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A PERFORMANCE MEASUREMENT FRAMEWORK AND SOLUTION APPROACH FOR THE INTEGRATED FACILITY LAYOUT PROBLEM WITH UNCERTAIN DEMAND

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Abstract

The integrated facility layout problem (IFLP) focuses on the simultaneous determination of the relative locations of multiple copies of capacitated equipment or machinery in a facility, as well as the material flow between these units. In this paper, we consider the IFLP in the existence of uncertain demand for the products of the facility. Motivated by the framework for next generation facility layouts by Benjaafar et al. (2002), we extend the approaches in the literature for distributed facility layouts to the case of dynamic demand and the possibility of relayouts, and propose a heuristic solution approach to minimize the expected total material handling cost over the planning horizon. We also analyze the performance of the resulting solutions in terms of empty travel of the material handling equipment and waiting time. Our computational results reveal that when demand is dynamic and stochastic, the relationship between the level of uncertainty and relayout cost plays an important role in determining layout performance, and therefore a priori assumption of using a certain layout type may lead to detrimental results.

1 Introduction

Facility layout problem involves determining the relative locations of functional areas, workstations, or machines within specified boundaries of a facility, without overlapping of these. The problem has widespread application and varieties in practice, and is costly in its nature, accounting for a possible 20-50% of the total operating budget of a manufacturing company (Tompkins et al. 2010). Owing to these, the facility layout problem has been extensively studied in the literature. Recent reviews on various aspects of the problem are provided by Singh and Sharma (2006), Drira et al. (2007), and Kulturel-Konak (2007).

The traditional approach to facility layout planning takes the material flow between the functional areas or machines in the facility as input. In the existence of multiple copies of the same machine, the *integrated facility layout problem* (IFLP) aims to determine the material or product flows among the machines, in conjunction with the locations of these within the facility. The problem can arise in many different situations; such as when the demand may or may not change over time (*static* and *dynamic* demand, respectively), the areas requirements of the machines may or may not be equal, and the copies of the same machine type may or may not have to be placed in adjacent locations (Benjaafar and Sheikhzadeh 2000).

In many real-life manufacturing environments, the IFLP is exacerbated by the fact that at the time of the layout planning process, the amount of demand for the products to be produced or processed in the facility is not known in advance. This motivates the definition of the *stochastic IFLP*, where only probabilistic information is available on the demand amounts, thereby on the flow amounts between each machine type pair. The dynamic version of the stochastic IFLP focuses on the cases where the demand is not only uncertain, but the nature of uncertainty changes over time.

The literature on the stochastic IFLP is based on the assumption that the nature of the demand is static. However, given the recent trends in the manufacturing industry, high product variety, product demand volatility, low production volumes and short product life cycles, existing layout schemes for IFLP fail to capture the need for responsiveness and reconfigurability. Motivated by this, we consider the stochastic IFLP in a dynamic demand setting. To the best of our knowledge, this paper is the first to consider the dynamic version of the stochastic IFLP.

The dynamic and stochastic nature of the IFLP leads to the consideration of two important aspects of the problem environment, namely relayout cost and level of uncertainty. These have been of focus in the definition of *next generation facility layouts* (Benjaafar et al. 2002), which not only provides a framework for classifying layout types based on these two aspects, but also questions using material handling cost as the sole performance measure in evaluating layout performance and defines additional performance measures to reflect today's manufacturing characteristics. In this paper, we make use of the next generation facility layout and performance measurement framework to determine analyze the proposed solutions to the dynamic and stochastic IFLP.

The remainder of this paper is organized as follows: In Section 2, we provide a detailed overview of the next generation facility layouts, whereas Section 3 presents an overview of the literature on the stochastic IFLP. Section 4 describes the problem settings for the dynamic and stochastic IFLP, and presents a solution approach. A set of computational experiments are presented in Section 5, before the paper is concluded in Section 6.

2 Next Generation Facility Layouts

We address the stochastic IFLP in the light of *next generation facility layouts* (Benjaafar et al. 2002), representing a new framework in layout design motivated by changing production and flexibility characteristics of today's manufacturing environments, including high product variety, demand volatility, short life cycles, and the need for responsiveness and reconfigurability. The framework classifies layout types into four groups based on the uncertainty level and cost of relayout, as summarized in Table 1. In what follows, we present brief descriptions of these four layout types.

Table 1: An overview of next generation facility layouts (Benjaafar et al. 2002)

	Uncertainty of future production requirements	
Cost of relayout	Low	High
Low	Dynamic	Reconfigurable
High	Robust	Distributed

When relayout costs are low, relayout costs can be more readily sacrificed in each period to minimize the material handling cost of that period. Depending on the level of uncertainty in this case, the two choices are dynamic layout and reconfigurable layout. Under high relayout cost, relatively stable layouts, namely robust or distributed layouts, are used. In these environments, there is a need to design layouts that are either easily reconfigurable or robust enough so that they offer acceptable performance under most likely product demand scenarios.

Distributed layout is the layout type having functional departments disaggregated into smaller subdepartments, which are distributed strategically throughout the facility. By this disaggregation and distribution, the distances between departments can be reduced and the accessibility to all departments from different parts of the layout can be increased. As a result, efficient flows can be more easily found for a larger set of product routings, which in turn tends to diminish the need for rearranging the layout even when production requirements change significantly.

Dynamic layout applies to cases where the material flow in each period is deterministic or uncertainty is low. Facility layout arrangements are determined for each period by balancing material handling costs with the relayout costs involved in changing the layout between periods.

For robustness, facilities may adopt a single layout that balances the material flow requirements of all future periods. This can be viewed as an instance of a dynamic layout where relayout costs are prohibitively expensive. In this case, the challenge is to ensure that a selected layout guarantees an acceptable degree of efficiency in each period. In practice, robustness tends to be more widely applied than reconfigurability.

Manufacturing firms are reluctant to incur the disruption to production that is usually associated with relayout. Consequently, firms adopt layouts that are sufficiently flexible to accommodate a wide range of production requirements. In most cases, this translates into functional layouts where resources of the same type are grouped into functional departments.

Reconfigurable layout differs differs from dynamic layout in that only the current and upcoming planning periods are considered (Heragu and Kusiak 1988). Based on the layout in the current period, it designs a layout that minimizes the relocation cost while maximizing the potential saving in material flow cost and inventory cost for the next period. Reconfigurable layout also differs from robust layout in that it designs a layout based on the deterministic product mix for the next planning period immediately after the data are available.

An additional aspect of the next generation facility layout framework is the use of performance measures that better evaluate the responsiveness of layouts to the requirements of today's manufacturing environments. Hence, in addition to material handling costs, the use of other measures such as lead time, waiting time, congestion, and empty travel time is proposed.

This study is motivated in response to two main issues in the facility layout design literature in the context of next generation facility layouts: (1) Despite the existence of this framework, the effects of uncertainty and relayout costs on the IFLP and layout design problems in general are yet to be quantified and structurally analyzed. (2) The performance measures to reflect the needs of current production environments are still seldom used and almost never combined together. Consequently, we treat the IFLP in a dynamic and stochastic environment, propose a solution approach, and analyze the effects of uncertainty and relayout costs on the material handling costs as well as other performance measures.

3 Models and Solution Approaches for the Stochastic IFLP

To the best of our knowledge, the dynamic and stochastic versions of the IFLP have received limited attention in the literature.

Lahmar and Benjaafar (2005) consider the distributed layout problem in a setting where product demand and product mix vary from period to period. They present a multi-period model to design layouts for each period balancing relayout costs between periods with material flow efficiency within each period. A decomposition-based solution procedure is proposed to determine the layout and flow allocation, which yields the conclusions that distributed layouts work well when demand variability is high or product variety is low and that most of the benefits of a fully distributed layout are realized with few duplicates of each department type. Our study mainly differs from Lahmar and Benjaafar (2005) by incorporation of stochasticity into the dynamic nature of demand.

In Taghavi and Murat (2011), the deterministic and static version of the IFLP is considered for machines of unequal areas and multiple copies. Due to the nonlinear nature of the resulting model, a heuristic procedure is developed that consists of an alternating heuristic, a perturbation algorithm, and a sequential location heuristic.

Zhao and Wallace (2014) develop a greedy heuristic, called the *flow-map heuristic*, for the static version of the stochastic IFLP. Their formulation for stochastic IFLP is based on the formulation by Benjaafar and Sheikhzadeh (2000). The heuristic starts by finding a set of flows between copies of different machines by assuming the maximum demand levels and solving a modified version of the flow assignment problem. To find the flow assignments, two heuristic procedures are proposed. Once the flows are determined, the resulting quadratic assignment problem is solved to obtain the layout.

The aforementioned studies on the IFLP all focus on a distributed layout scheme, which implies a tacit assumption of high uncertainty in the environment and expensive relayout. Throughout our analysis, we investigate the validity of this inherent assumption in various cases, and propose an approach which finds a near-optimal layout that does not depend on this assumption and considers the proposed performance measures as well as material flows. In addition, to the best of our knowledge, our study is the first one to consider the stochastic IFLP in a dynamic demand setting.

4 The Multi-Period Stochastic IFLP

The heuristic solution procedure for the multi-period stochastic IFLP involves solving the single-period version of the problem for each period. Thus, we begin this section by describing the mathematical model and a heuristic solution approach for the static stochastic IFLP.

The static version of the stochastic IFLP in an equal-area setting can be modeled as a two-stage stochastic program (Benjaafar and Sheikhzadeh 2000) with the following index sets, parameters, and decision variables:

Index Sets

N: Machine types
N_i: Copies of machine type i
K: Locations
S: Products
R: Demand scenarios

Parameters

d_{kl}: Distance between location k and location l

C_i: Available processing time for each machine copy of type i

t_{si}: Processing time per unit product on machines of type i for product s

P_s: Probability of product s being processed in a production period

P_s^r: Probability of job s having volume scenario r

V_{sij}^r: Volume of flows between machine types i and j of product s in demand scenario r

Decision variables

x_{n_ik}: $\begin{cases} 1, & \text{if } n\text{th machine of type } i \text{ is assigned to location } k \\ 0, & \text{otherwise.} \end{cases}$

$v_{n_im_j}$: Flow volume between nth copy of type i and mth copy of type j for a given demand level of the product

The resulting two-stage stochastic program is then given by:

$$\min \quad \sum_{s=1}^{S} P_s \sum_{r=1}^{R} P_s^r \pi(x,s,r) \tag{1}$$

$$s.t. \quad \sum_{k=1}^{K} x_{n_ik} = 1 \qquad \forall i \in N,\ n_i \in N_i \tag{2}$$

$$\sum_{i=1}^{N} \sum_{n_i=1}^{N_i} x_{n_ik} = 1 \qquad \forall k \in K \tag{3}$$

$$x_{n_ik} \in \{0,1\} \qquad \forall i \in N,\ n_i \in N_i,\ k \in K, \tag{4}$$

where $\pi(x,s,r)$ is the optimal objective value of:

$$\min \quad \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{n_i=1}^{N_i} \sum_{m_j=1}^{N_j} \sum_{k=1}^{K} \sum_{l=1}^{K} v_{n_im_j} d_{kl} x_{n_ik} x_{m_jl} \tag{5}$$

$$s.t. \quad \sum_{i=0}^{N} \sum_{n_i=1}^{N_i} v_{n_im_j} t_{sj} \leq C_j \qquad \forall j \in N,\ m_j \in N_j \tag{6}$$

$$\sum_{n_i=1}^{N_i} \sum_{m_j=1}^{N_j} v_{n_im_j} = V_{sij}^r \qquad \forall i \in N,\ j \in N \tag{7}$$

$$\sum_{i=0}^{N} \sum_{n_i=1}^{N_i} v_{n_im_j} = \sum_{i=0}^{N} \sum_{n_i=1}^{N_i} v_{m_jn_i} \qquad \forall j \in N,\ m_j \in N_j \tag{8}$$

$$v_{n_i m_j} \geq 0 \qquad \forall i \in N,\ j \in N,\ n_i \in N_i,\ m_j \in N_j. \tag{9}$$

Here, objective function (1) minimizes the total expected flow distance, Constraints (2) and (3) assign each machine copy to a single location and each location to a single machine copy, Constraint (6) enforces machine capacities, Constraint (7) enforces all demand to be met, and Constraint (8) defines flow balance for each machine copy.

The nonlinear nature of objective function (1) poses extensive computational requirements and prevents the optimal solutions to be found for as small instances as those with 3 machines, 10 copies in total, and 5 products. This challenge is overcome by means of heuristic approaches such as decomposition of the two stages (Benjaafar and Sheikhzadeh, 2000) or robust flow assignments (Zhao and Wallace 2014).

To solve the single-period problem heuristically, we use the *increasing flow* heuristic algorithm by Zhao and Wallace (2014). Here, we let binary decision variable $y_{n_i m_j}$ determine whether positive flow exists between machine copies n_i and m_j, and positive variable $v_{s n_i m_j}$ determine the corresponding flow amount. Then, by assuming maximum possible demand amounts (M) for each product, we solve the following mixed integer program:

$$\min \quad \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{n_i=1}^{N_i} \sum_{m_j=1}^{N_j} y_{n_i m_j} \tag{10}$$

$$s.t. \quad v^r_{s n_i m_j} \leq M y_{n_i m_j} \qquad \forall s \in S, r \in R, i, j \in N,\ n_i \in N_i, m_j \in N_j \tag{11}$$

$$y_{n_i m_j} = y_{m_j n_i} \qquad \forall i, j \in N,\ n_i \in N_i, m_j \in N_j \tag{12}$$

$$\sum_{i=0}^{N} \sum_{n_i=1}^{N_i} v^r_{s n_i m_j} t_{sj} \leq C_j \qquad \forall s \in S, r \in R, j \in N,\ m_j \in N_j \tag{13}$$

$$\sum_{n_i=1}^{N_i} \sum_{m_j=1}^{N_j} v^r_{s n_i m_j} t_{sj} = V^r_{ij} \qquad \forall s \in S, r \in R, i, j \in N \tag{14}$$

$$\sum_{i=0}^{N} \sum_{n_i=1}^{N_i} v^r_{s n_i m_j} = \sum_{i=0}^{N} \sum_{n_i=1}^{N_i} v^r_{s m_j n_i} \qquad \forall s \in S, r \in R, j \in N,\ m_j \in N_j \tag{15}$$

$$v^{r+1}_{sn_im_j} \geq v^{r}_{sn_im_j} \qquad \forall s \in S, r \in (R-1), i,j \in N,\ n_i \in N_i, m_j \in N_j \tag{16}$$

$$y_{n_im_j} \in \{0,1\} \qquad \forall i,j \in N,\ n_i \in N_i, m_j \in N_j \tag{17}$$

Constraint (11) guarantees that there is no flow between machine pairs if these two machines are not connected. Constraint (12) ensures that once there exists an edge between a pair of machines, flow is allowed in both directions. Constraints (13)-(15) are used to assign flows, and these are the same as constraints (6)-(8). Constraint (16) guarantees that flows stay the same or increase as the demand level increases for product s.

The literature on the stochastic IFLP focuses on minimizing the conventional objective of flow-weighted travel distance. Motivated by the next generation facility layout framework, we propose three different performance measures that capture the needs of today's manufacturing environments in a more realistic manner. The proposed measures are the following:

1. Flow-weighted total travel distance of the products
2. Empty travel distance of the forklifts
3. Weighted waiting time of the products

Travel distance for the products can be found by solving the mathematical model defined by Constraints (1)-(9). Waiting time of the products are determined by simulation. To find the expected empty travel time of a forklift, we use the framework by Fu and Kaku (1997), where the following formula is proposed:

$$\sum_{i=1}^{N-1} \sum_{j=2}^{N} \frac{d_{ij}}{v} \frac{f_i^{\rightarrow}}{f} \frac{f_j^{\leftarrow}}{f}.$$

Here, $f_i^{\rightarrow} = \sum\limits_j f_{ij}$ is the total flow from location i, $f_j^{\leftarrow} = \sum\limits_j f_{ji}$ is the total flow into location i, $f = \sum\limits_i f_i^{\rightarrow} = \sum\limits_i f_i^{\leftarrow}$ is the total flow in the system, v is the average velocity of a forklift, and d_{ij} is the distance between locations i and j.

For the multi-period version of the stochastic IFLP, we assume that the products have different demand distributions in each period, and these distributions are known in advance. For each period, we enumerate all possible machine assignments with the given machine types, machine copies, and locations. For each assignment, we first determine the flows of jobs between each machine copy using the *increasing flow* algorithm. These assignments constitute the nodes on a shortest path network. There is an outgoing arc in this network from each possible assignment in period t to each assignment in period $t+1$. The cost of each arc is given by the sum of (i) relayout cost from layout in t to $t+1$, (ii) expected product flow cost in $t+1$, (iii) expected empty travel cost in $t+1$, and (iv) expected waiting cost in $t+1$. A dynamic programming algorithm finds the optimal path starting from each layout in the first period until the last period is reached.

The simulation model that calculates the total cost of material handling, waiting time, and empty travel is implemented on MATLAB Simulink, and takes as input the following parameters:

- Number of machine types
- Number of copies for machine type
- Number of job types
- Processing route of each job type
- Distance matrix between machine copies located according to the increasing flow heuristic by Zhao and Wallace (2014)
- Total demand of each job type in each period
- Processing time and job type on each machine type

In different replications of the simulation, we generate different demand amounts for each job type. Jobs arrive consecutively according to a random order. An arriving job is assigned a certain type by a discrete distribution according to the demand mix of the current period. The job follows its processing route and can visits the copy of each machine in its processing route. Selecting a certain duplicate is determined by the flow allocation decisions in the increasing flow heuristic solution.

Throughout the simulation, a transporter is used for carrying the jobs between departments. An arriving job directly goes to its first processing machine without using the transporter. In other words, transporter is not used for incoming and outgoing jobs; but rather for transportation between machine copies. When a job arrives at a machine, it first waits in the input buffer of the machine until it is processed. After being processed, it waits in the output buffer, which is a common queue for the transporter. Every job processed in any machine copy waits in this common transporter queue to be transported. The transporter serves the products according to the first-come, first-served queue discipline.

5 Computational Experiments

Using the solution approach in Section 4, we perform computational experiments on the 10-machine instances given in Zhao and Wallace (2014). We focus on the cases

Table 2: An example with three products, each with given production routes

Product type	Product route	Demand distribution
Product #1	Door $\rightarrow$ 3 $\rightarrow$ 2 $\rightarrow$ 1 $\rightarrow$ Door	Beta (0, 3, 10, 190)
Product #2	Door $\rightarrow$ 3 $\rightarrow$ 2 $\rightarrow$ 4 $\rightarrow$ Door	Beta (0, 4, 6, 270)
Product #3	Door $\rightarrow$ 1 $\rightarrow$ 4 $\rightarrow$ 3 $\rightarrow$ 2 $\rightarrow$ Door	Beta (0, 2, 6, 180)

3^3	2^3	3^4
3^2		1^3
2^1	1^2	3^1
1^1	2^2	D

	1^3	2^2
3^2	3^3	2^3
3^1	3^4	1^1
2^1	1^2	D

1^3	1^2	1^1
3^2	2^3	3^1
2^2		2^1
3^4	3^3	D

Figure 1: Three alternative layouts for the example

where there are 3 or 5 machine types with multiple copies, and extend the instances to four periods. By varying the relayout costs (set as 1, 20, 100, 200, and 1,000 for our instances) and demand distributions (by using the single-period demand distribution, modifying the p_s values for the remaining periods for each product) in each period, we point to cases where uncertainty in demand, coupled with relayout costs, might dictate a change in layout. Furthermore, we underline the importance of using the proposed total cost measure as opposed to one that solely considers material flows, as is the case in the literature.

To exemplify how the computational experiments are performed, we provide an instance with three products, three machine types, where the first two machines have three copies and the last one has four, in Table 2. The second column of the table shows the production route of each product, whereas the last column gives the demand distributions. There are three periods in the planning horizon.

Throughout our computational experiments, we generate all possible layouts for each period. For illustrative purposes, we use only three of these for the example. These layouts are given in Figure 1. These alternatives are based on a facility with 12 positions, one occupied by the door and one empty space.

Assuming that we start with the first alternative layout in the first period, Figure 2 displays the alternative solutions for this example, depending on the layout cost. For each arc, the upper value is the net change in the weighted loaded flow and empty travel, whereas the lower value is the net change in the waiting cost. At the end of the first period, no matter what the relayout cost is, it is optimal to keep using the first alternative, as the decrease in total travel and waiting cost offsets all alternatives. At the end of the second period, a high value of the relayout cost means that the first alternative should be kept, despite the increase in travel and waiting costs. If the relayout cost is sufficiently low, it is optimal to switch to the second alternative.

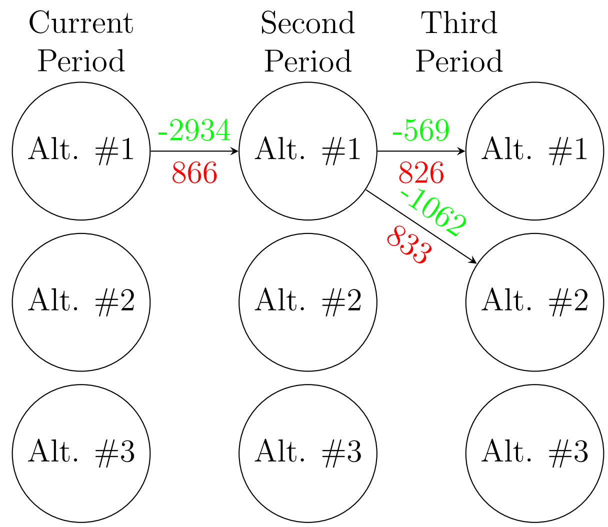

Figure 2: Alternative solutions for the example, depending on the relayout cost. Green values show the change in total cost of loaded and empty travel, whereas red values show the change in the cost due to waiting

This simple example shows that in multi-period environments, the inherent assumption of high relayout costs and hence using a distributed layout as in Zhao and Wallace (2014) may be detrimental for the system. Using more extensive experiments, we analyze this aspect in more detail.

Our first analysis regarding our computational experiments is the comparison of the material handling costs resulting from the increasing flow algorithm solution to the distributed layout problem to those for the dynamic stochastic IFLP, which is summarized in Table 3. It should be noted here that for the sake of comparison, the total material handling cost for the latter has been divided by four to normalize for a single period.

As can be inferred from Table 3, when relayout costs are negligible, average material handling costs decrease by around 13% and 4% for the 3- and 5-machine type cases, respectively. This can be explained by the fact that despite the demand is dynamic in this case, the ability to relayout the facility virtually without any cost eliminates the detrimental effects of the dynamic environment. The improvements in the material handling cost are possibly due to favorable occurrences of demand in the upcoming periods, compared to the static case. On the other hand, when relayout costs are high enough to prevent any machine movements between periods, average material handling costs increase by 17% and 24%, compared to the static case. These differences are due to the effect of not being able to react to the changing demand, thereby showing the importance of considering the possibility of relayouts in the stochastic IFLP when demand is dynamic.

Table 3: Average, minimum, and maximum material handling costs for the distributed layout problem solved by the increasing flow algorithm and for the multi-period stochastic IFLP solved by the proposed heuristic (averages of 16 replications)

Number of m/c types	**Number of instances**	**Distributed Layout**			**Dynamic Solution**			
		Avg.	**Min**	**Max**	**Rel. cost**	**Avg.**	**Min**	**Max**
3	33	14,236	13,569	15,265	1	12,360	11,565	14,456
					20	12,856	11,232	14,525
					100	14,582	14,201	16,588
					200	15,250	16,663	17,123
					1,000	16,596	16,255	18,582
5	33	15,235	15,123	16,786	1	14,565	14,012	15,633
					20	14,965	14,369	15,866
					100	16,599	16,023	16,989
					200	17,967	16,898	18,088
					1,000	18,966	17,856	19,032

Table 4 presents the average, minimum, and maximum empty travel distances and demand-weighted waiting times, along with the average number of machine moves for the same set of instances under the multi-period settings. It should be noted here that since Zhao and Wallace (2014) assume the processing of a single product in the production period, empty travel distances and waiting times do not apply to their model.

From Table 4, we observe that average empty travel distances increase with increasing relayout cost. This is expected, since certain machine copies that would need to be closer in a given period are less likely to be so due to fewer relayout moves. This results in the transport vehicle to cover a larger amount of distance while traveling empty. On the other hand, when waiting times are considered, the increasing pattern changes after a certain relayout cost level, which can be explained by the fact that products are more uniformly assigned to the machines and less waiting occurs as a result.

6 Conclusions and Further Research Directions

Motivated by the next generation facility layout framework, this paper proposes a performance measurement scheme and a solution approach for the multi-period stochastic integrated facility layout problem. By using heuristics for the single-period version of the problem, we develop a dynamic programming based heuristic approach to solve the problem. Through computational experiments, we are able to show that the tacit assumption of assuming a certain type of layout may not be beneficial for the overall efficiency of the system, particularly when demand changes over time and relayout

Table 4: Average empty travel distances demand-weighted waiting times, and number of machine moves due to relayout for the multi-period stochastic IFLP solved by the proposed heuristic (averages of 16 replications)

Number of m/c types	**Relayout cost**	**Empty travel distance**			**Demand-weighted waiting time**			**Avg. number of m/c moves**
		Avg.	**Min**	**Max**	**Avg.**	**Min**	**Max**	
3	1	1,125	789	1,565	1,469	1,101	1,903	18.2
	20	2,140	1,565	2,965	2,484	1,909	3,309	16.7
	100	2,544	1,852	2,819	2,566	2,259	3,356	11.7
	200	2,652	2,123	3,012	2,996	2,467	3,566	11.4
	1,000	3,012	2,036	3,145	2,899	2,256	3,988	0
5	1	1,326	1,126	1,656	2,000	1,470	2,654	20.8
	20	1,989	1,784	2,232	2,333	2,256	2,759	17.4
	100	2,568	2,105	2,788	2,987	2,745	3,068	14.4
	200	2,955	2,565	3,244	3,299	2,909	3,588	13.9
	1,000	3,789	3,308	4,356	2,736	2,589	3,918	0

costs are present.

An immediate extension of this study is the development of more efficient solution approaches for the problem without the need for extensive enumeration and simulation. Determination of the number of machine copies and how to make use of the empty positions by addition of new machine copies are among research directions that might improve upon the findings in this study.

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