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Multi-objective optimisation of dynamic scheduling in robotic flexible assembly cells via fuzzy-based Taguchi approach

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ABSTRACT

This paper presents Taguchi method coupled with fuzzy logic for dealing with multi-objective optimisation problems for dynamic scheduling in robotic flexible assembly cells (RFACs). This is the first study to address these particular problems. In this study, Taguchi optimisation method has been applied to reduce the number of experiments required for scheduling RFACs. The experiments are implemented with four different scheduling factors, namely sequencing rule, dispatching rule, cell utilisation and due date tightness. These factors are difficult to optimise considering the objectives of multiple functions instead of a single objective. Therefore, a multiple performance characteristics index (MPCI) based fuzzy logic approach has been developed to derive the optimal solution. The predicted results of MPCIs have been verified via a confirmation test. Results of the confirmation test show significant improvement in MPCI using the optimal levels of the scheduling factors.

1. Introduction

Flexible manufacturing systems have attracted significant attention in recent years, due to their flexibility and dexterity in dealing with unexpected events. One class of such systems is called robotic flexible assembly cells (RFACs). RFACs are highly modern systems, structured with industrial robot(s), assembly stations and an automated material handling system, all monitored by computer numerical control (Manivannan, 1993; Marian, Kargas, Luong, & Abhary, 2003; Sawik, 1999). The design of RFACs with multi robots leads to increased productivity in a shorter cycle time and with lower production costs (Xidias, Zacharia, & Aspragathos, 2010). However, there are certain difficulties that have arisen with this design concept. For example, more than one robot operating simultaneously in the same work environment requires a complex control system to prevent collisions between robots (Nof & Chen, 2003), and also to prevent deadlock problems (Lee & Lee, 2002). Moreover, industrial robots must be employed as effectively as possible due to high cost of the robots (Xidias et al., 2010). To overcome the above difficulties, efficient scheduling of RFACs is required.

Few studies have been devoted to scheduling RFACs. These studies may be categorised according to the approaches adopted. In the first category are those studies which applied heuristic approaches to solve scheduling problems such as (Jiang, Seneviratne, & Earles, 1998; Lee & Lee, 2002; Lin, Egbelu, & Wu, 1995; Nof & Drezner, 1993; Pelagagge, Cardarelli, & Palumbo, 1995; Rabinowitz, Mehrez, & Samaddar, 1991; Sawik, 1995). The studies in the second category which investigated simulation as an approach to scheduling RFACs, for instance (Basran, Petriu, & Petriu, 1997; Gilbert, Coupez, Peng, & Delchambre, 1990; Hsu & Fu, 1995). There are only two studies in the third category, by Del Valle and Camacho (1996) and Van Brussel, Cottrez, and Valckenaers (1990) who implemented expert systems approaches to solve scheduling problems. The major limitation of all the above studies concentrated only on assembly of one type of product at a time.

Scheduling RFACs in a multi-product assembly environment is presented in four recent studies: first, a scheduling scheme of RFACs (Abd, Abhary, & Marian, 2011a); second, a strategy for scheduling RFACs using simple scheduling rules (Abd, Abhary, & Marian, 2011b); third, a methodology to select the best scheduling rule of RFACs using a multiple criteria decision-making method (Abd, Abhary, & Marian, 2011c); and fourth, a new scheduling rule based on Fuzzy Logic for scheduling RFACs and then validating the performance of the suggested rule using a simulation program (Abd, Abhary, & Marian, 2012a, 2012b). Even though these recent studies have been devoted to scheduling RFACs in a multi-product assembly environment, they concentrated only on the static scheduling of RFACs.

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The dynamic scheduling of RFACs adds more complexity to finding optimal solutions to the multi-objective optimisation problems. As far as we know, this is the first study that addresses these particular problems. Therefore, the main contribution of this paper is to apply an intelligence approach to deal with multi-objective optimisation scheduling problems for RFACs in a dynamic environment.

In the last few years, the application of Taguchi based fuzzy logic approach, to solve optimisation problems in a wide range of applications, has attracted significant attention, for example, in engineering design (Lin & Kuo, 2011; Sun, Fang, & Hsueh, 2012), the electronics industry (Tsai, 2011) and material cutting (Gupta, Singh, & Aggarwal, 2011; Hsiang, Lin, & Lai, 2012; Pandey & Dubey, 2012; Sharma, Chattopadhyaya, & Hloch, 2011). In this study, a Taguchi approach incorporated with a fuzzy logic approach is applied to multi-objective optimisation problems of scheduling RFACs.

2. Fuzzy logic based Taguchi optimisation methodology

The Taguchi approach has been developed as an optimisation technique by Genichi Taguchi since the 1950s. The potential benefit of the Taguchi method is its ability to solve complex problems by drastically reducing the number of experiments to be performed, accordingly reducing the cost of experiments (Bendell, Disney, & Pridmore, 1989; Ross, 1988). Taguchi designed special orthogonal arrays based on the number of factors affecting the decision and their levels. These arrays determine the number of necessary experiments. Taguchi defined a performance measure called signal-to-noise (S/N) ratio. The S/N ratio characteristic is classified into three categories depending on the goal of the problem: the smaller the better, the larger the better and the nominal the best (Lee, 2000). According to Taguchi, the S/N ratio results can be analysed using the analysis of mean (ANOM) and analysis of variance (ANOVA), to determine the optimal conditions affecting the performance characteristics (Mori, 1990; Taguchi, 1993; Taguchi, Elsayed, & Hsaing, 1989).

For a single performance measure, in the Taguchi method, the optimum level of the process parameters is the one having the highest S/N ratio. Multi-performance measure optimisation is not as straightforward as that of a single process response optimisation. An overall evaluation of S/N ratios is required for the optimisation of the multi-process response due to the fact that a higher S/N ratio for one process response may correspond to a lower S/N ratio for another process response (Rao, 2011). To overcome this problem, a multiple performance characteristics index (MPCI) based fuzzy logic approach is developed to derive the optimal solution.

Fuzzy logic (FL) was introduced first by Zadeh (1965). FL is a nonlinear mapping of an input data vector into a scalar output. In general, a fuzzy logic system (FLS) consists of four components (Mendel, 1992; Zadeh, 1976): knowledge base, fuzzification, inference engine and defuzzification. The knowledge base stores both membership functions (MF) and fuzzy rules. A membership function (MF) embodies a fuzzy set $\tilde{A}$ graphically. The values of the MF are between 0 and 1, denoted by $\mu\tilde{A}(x)$ where x is an element of $\tilde{A}$; these values are called degree of membership. Triangular and trapezoidal, as shown in Fig. 1, are the most well-known of membership functions shapes (Mendel, 1992). A fuzzy rule is structured to control the output variable, such rules reflect a human reasoning mechanism. A fuzzy rule has two parts; the antecedent and the consequent IF <antecedent> THEN <consequent>.

Fuzzification represents the process of converting the S/N ratios obtained by the Taguchi method into fuzzy inputs, using the membership functions. The inference engine maps from fuzzy input to fuzzy output, using IF-THEN type fuzzy rules. Defuzzification translates the fuzzy output into a MPCI, using the membership functions of the output variable.

In this study, the Taguchi approach is coupled with fuzzy logic for multi-objective optimisation problems of scheduling RFACs. The proposed optimisation methodology comprises five steps as depicted in Fig. 2.

i. Identifying the scheduling problems' characteristics, and then determining scheduling factors and the number of levels for each factor.
ii. Choosing the appropriate orthogonal array (L_9) to conduct the experiments, and transforming the analytical results of the experiments into S/N ratio for each objective function. The experimental runs will be conducted under different combinations of scheduling factors using simulation software package SIMPROCESS (Swegles, 1997).
iii. Converting the S/N results to a value range between 0 and 1. This process is called normalisation.
iv. Applying fuzzy approach, using fuzzified, inference engine and defuzzified operation to obtain the multiple performance characteristics index (MPCI).
v. Analysing and verifying the results statistically, using a variance analysis (ANOVA) and confirmation test respectively.

3. Outline of the RFACs model

3.1. RFACs description

The present RFACs model consists of six resources: two robots (R_1 and R_2) for fetching the assembled parts and placing them at

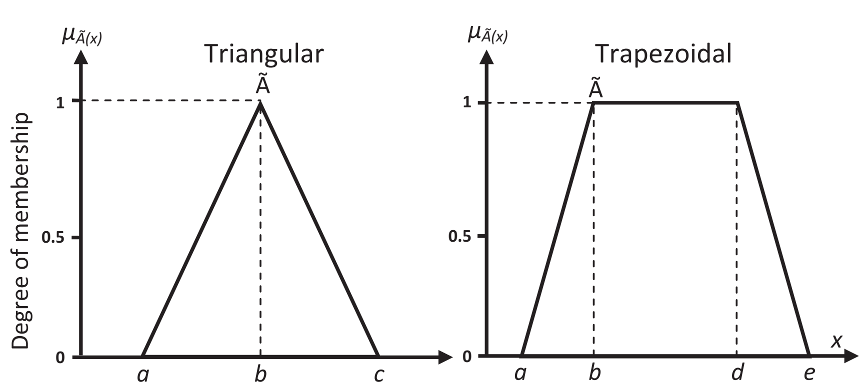

Fig. 1. Two examples of fuzzy numbers, triangular and trapezoidal.