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Technical paper

Robust manufacturing system design using multi objective genetic algorithms, Petri nets and Bayesian uncertainty representation

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ABSTRACT

Decisions involving robust manufacturing system configuration design are often costly and involve long term allocation of resources. These decisions typically remain fixed for future planning horizons and failure to design a robust manufacturing system configuration can lead to high production and inventory costs, and lost sales costs. The designers need to find optimal design configurations by evaluating multiple decision variables (such as makespan and WIP) and considering different forms of manufacturing uncertainties (such as uncertainties in processing times and product demand). This paper presents a novel approach using multi objective genetic algorithms (GA), Petri nets and Bayesian model averaging (BMA) for robust design of manufacturing systems. The proposed approach is demonstrated on a manufacturing system configuration design problem to find optimal number of machines in different manufacturing cells for a manufacturing system producing multiple products. The objective function aims at minimizing makespan, mean WIP and number of machines, while considering uncertainties in processing times, equipment failure and repairs, and product demand. The integrated multi objective GA and Petri net based modeling framework coupled with Bayesian methods of uncertainty representation provides a single tool to design, analyze and simulate candidate models while considering distribution model and parameter uncertainties.

1. Introduction

Robust manufacturing system design involves finding a manufacturing system configuration that yields better performance measures such as throughput and WIP under different manufacturing system uncertainties (such as uncertainties in processing times, equipment failure and repairs and product demand). Typical examples of manufacturing system configuration design include finding optimal number of resources in different manufacturing cells in a plant, devising optimal production planning or inventory management strategies, designing layout plans for efficient product flow. In the context of this paper, manufacturing system configuration design is referred to as finding optimal number of resources in different manufacturing cells within the plant.

Decisions involving robust manufacturing system configuration design are costly and involve long term resource allocation. These decisions typically remain fixed and failure to design a robust manufacturing system can lead to high production and inventory costs, and lost sales. The design decisions become more complex when new systems are being designed, or new products are being launched as sufficient information about underlying uncertainties is not accurately available.

Two important aspects of robust manufacturing system design involve: problem space search and accurate uncertainty representation. The approach used for searching different design configurations should be able to explore broader set of design solutions and provide insights into relative advantages and disadvantages of each design configuration. In addition, it is also important to accurately account for different manufacturing system uncertainties. A common approach to model uncertainties involve fitting a distribution model to the available data and then randomly sampling points from the distribution model to account for variability. The correct selection of distribution model and its parameters is highly dependent on the data quality (number of data point available and variability in the dataset). The selection of correct distribution model and its parameters become more critical when new systems are being designed due to lack of information and uncertainties in process behavior. For such systems, it is important to account for model and parameter uncertainties.

Model uncertainties are uncertainties involved in selecting a correct distribution model, and parameters uncertainties are uncertainties involved in selecting the correct distribution parameters for the selected distribution model (See Draper [1], Chick [2–4], Andradóttir and Bier [5], Zouaoui and Wilson [6–8] and Henderson

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[9] for more details). Current literature review shows use of sensitivity analysis or experimental design based approaches to account for parameter uncertainties. However, the methods used to select the sensitivity parameters or experimental design settings have not been well described in the literature. The literature review does not suggest any approach to account for model uncertainties in manufacturing system design.

This paper presents a novel approach involving multi objective genetic algorithms, Petri nets and Bayesian model averaging for robust manufacturing system design. The proposed approach is demonstrated on a manufacturing system configuration design problem to find optimal number of machines in different manufacturing cells in a manufacturing system producing multiple products. The objective function aims at minimizing makespan, mean WIP and number of machines. Uncertainties in processing times, equipment failure and repairs, and product demand are considered. It is assumed that reconfiguration costs are high, so the design configuration obtained at the beginning of planning horizon will remain fixed for entire planning horizon.

Multi objective GA is used to provide a Pareto front of design solutions against different decision metrics (i.e. makespan, mean WIP and number of resources). This allows the designers to weigh-in relative merits of each design configuration and evaluate the sensitivity of design solutions against variability in the cost functions associated with each decision metrics. In addition, this approach eliminates the need to re-explore different design configurations if the cost functions changes.

A Bayesian model averaging (BMA) based approach has been considered to represent different uncertainties. It provides a unified framework to incorporate *model*, *parameter* and *stochastic* uncertainties. Recent work of Chick [2–4], Zouaoui and Wilson [6–8] and Henderson [9] clearly show the advantages of using BMA. We show the effects of ignoring *model* and *parameter* uncertainties for a robust manufacturing system design and show that ignoring these uncertainties underestimate the decision metrics that can lead to improper design decisions. Our results reveal that Bayesian framework provides better uncertainty representation as compared to classical methods using sensitivity analysis and ignoring demand variations. The Bayesian framework has been integrated with Petri nets for modeling and performance analysis of manufacturing systems. Petri nets based formalism not only incorporate properties of discrete event simulation but their formalism can be translated for manufacturing system monitoring and control in future.

The following approach is used for finding a robust manufacturing system configuration design. A multi objective GA coupled with Petri net is first used to find candidate configurations against makespan and WIP under processing and arrival rate uncertainties, which are represented in a Bayesian framework. The candidate configurations are then evaluated against demand variations that can arise in future planning periods. The design configuration which results in lowest overall cost at the end of all the planning periods is selected as a robust configuration.

The paper is organized as follows. Section 2 provides literature review of work done in robust manufacturing system design, Section 3 provides the problem formulation, Section 4 describes the proposed approach, and Section 5 describes the results obtained for robust design problem. Finally, Section 6 provides the summary and future work for the paper.

2. Relevant work

One of the most widely used approaches for robust design is Taguchi's signal to noise ratio based experimental design. The approach finds design solutions such that they are more robust against uncontrollable variations. The approach usually involves using orthogonal arrays and signal to noise ratios for finding a robust configuration. The signal to noise ratio takes into account both variability in response data and the closeness of average response to target value (Mezgar et al. [10]). Current literature also shows use of other design of experiments based approaches such as fractional factorial design and response surface methodologies integrated with Taguchi's methods for robust design.

Madu and Madu [11] demonstrated an application of Taguchi based approach using orthogonal arrays and signal noise ratio to maximize equipment utilization for a maintenance cell. The approach provided best design point from a limited number of design points and with minimal experimentation time. Lim et al. [12] used Taguchi's methods for finding optimal configuration of operating policies for a manufacturing system to maximize throughput and minimize flow time. Bulgak et al. [13] used orthogonal arrays and normal probability plots for finding robust design with considerations of variation in uncontrollable factors such as jam rates and jam clear times in a assembly line. Mezgar et al. [10] used design of experiments and artificial neural network based technique for design and real time reconfiguration of manufacturing systems. Sanchez et al. [14] provided a framework for designing, analyzing and improving systems by combining discrete event simulation and response surface meta modeling. Chen and Chen [15] presented a Taguchi concept and response surface based methodology for designing a robust manufacturing system configuration. The authors presented a nine step procedure which uses weighted design measure as performance evaluation criteria. Shang [16] used a Taguchi and response surface methodology (RSM) for finding a robust design of a material handling system.

When number of controllable and uncontrollable factors is large, finding a robust design solution becomes more complex and time consuming. For such cases, heuristic methods such as genetic algorithms (GA) or simulated annealing (SA) can be used. Saitou et al. [17] used a GA and Petri net based approach for finding robust manufacturing system configuration that underwent forecasted production plan variations. Their approach however, does not consider uncertainty in operating times of different resources and uses a single objective function. Kazancioglu and Saitou [18] presented a methodology for allocating production capacity among flexible and dedicated machines under uncertain demand forecasts by quantifying the expected values of product quality and cost. Hamza et al. [19] used a NSGA-II based multi objective GA approach to optimize assembly sequence plan, and to find type and size of assembly stations for a production shop that produced wind propelled ventilators.

In other related work, Gaury and Kleijnen [20] presented a risk analysis based approach for robust system design, in which risk is evaluated by simulating the system over a sample of environmental scenarios. Kleijnan and Gaury [21] presented a methodology which includes simulation, optimization, uncertainty analysis and bootstrapping for robustness modeling. Pierreval and Durieux [22] presented a two stage optimization technique in which heuristic search methods are first used to determine near best solutions and their performance. In the second stage, several possible environmental scenarios are considered and evaluated according to their performance using reference curves. Pierreval and Durieux-Paris [23] suggested a heuristic method to measure and compare the robustness of solutions using simulation against a base environment. The proposed approach uses decision theoretic methods and involves decision maker's knowledge in decision making process.

Different types of evolutionary algorithms have been applied to solve different aspects of manufacturing system design. Wang and Koren [24] employed a genetic algorithm based optimization methodology to identify the most economical way to reconfigure a manufacturing system to meet new demand. Paydar et al. [25] presented a simulated annealing based approach to design cellular