

Simulation Optimization Approach for Facility Layout Problem-A Queuing Theory Based Approach

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Abstract: One of the most important issues in facility layout problem is to find the location of the Input/ Output points. We consider single loop path as material flow path for a given layout and find locations of Input/Out points on perimeter of the loop in the uncertain environment. The uncertainty is derived from production time of each department. Our objective is to minimize total time of AGV system after conveying all departmental material flows, we solve an uncertain queuing problem and due to difficulty of the queuing problem, an efficient simulation optimization approach is proposed using simulated annealing algorithm.

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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 (Tompkins et al., 2003). Determining the most efficient arrangement of physical departments within a facility is defined as a facility layout problem (FLP) (Garey and Johnson, 1979). Tompkins (1997) stated that 8% of the United States gross national product (GNP) has been spent on new facilities annually since 1955. Layout problems are known to be complex and are generally NP-Hard (Garey and Johnson, 1979).

If the building size and shape are given, then the three principal and interdependent design decisions in the facility layout design problem are: (1) the determination of the shapes and locations of departments within the facility, which is called the conceptual block layout problem; (2) the determination of the locations of the input and output (I/O) points on the perimeter of each department; and (3) the design of the material flow paths or aisles that connect these I/O points (Kim and Goetschalckx, 2005).

In a basic layout design, each cell is represented by a rectilinear, but not necessarily convex polygon. The set of fully packed adjacent polygons is known as a block layout (Asef-Vaziri and Laporte, 2005). The two most general mechanisms in the literature for constructing such layouts are the flexible bay and the slicing tree (Arapoglu et al., 2001). A slicing structure can be represented by a binary tree whose leaves denote modules, and internal nodes specify horizontal or vertical cut lines (Wu et al., 2003). The bay-structured layout is a continuous layout representation allowing the departments to be located only in parallel bays with varying widths. The width of

each bay depends on the total area of the departments in the bay (Konak et al., 2006).

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. We focus on single flow path AGV, one of the four well-known general types of design used in production systems (Apple, 1977). It lends itself to both product and production simplicity (Afentakis, 1989).

In determination of I/O points location, there are many research in the literature of facility layout problem. For example, Arapoglu et al., (2001) develop three constructive heuristics, a genetic algorithm (GA) and a simulated annealing (SA) algorithm to find location of I/O points. One of their three heuristic algorithms was deterministic and the other improved the first heuristic using uncertain parameters. They compared results of GA and SA algorithm with those of relaxed formulation and heuristics methods. Norman et al. (2001) and Kim and Goetschalckx (2005) integrate design of block layout and I/O points location problem. Norman et al. developed a heuristic algorithm to find I/O points location embedded in a GA algorithm. GA algorithm determined facility layout problem using bay. Kim and Goetschalckx (2005) develop a SA algorithm to complete partial solution of layout developed by mixed integer programming (MIP) formulation and three heuristics are embedded in SA algorithm to find I/O points location. Ardestani Jaafari et al. (2010) consider I/O point location problem considering time value of money. They propose an MIP formulation to solve the problem considering I/O

stations with different capacity and costs of installment and maintenance.

Conventional approach for encountering with facility design problem was tended to consider all parameters in deterministic environment. This assumption is not appropriate in real world problems. There are two types of uncertain facility layout problem: material flows change in each period and they are deterministic in each period (dynamic layout) and in the latter, material flows change as random variables with known parameters in a single period (stochastic layout). Kulturel-Konak (2007) reviewed the importance of the uncertainty in the future of the facility layout problem.

One of the most important parameters in the facility layout problems is the production time of each department. When an AGV is used for transporting system, material flows have to wait for arriving an empty vehicle due to low capacity of vehicle. Using more than one AGV vehicle or vehicles with more capacity increase the cost of installment and maintenance of AGV systems. Transporting departmental material flows is a type of queuing problem. Finished goods and AGV vehicle are as customers and service provider respectively. There are a few researches in the literature of facility layout problem as the queuing problems.

Raman et al. (2009) discussed the development of a two step analytical approach to determine the quantity of material handling equipment that it is necessary for effective handling of products among facilities. At first, a solution is found by considering the time required for loading and unloading products, loaded travelling, empty travelling and breakdown of material handling equipment. Then a model is proposed to select the best alternatives between those generated from the first part in the stochastic nature. Jain et al. (2008) developed a queuing model for the prediction of flexible manufacturing systems performance using mean value. Smith (2009) presented some topological network design problems for material handling system design considering queuing network models.

In this paper, we discuss I/O points location problem as a queuing problem. Due to difficulty of the problem, we use simulation based optimization approach. A SA algorithm is developed to solve I/O point location problem in stochastic environment based on simulation optimization method. Each I/O point is as customer and AGV is service provider. Our objective is to minimize total time of traveling by AGV. We focus on single loop path; however our approach can be used for tandem. We also consider a single point I/O for each department and it can easily be extended to multiple I/O point with distinct point for input and output points of each department. Our

approach can also be useful in routing problem when there multiple suppliers instead of a hub of supplier. The remainder of paper is organized as follows. Section 2 develops a SA algorithm. Section 3 gives computational results and efficiency of our approach in comparison with deterministic approach. Finally, section 4 concludes the paper and recommends some future studies.

2. SA Algorithm

To solve combinatorial optimization problems, simulated annealing algorithm is first proposed by Kirkpatrick et al. (1983). The name of SA algorithm is attained from the simulation of the annealing of solids. Annealing refers to a process of cooling material gradually to reach a steady state. In this process, a solid is heated until it melts, and then the temperature of the solid is slowly decreased (according to an annealing schedule) until the solid reaches the lowest energy state or the ground state (McKendall et al. 2006). SA algorithm is a well-established stochastic neighborhood search technique has a potential to solve complex combinatorial optimization problems (Gindy and Baykasoğlu 2001).

SA algorithm starts with a solution that is generated randomly. We represent an initial solution as a string that i th cell of the string shows the I/O point location of the i th department. We change location of I/O point of each randomly selected department. Enhancing moves are always accepted while non enhancing moves are accepted if

$$R = \exp\{-\Delta F / T\}$$

where R is a random number, ΔF is the increase in objective function and T is the current temperature. Temperature is decreased as follows:

$$T_{new} = \beta \cdot T_{old}$$

We terminate SA algorithm when temperature is decreased to T_{end} . Since our input data are derived from the uncertain sources for each instance, we repeat running the SA algorithm to reach stable results.

3. Computational Results

It is important for any meta-heuristic algorithm to optimize their parameters, so we implement several experimental results to tune the parameters of the SA algorithm. The parameters are defined as follows:

T_0	Initial temperature
T_{end}	Final temperature
β	Cooling coefficient
M	Number of moves in each temperature

We consider a range of 100 to 150 for initial temperature, 0 to 10 for final temperature, 0.9 to 0.99 for cooling coefficient and 1000 to 1500 for the number of moves in each temperature. After running about 2000 randomly generated test problems with 10 types of size from 10 to 100, we set SA parameters as follows:

T_0	120
T_{end}	10
β	0.92
M	1200

We propose an approach for generating test problems as follows. We need to generate a block layout with its shortest path single loop as well as probability density function, PDF, for production time of each department. We assume that AGV velocity is constant and equal to 1m per second. We consider production time of each department as $N(\mu_i, \sigma_i^2)$ that μ_i and σ_i^2 are randomly between (10,15) and (1,3) for each department respectively. We also generate matrix of material flow randomly between (1,10). AGV vehicle moves on the perimeter of the single loop path and loads the first finished goods. We consider single AGV vehicle with a unit capacity. When AGV is occupied, it is impossible to service other finished goods and material flow and they must wait for empty AGV. Moreover, location of I/O point is important in total time of the problem, because an I/O point can support more than one department at the same time. We generate 5 instances for 10 sizes ranging from 10 to 100 departments, merely 50 instances totally. We consider objective function as a probability variable labeled by X . Each instance is solved in several scenarios until the objective function is converged. For each instance, we have n scenario with x_i objective function ($i=1,2,\dots, n$). We show average of objective function of each scenario as follows.

$$\bar{x} = \sum_{i=1}^n x_i / n$$

We know that the difference between expected value of X and its estimator \bar{x} divided by standard deviation of \bar{x} is a random variable with density function of t-student with parameter n , namely:

$$(E(X) - \bar{x}) / SD(\bar{x}) \sim t_{n-1}.$$

Using this equation, we find number scenarios for each instance equal to n .

Table 1 gives computational results. Objective function is total working time of AGV system and CPU time shows computational time to solve the problem in each instance. SA algorithm is coded in MATLAB software in a PC with 2.3 GHz Core2 Duo CPU and

1GB RAM. In the first and second columns, size and number of each department are indicated respectively and in the third column, average total time of each size is shown. In Table 2, a comparison between the proposed approach and mean value approach is stated. We compare two approaches in four situations as follows:

1. Production time of each department is equal to μ_i
2. Production time of each department is equal to $\mu_i + \sigma_i^2$
3. Production time of each department is equal to $\mu_i - \sigma_i^2$
4. Production time of each department is a random number of Normal probability distribution $N(\mu_i, \sigma_i^2)$, Random Situation (RS).

We show efficiency of our proposed method respect to mean value method in different situations. We use a measure to show the effectiveness as follows:

$$(1 - Z_2 / Z_1) \times 100$$

where Z_1 is the objective function of mean value method and Z_2 is the objective function of our proposed method. Our proposed method is reasonably better than mean value method except situation 1, however, there is not any significant difference between two methods (less than 4% gap). In other 3 situations, especially in RS, there are a significant difference between two approaches with 13.7%, 13.6% and 16.3% in average for situations 2, 3 and 4 respectively.

4. Conclusions and recommendations

In this paper, we consider I/O point location problem with stochastic nature as a queuing model. We consider AGV vehicle as a single channel service provider and each department with uncertain production time. Computational results indicate flexibility of our proposed method in various situations. The proposed approach can be useful in many manufacturing systems. We recommend some extensions as follows. It can be useful to consider several AGV vehicles with multi capacity and investigate material handling cost and installation and maintenance costs. It is also recommended to present an approximation algorithm to estimate effectiveness of the proposed queuing model.

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Table 1. Computational results

Size	No	Objective	CPU Time	Size	No	Objective	CPU Time
10	1	1096	22	60	26	2855	1211
	2	1022	16		27	2830	1256
	3	1010	14		28	2988	1125
	4	1092	25		29	2942	1218
	5	1063	23		30	3044	1334
20	6	1548	28	70	31	3423	2617
	7	1597	39		32	3220	2555
	8	1592	28		33	3331	3654
	9	1596	28		34	3483	3720
	10	1514	27		35	3680	3649
30	11	1736	158	80	36	3611	3379
	12	1728	159		37	3624	4434
	13	1767	123		38	3534	3817
	14	1747	104		39	3769	2758
	15	1721	111		40	3770	3064
40	16	2376	414	90	41	4578	3650
	17	2134	246		42	4241	4208
	18	2214	340		43	4261	3579
	19	2274	426		44	4561	5218
	20	2107	311		45	4364	4226
50	21	2519	682	100	46	4545	4867
	22	2541	782		47	4489	5720
	23	2812	765		48	4775	6541
	24	2841	756		49	4611	7864
	25	2659	906		50	4252	7720

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Table 2. Comparing proposed approach with deterministic approach

Size	No	μ	$\mu + \sigma$	$\mu - \sigma$	RS	Size	No	μ	$\mu + \sigma$	$\mu - \sigma$	RS
10	1	-0.2	7.3	7.3	9.9	60	26	-1.9	15.5	14.5	13.0
	2	-0.5	9.6	9.6	9.1		27	-1.8	15.1	21.5	12.2
	3	-0.3	5.5	5.5	8.0		28	-0.6	17.2	21.4	19.2
	4	-0.2	9.0	9.0	8.6		29	-2.1	14.9	14.1	15.6
	5	-0.1	9.3	9.3	6.3		30	-1.4	21.2	20.7	19.9
20	6	-0.9	14.4	15.1	8.7	70	31	-1.9	15.9	16.3	24.3
	7	-1.0	14.5	8.5	8.9		32	-2.7	13.3	11.1	20.4
	8	-0.9	11.7	12.8	10.8		33	-0.5	14.5	11.1	11.7
	9	-1.4	11.5	8.4	9.1		34	-2.9	16.3	14.4	10.1
	10	-0.3	8.4	8.9	10.3		35	-1.9	14.7	14.1	22.8
30	11	-0.2	10.4	16.1	14.5	80	36	-1.6	15.9	15.4	22.9
	12	-1.1	15.7	9.0	13.3		37	-1.1	15.7	12.2	19.2
	13	-0.5	16.6	14.7	13.8		38	-0.9	11.1	11.2	18.7
	14	-1.9	12.5	10.4	14.8		39	-0.3	10.3	14.5	21.5
	15	-1.4	16.4	13.5	9.5		40	-0.5	11.2	10.9	22.0
40	16	-0.16	15.2	15.9	23.7	90	41	-2.7	11.3	11.1	20.1
	17	-0.15	16.7	16.5	16.8		42	-3.7	16.1	16.8	17.2
	18	-1.8	15.7	12.4	18.9		43	-2.1	13.5	12.3	20.8
	19	-0.27	13.9	21.1	20.1		44	-1.5	10.4	13.3	23.5
	20	-1.51	14.4	13.6	21.5		45	-1.4	10.7	15.2	20.2
50	21	-2.9	15.3	20.9	22.6	100	46	-2.2	10.6	13.0	17.7
	22	-2.9	15.7	12.7	16.0		47	-2.5	12.7	16.1	22.5
	23	-2.2	20.9	14.9	19.1		48	-3.3	10.3	12.8	15.3
	24	-1.4	21.8	18.7	10.0		49	-2.4	14.3	16.9	21.7
	25	-1.0	19.5	13.0	22.0		50	-3.0	12.2	13.2	16.8

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