene
- mutation_rate: probability of mutation for each chromosome
- cross_rate: probability of crossover for each pair of chromosomes

We use chromosome representation of Arapoglu et al. (2001) in which each gen shows a potential location selected for I/O points of department. We use two-point crossover for crossing each two children. For mutation operator, we change location of I/O point for a randomly selected department. The advantage of this representation is that there is not any clumsy after crossover and mutation. For each chromosome, we search its neighborhoods to find better solution than the case where a gen of chromosome is changed at any times. If one of chromosome neighborhood has a better solution than it, chromosome's neighborhood is considered as chromosome and this procedure continues until we have improvement in objective function. For this selection procedure, we use a tournament selection in which the chromosome with the best objective function between four randomly selected chromosomes is selected as child.

4. Taguchi method

The most exhausting issue in the successful implementation of genetic algorithms is to find good parameter setting. In this paper, we present an efficient experimental design method for parameter optimization in a genetic algorithm using Taguchi method. In an experimental design when the number of factors increases, the number of treatment combinations increases more rapidly. In these cases we can consider and examine only some of treatment combinations instead of all of them calling fractional factorial experiment. One of the approaches to deal with such experiments is Taguchi method. Dr. Taguchi introduces different orthogonal arrays for different kinds of experimental designs. Taguchi considers two types of factors in every process. First controls factors which is assigned to the inner array and directly decides the desired value of the output and second controls noise factors which are assigned to the outer array and can be measured by an appropriate signal-to-noise ratio which is measured as follows:

$$\text{S/N ratio} = -10\log_{10}^{(\textit{objective function})^2}$$

Taguchi classifies objective functions into three categories: the-smaller-the-better (SB) the-larger-the-better (LB), and a-specific-target-best (TB) cases. Taguchi method aims to determine best levels of control factors. In turn, the best levels of control factors are those which maximize the signal-to-noise ratios. Such a parameter design is called a robust design. In this paper there are five control factors of interest that influence the efficiency of genetic algorithm:

1. Crossover rate with four levels
2. Mutation rate with four levels
3. Gene mutation rate with four levels
4. Stopping condition with three levels
5. Population size with three levels

These control factors and levels of each are shown in Table 1. As mentioned before, since examining all treatment combinations of these factors is difficult and time-intensive, we employed Taguchi method to perform the experiment.

Table 1: Levels of each factor

Factor	Symbol	Level			
		1	2	3	4
Crossover rate	A	0.2	0.4	0.6	0.8
Mutation rate	B	0.1	0.3	0.5	0.7
Gene mutation rate	C	0.2	0.4	0.6	0.8
Stopping condition	D	10	15	20	
Population size	E	20	20	50	

Table 2. Modified orthogonal array L18

	Control factors and levels				
Trial	A	B	C	D	E
1	A(1)	B(1)	C(1)	D(1)	E(1)
2	A(1)	B(2)	C(2)	D(2)	E(2)
3	A(1)	B(3)	C(3)	D(3)	E(3)
4	A(1)	B(4)	C(4)	D(1)	E(1)
5	A(2)	B(1)	C(2)	D(3)	E(3)
6	A(2)	B(2)	C(1)	D(1)	E(1)
7	A(2)	B(3)	C(4)	D(1)	E(1)
8	A(2)	B(4)	C(3)	D(2)	E(2)
9	A(3)	B(1)	C(3)	D(1)	E(1)
10	A(3)	B(2)	C(4)	D(3)	E(3)
11	A(3)	B(3)	C(1)	D(2)	E(2)
12	A(3)	B(4)	C(2)	D(1)	E(1)
13	A(4)	B(1)	C(4)	D(2)	E(2)
14	A(4)	B(2)	C(3)	D(1)	E(1)
15	A(4)	B(3)	C(2)	D(1)	E(1)
16	A(4)	B(4)	C(1)	D(3)	E(3)

Table 3. ANOVA chart

Factor	DF	SS	MS	F	Percent	Cumulative	P_Value
A	3	6.65	2.22	1.25	4.15	20.99	0.07
B	3	7.98	2.66	1.50	8.25	46.51	0.06
C	3	2.03	0.68	0.38	10.08	51.71	0.21
D	2	10.08	5.04	2.85	20.15	84.99	0.03
E	2	2.18	1.09	0.62	4.16	91.29	0.13
Error	2	0.34	1.77				
Total	15	29.27					

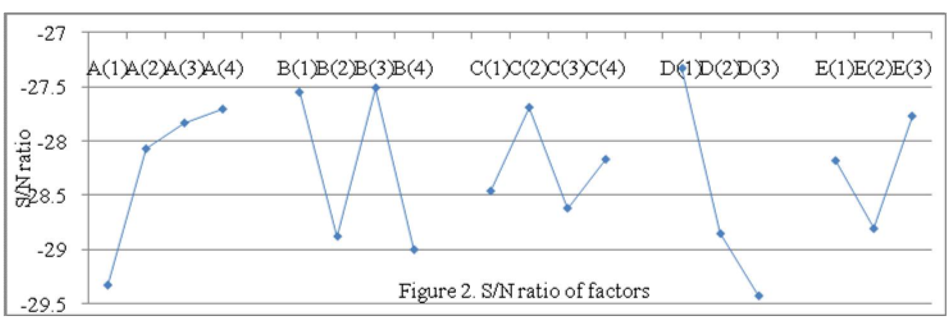

Figure 2. S/N ratio of factors

Table 4. Improvement in objective function compared with single vehicle

Size	No	Improvement%	Size	No	Improvement%
10	1	15.7	60	26	10.1
	2	6.5		27	11.7
	3	8.6		28	8.8
	4	15.4		29	10
	5	11.3		30	12.1
20	6	6.5	70	31	7.4
	7	12		32	11.4
	8	13.2		33	7.6
	9	14		34	8.8
	10	6		35	9.7
30	11	13.4	80	36	8.2
	12	14.7		37	13.7
	13	14.3		38	15.3
	14	6.8		39	8
	15	14.1		40	10.1
40	16	13.1	90	41	14.5
	17	6.8		42	6.2
	18	12.1		43	11.1
	19	15.9		44	6.9
	20	10.3		45	14.8
50	21	8.7	100	46	7.7
	22	15.4		47	13.9
	23	11.1		48	12.5
	24	15.5		49	13.1
	25	7.8		50	6.7

Total degree of freedom of these five factors is 16. Therefore, the selected orthogonal array should have a minimum of 13 rows and 5 columns to accommodate all of these factors. From the standard table of orthogonal arrays the fittest orthogonal array, L16 is selected. L16 is composed of 5 factors with 4 levels each and our problem consists of three four-level factors and two three-level factors. Therefore, we should adapt the selected orthogonal array to our experimental design. To do so, we added two extra levels to factors. We doubled level 1 of factor D and level 1 of factor E and considered them as level 4.The modified orthogonal array L18 is presented in Table 2. By implementing GA in MATLAB 7.5.0 running on a personal computer, we replicated each trial 40 times specifying 40 samples of each trial. The value of objective function gained from each run was recorded. In next step analysis of variance (ANOVA) was conducted and the relative significance of individual factors in terms of their main effects on the objective function was explored. S/N ratio of each factor is indicated in Figure 2. Table 3 shows ANOVA chart in which significant and insignificant levels are distinguished.

5. Computational results

The genetic algorithm is coded in MATLAB 7.5.0. All the test problems are solved on a Pentium 4 computer with 1024 MB of RAM and 2.26 GHz Core2 Due CPU. We solve test problems generated by Fatemi and Ardestani (2011). We implement a simulation optimization as follows. We run GA algorithm for randomly generated production time and we check which locations are selected as I/O point locations with respect to others in all scenarios and consider them as I/O point locations. In Table 4, multi capacity multi vehicle AGV system is compared with single capacity single vehicle AGV system and in Table 5, a comparison between simulation approach and deterministic approach in a situation with random production times are made.

6. Conclusions

In this paper, a GA algorithm is developed to solve I/O points location problem in multi capacity multi vehicle AGV system in uncertain environment. We show effect of AGV number and their capacity type on working time of AGV system, moreover we show efficiency of simulation optimization approach compared with deterministic approach.

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