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Design of a robust layout with information uncertainty increasing over time: A fuzzy evolutionary approach[☆]

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ABSTRACT

One of the problems encountered in the design of manufacturing systems is how to arrange the machines on the surface of the workshop, which is commonly referred to as a layout problem. Such a problem has been widely investigated in the literature. Most approaches use optimization technique to determine the position of each facility, assuming that the required data is available. Unfortunately, this assumption is often unrealistic, since the study design of a workshop is obviously conducted much before it is operating, so that data related to customer demands, for example, is generally not known with enough precision. Indeed, if good forecasts about what is to be produced in the next weeks can be available, they will obviously become more and more unreliable as the considered period of time will increase, so that layout found using classical approaches can turn out not to be relevant on the medium or long term. We propose an approach to design a robust layout in a context where the certainty of the information available decreases over time, which is usually the case for real applications. We propose a resolution approach based on a fuzzy evolutionary algorithm, which includes uncertain customer demands for each product. We show how this problem can be stated as a fuzzy dynamic layout problem with growing uncertainty over time. We suggest an evolutionary algorithm with adapted operators. Their performances are first tested using 2 crisp layout problems already published. Then the impact of increasing uncertainty is studied using a suggested benchmark. The results of our experiments show the importance of considering the degradation of the information for designing robust layouts.

1. Introduction

Layout problems are generally addressed using optimization approaches (Drira et al., 2007). Unfortunately, at the time when a system is designed, the information required for this optimization about the production to be carried out by the future system is not known with certainty. This is typically the case for the production demand of each part. Forecasts can be used but, if they can be accurate on the short term, they turn out to be much more difficult to obtain on the medium terms and can even become inaccurate on the long term. Indeed, it is known that the markets are subjected to strong fluctuations and the customers' demand can change over time. As noted in Gupta and Seifoddini (1990) and Page (1991), 1/3 of USA companies undergo major reorganization of the production facilities every 2 years and on average, 40% of a company's sales come from new products. Thus, far forecasts are much less reliable than close ones (Balakrishnan and Cheng, 2009). In such circumstances, the problem that arises is how to design an efficient layout of machines on the surface of a workshop, while taking into account the fact that the farer a forecast the less reliable the quality of the information is? In this respect, in the following, we suggest an approach that takes into account the fact that data related to the future production to fulfill becomes more and more uncertain. In this respect, we propose a resolution strategy that divides the time into several periods and associates an uncertain production demand at each of these periods. The uncertainty increases as the considered period is farer from the present, which seems to be a realistic view of the problem.

The paper is organized as follows. In Section 2, we introduce other published works dealing with uncertainty and fuzziness in layout design. In Section 3,we suggest an approach to layout design with accounts for this increase of uncertainty over time. The corresponding fuzzy problem is then more formally stated in Section 4. Finally, in Sections 5 and 6, we propose an evolutionary

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approach and experiment it on several test examples. The conclusion and future works terminate the article.

2. Dealing with uncertainty in layout design: Related research

According to Azadivar and Wang (2000), a facility layout problem is defined as the determination of the relative locations for, and allocation of, the available space among a given number of facilities. To arrange these facilities, it is necessary to use several types of data related to the production, which typically includes quantities of products to be manufactured. Numerous research works are concerned with layout design in the literature. Recently, uncertainty in the layout design has emerged as an important issue (Kulturel-Konak, 2007).

Drira et al. (2007) have published an extended survey of the research in layout design. From this work, we can note that most published researches address static problems, which assume that the production data, once established, are relevant enough to characterize the conditions for future production of the system. Unfortunately, this assumption is far from reality. As a consequence, several authors have suggested to incorporate uncertainty and/or imprecision in their resolution approaches. Among these works we can distinguish, stochastic formulations (Meng et al., 2004) and fuzzy formulations, which seems to be the most commonly adopted. Grobelny (1986, 1987a, 1987b) presents a fuzzy approach applied to layout problems where the factors affecting the layout are described by linguistic variables. Inference rules are used to link the fuzzy input variables to fuzzy output variables. For each pair of facilities, these rules are combined and the result is then defuzzified and exploited in construction heuristics. In this way, Dweiri and Meier (1996) and Dweiri (1999), consider the product flow, information flow, personal flow, material handling equipment flow, environmental conditions and personal supervision as fuzzy factors that affect the layout. The weights associated to each factor are estimated by an Analytic Hierarchy Process (AHP) which is based on the relative importance given by the decision maker. Then, a construction heuristic allows the design of the layout. Deb and Bhattacharyya (2003, 2005) address the problem of placing facilities using a multi-input fuzzy system: the flow of personnal, supervisory relationships, environmental conditions and the flow of information. The fuzzy inference rules link all factors to the output variable, which is the proximity rate. Defuzzification specifies, for each pair of facilities, the rate of proximity and the one who has the higher rate has priority to be placed. However, these approaches address qualitative, but not quantitative aspects of the layout, such as production requests, flows between machines, etc. A limited number of articles are concerned with such characteristics. In this context, fuzzy numbers can offer interesting possibilities to deal with the uncertainties and inaccuracies (Aiello and Enea, 2001). The use of fuzzy numbers is introduced in Gen et al. (1995). The authors address a multi-line layout. They model clearances between adjacent facilities with fuzzy numbers. The membership degree of horizontal distances and vertical distances between pairs of facilities is to be maximized. Genetic algorithms are used as resolution approach. Cheng et al. (1996) represents the flows between facilities by fuzzy numbers and solve the resulting optimization problem using a genetic algorithm. In the same context, Aiello and Enea (2001) show the interest of fuzzy numbers to model uncertainty in the market demands and incorporate constraints on the maximum capacities of the departments. The authors apply their approach to a simple case of a linear layout with 4 facilities to minimize the total material handling cost. Enea et al. (2005) consider departments with finite production capacity and flows between them are modeled by triangular fuzzy numbers. Authors developed a genetic fuzzy algorithm and the comparison of layouts is based on the integral value. The efficiency of their approach is tested on 6 departments' facility layout.

An important limitation of these works is that, although they use fuzziness to represent uncertain situations, they assume that the fuzzy characterization of the demand does not change over time. Nevertheless, it is well known that nowadays, manufacturing plants must be able to respond quickly to changes in demand, production volume and product mix (Dégrés et al., 2008). Page (1991) reported that, on average, 40% of a company's sales come from new products. However, the change in product mix yields to modify the production flow and thus affects the layout. Gupta and Seifoddini (1990) stated that 1/3 of USA companies undergo major reorganization of the production facilities every two years. To cope with this drawback, certain researchers have suggested layout design approaches with several time periods (i.e., dynamic layouts), and have used probabilistic distributions to take into account possible changes (Yang and Peters, 1998; Braglia, et al., 2003). Yang and Peters (1998) consider rolling horizons of planning and assume that demands are subject to multiple scenarios, each one with a probability of occurrence. The problem is solved using a matrix of flow weighted by the probabilities. On each time window, composed of a number of periods, a robust layout is defined. This layout is rearranged on the next time window. Braglia et al. (2003) study the case where demands vary according to a probability law. They present indicators to decide whether the layout must be robust or dynamic; a robust layout is an effective arrangement of facilities that do not change for multiple periods (Pillai et al., 2011). Unfortunately, certain probabilities may turn out to be quite difficult to estimate in practice. Moreover in such research works, the authors do not take into account the degradation of the available information over time. The fact that the information quality can decrease as time advances, has been evocated in Balakrishnan and Cheng (2009). The authors discuss a dynamic layout problem where requests for production are subject to forecast errors that increase over time. The margins of error are fixed in each period and can be positive, negative or zero with equal probabilities. They compare two existing crisp algorithms on rolling horizons and show that such considerations are important, but they do not suggest an approach to find a layout in such a context. As a consequence, although there exist approaches that include some sort of uncertainty in their resolution strategy, there is still a need for a new method that can solve robust layout problems while taking into consideration the important fact that forecasts become less and less reliable as they become farer from the current time.

3. Dealing with less and less reliable information

3.1. Uncertainty

During the design phase of a workshop, it often arises that the product types to be manufactured are reasonably known, but the quantities that will be ordered for these products are not well known, so that rough approximations, deduced from a market study can be used. Hence, the future production volumes are uncertain. The decision maker gives, for each product p, a demand value d_p^{pl}, which is thought to be the most plausible. This demand can fluctuate between two values, minimum $d_p^{\min}$ and maximum $d_p^{\max}$. For each product p, the production demand is represented by a triangular fuzzy number $\tilde{D}_p$ characterized by the triplet $(d_p^{\min}, d_p^{pl}, d_p^{\max})$ (Godjevac, 1999). Fig. 1 illustrates different representations of production demands: crisp and uncertain.