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OPTIMIZATION OF BUFFER SIZES IN ASSEMBLY SYSTEMS USING INTELLIGENT TECHNIQUES

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ABSTRACT

When the systems under investigation are complex, the analytical solutions to these systems become impossible. Because of the complex stochastic characteristics of the systems, simulation can be used as an analysis tool to predict the performance of an existing system or a design tool to test new systems under varying circumstances. However, simulation is extremely time consuming for most problems of practical interest. As a result, it is impractical to perform any parametric study of system performance, especially for systems with a large parameter space. One approach to overcome this limitation is to develop a simpler model to explain the relationship between the inputs and outputs of the system. Simulation metamodels are increasingly being used in conjunction with the original simulation, to improve the analysis and understanding of decision-making processes. In this study, artificial neural networks (ANN) metamodel is developed for simulation model of an asynchronous assembly system and ANN metamodel together with simulated annealing (SA) is used to optimize the buffer sizes in the system.

1 INTRODUCTION

When the systems under investigation are complex, as are often the case in manufacturing or other practical environments, analytical solutions to these systems become impossible. Because of the complex stochastic characteristics of these systems, simulation can be used as an analysis tool to predict the performance of an existing system or a design tool to test new systems under varying circumstances. When designing a new system, the best combination of design variables (i.e., inputs) is investigated to optimize performance measures (i.e., outputs) of the simulation model. This procedure is simulation optimization. In this procedure, simulation model can be viewed as a stochastic objective function since it is not explicitly expressed in terms of decision variables. Different approaches for simulation optimization are available in the literature. These approaches include standard non-linear programming techniques, response surface methodologies, stochastic approximation techniques, pattern search techniques and random search techniques. A drawback of such approaches is that they terminate upon finding a local optimum. Recently, metaheuristics such as simulated annealing, genetic algorithms and tabu search have been successfully used in simulation optimization problems. Comprehensive reviews of literature on simulation optimization have been provided by Glynn (1989), Meketon (1987), Jacobson and Schruben (1989), Safidazeh (1990), Fu (1994a,b), Carson and Maria (1997), Azadivar (1999) and Swisher et al (2000). However, simulation is extremely time consuming for most problems of practical interest. As a result, it is impractical to perform any parametric study of system performance, especially for systems with **a** large parameter space. Systematic performance studies of most real world problems are beyond reach, even with supercomputers, unless substantial improvement in the speed of the performance evaluation process can be achieved. One approach to overcome this limitation is to develop a simpler model to explain the relationship between the inputs and outputs of the system. Simulation metamodels as simplified versions of simulation models are increasingly being used in conjunction with the original simulation, in an attempt to improve the analysis and understanding of decision making processes.

In this study, an artificial neural networks (ANN) metamodel was developed for simulation model of an asynchronous assembly system and ANN metamodel together with simulated annealing (SA) was used to optimize the buffer size in the system.

2 LITERATURE REVIEW

Barton (1992) had reviewed different simulation metamodelling techniques and illustrated that the methods based on parametric polynomial response surface approximations are the most common. Recent years, artificial neural networks (ANN) have been used to obtain a simulation metamodel. Although, Fishwick (1989) showed that regression metamodels were better than ANN metamodels, opposite results had been obtained by following studies. Pierreval and Huntsinger (1992) proposed the use of ANN as a metamodelling technique for job-shop and percolator coffeepot simulation models. Kilmer and Smith (1993) demonstrated that ANN metamodels show improved performance compared to first and second order linear regression metamodels for discrete event simulation models. Kilmer, Smith and Shuman (1994) used input-output training pairs from inventory simulation model to train two ANN, one estimating mean total cost and the other estimating the variance of total cost. They then used estimates of the mean and the variance of the cost produced by the ANN to predict confidence intervals for the inventory cost. Hurrion (1997) have used ANN to find optimum number of kanbans in a manufacturing system. In the study, after an ANN metamodel for simulation model of the manufacturing system was developed, the metamodel was used together with exhaustive search method to find optimum number of kanbans. Badiru and Sieger (1998) used the ANN as a simulation metamodel in the economic analysis of risky projects and investigated the effect of transfer functions on the performance of the ANN metamodels. Mollaghasemi et al**.** (1998) demonstrated that ANN can be used in conjunction with simulation models to provide a decision support system for designing manufacturing systems. In the study, ANN metamodel was developed to answer inverse questions (i.e., to estimate the inputs that are required to obtain specific outputs) and authors investigated the performance of the ANN metamodel. Hurrion (1999) studied the effect of factorial and random experimental design methods for the development of regression and neural network simulation metamodels and showed that, for two example problems (JIT system and job-shop system), ANN metamodels using randomized experimental design procedure are more accurate and efficient metamodels than those produced by similar sized factorial designs with either regression or neural networks. Chan and Spedding (2001) developed an ANN metamodel for the simulation model of the assembly system of optoelectronic products and they used ANN metamodel and response surface plot to find optimum six-sigma configuration of the assembly process. Sabuncuoglu and Touhami (2002) developed ANN metamodel for a jobshop system and carried out extensive computational tests to represent the effectiveness of ANN metatmodel.

As it is seen in literature review that the ANN metamodel was used successfully in different systems. Our purpose is to extend to applicability of ANN metamodel for AAS and use ANN metamodel as a part of a search algorithm in simulation optimization.

3 ASYNCHRONOUS ASSEMBLY SYSTEMS

A closed, single loop, asnchronous assembly system (AAS) with the topology as shown in Figure 1, which was described by Bulgak et al. (1995), was considered as a problem in the study. In this system, a set of assembly stations are arranged in tandem according to the order of assembly operations performed. The distance between any two adjacent stations (connected by a transfer chain or conveyor) and the pallet dimensions determine the number of pallets that can be accommodated between these adjacent stations. The maximum amounts for these work-in-process (WIP) inventories between each pair of stations in the system (b1, b2, b3... in Figure 1) constitute the buffer sizes (capacities). Selecting appropriate buffer sizes for the transport systems of automated manufacturing systems is a complex task that must account for random fluctuations in production rates by the individual stations as well as for transport delays that are a part of material handling system. If buffer sizes are too large, then transport delays are excessive and more in-process inventories must be input into the system to accommodate the large buffer sizes. If the buffer sizes are too small, then small processing delays will cause the buffer to fill, and upstream stations will be blocked from releasing complete work piece. With a fixed number of pallets in the system, there is always an optimal configuration capable of reducing blocking and starvation effects considerably to yield a maximum possible production rate. Extensive literature review can be seen in Bulgak et al. (1995).

The buffer size optimization problem in AAS is the following problem: Given a fixed total number of pallets to perpetually circulate in the system, find the optimal buffer configuration to yield maximum production rate for the AAS configuration depicted in Figure 1. Accordingly, the decision variables are the buffer sizes between the pairs of stations and the objective is to maximize the production rate. Fundamentally the problem is a stochastic, nonlinear, combinatorial optimization problem with discrete decision variables. Since no known closed-form expression exists to determine the expected value of the production rate, discrete event simulation is used to estimate this value.

Characteristics of the simulation model are given below:

- *Station Cycle Time.* The time required for a station to perform the prescribed assembly task (or set of

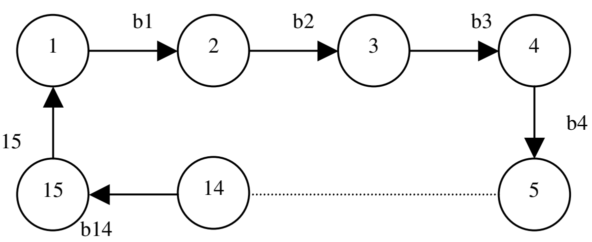

Figure 1: Scheme of the Asynchronous Assembly System

tasks) under normal operating conditions. This is the deterministic component of the station service time (6,22) and considered to be 5 time units.

- *Jam Rate.* Stations are subject to jam due to various reasons, such as system breakdowns, defective parts being assembled or a robotic assembly station accidentally dropping the part it is holding. Jam occurrences are random events. These are expressed in percentage for a particular station. In the study, while number of stations subject to jam was taken from 2 to 8 at intervals of 2 stations, jam rates for the stations were taken from 0.5% to 5% at intervals of 1.5%. The probabilities of selection of number of stations subject to jam and jam rates for any configuration are equal.
- *Jam Clear Time.* This is expressed in time units required to a jam. These times are geometric random variables with means of 18 time units.
- *Number of Pallets.* The total number of pallets circulating in the system has been kept fixed and is taken as 40.

In the study, decision variables are buffer sizes between the pairs of stations. The upper and lower limits of any single buffer have been fixed as 15 and 1, respectively. The expected value of the production rate that is function of buffer sizes, number of stations subject to jam and jam rates is obtained by simulating the system around 15000 time units, with 10 independent replications. For each replication a warm-up time of 500 time units is used to remove the initial transient.

4 OPTIMIZATION WITH ARTIFICIAL NEURAL NETWORK METAMODEL AND SIMULATED ANNEALING

4.1 Artificial Neural Network

Neural networks were inspired by the power, flexibility and robustness of the biological brain. They were computational (mathematical) analogs of the basic biological components of a brain – neurons, synapses and dendrites. Artificial neural networks (ANN) consist of many simple computational elements (summing units – neurons- and weighted connections-weights) that together in parallel and in series (Figure 2).

ANN begin in a random state and "learn" using repeated processing of a training set, that is, a set of inputs with target outputs. Learning occurs because the error between ANN output and the target output is calculated and used to adjust the weighted synapses of the ANN. This continues until errors are small enough or no more weight changes are occurring. The ANN is then trained and the weights are fixed. The trained ANN can be used for new inputs to perform estimation or classification tasks.

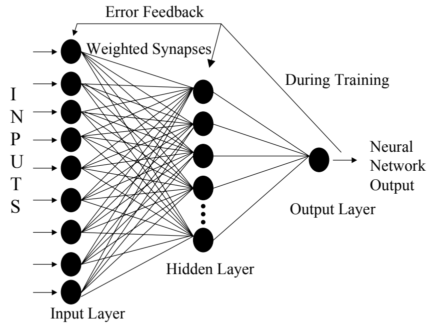

Figure 2: Structure of an ANN

In this paper, ANN metamodel was developed, or trained, based on the production rate of a set of buffer sizes, jammed stations, number of pallets and jam clear time for a given AAS. The ANN metamodel was used to estimate production rate as a function of the possible configuration during the search for optimal design (i.e., determination of buffer sizes). In this way, multiple estimates of production rate are available without using simulation model for each new configuration.

4.1.1 Developing ANN Metamodel

In this study, AAS with 15 stations that while some stations are subject to jam, others are jam free was considered. Since, there are AASs having different jam rates and different stations subject to jam in real world, we develop a general ANN metamodel for estimation production rate, which is function of different buffer sizes (bi), jam rates (jr) and number of stations (ns) subject to jam. A three layers feed forward network was constructed with thirty input neurons in the input layer and one neuron in the output layer to map the production rate to the thirty input variables. ANN model used buffer sizes between the pairs of stations and jam rate for each station as input. Output was production rate, which was a function of input. Discrete event simulation was used to estimate the value of production rate. Data set, which was used to train ANN, was generated randomly from the set of possible configurations. For each configuration in data set, buffer sizes between the pairs of stations, jam rates and number of stations subject to jam were determined randomly using their determined ranges of value. An example as an input for ANN is given in Figure 3. The training of ANN was carried out using backpropogation algorithm because of its powerful approximation capacity and its applicability to both binary and continuous inputs. The bipolar sigmoid function and normalized cumulative delta rule was used as a transfer function and learning rule, respectively. After preliminary experiments, a network architecture of 30 (15 buffer sizes, 15 jam rates) inputs, 15 hidden neurons in one hidden layer and a single output is developed. A data set of 200 configurations was split into training (140 configurations) and test-

Buffer size:

b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	b_{11}	b_{12}	b_{13}	b_{14}	b_{15}
5	4	1	3	4	7	9	15	6	8	11	4	5	6	4

Jam rates:

ws_1	ws_2	ws_3	Ws_4	ws_5	ws_6	ws_7	ws_8	ws_9	ws_{10}	ws_{11}	ws_{12}	ws_{13}	ws_{14}	ws_{15}
0	0	3.5	0	3.5	0	3.5	0	0	3.5	0	0	0	0	0

Figure 3: An Example to Input in ANN model

ing (60 configurations). Cross validation was used to stop over training. In cross validation, once the error term obtained from cross validation set starts to increase significantly then training is stopped. The training ANN was carried out with NeuralWorks Professional II/PLUS program. In training ANN model, learning coefficients for the hidden layer, the output layer and momentum are taken as 0.80, 0.10 and 0.70, respectively. To see the effectiveness of the developed ANN model, a regression metamodel were built based on same data set. After investigated several regression models it was determined that the exponential function on response best fits the data. It is important that any metamodel should be validated before it is used for its intended purpose. One method of validation, especially for a regression metamodel, is to use as independent set of configurations, which has not been used for either training or termination of training, and obtain the mean squared error of prediction. For validation and comparison purposes of two metamodels, an independent set with 100 randomly choosen configurations was obtained. Root mean squared error (RMSE), mean absolute deviation (MAD), maximum absolute deviation and percentage error of production rate were used as performance measures to compare two metamodels. Table 1 gives the results obtained from the metamodels with independent set. As it is seen in table that ANN metamodel is better than exponential metamodel. RMSE, MAD and % error decrease approximately 50% with ANN metamodel.

4.2 Search for Optimal Buffer Sizes

After a metamodel was developed for any simulation model, it can be coupled with a variety of search techniques with the purpose of optimization. In this study, simulated annealing (SA), which is a class of metaheuristic techniques, was used.

SA is based on an analogy to the cooling of materials in a heat bath. The fundamental idea is that if the amount of energy in a system is reduced very slowly, the system will come to rest in a more perfect state than if the energy is reduced quickly. When translated into terms pertinent to optimization, the energy in the system refers to the tolerance for pursuing apparently poorer solutions in an effort to avoid being trapped in local minima. As the search proceeds, this tolerance is slowly reduced until the search converges to a final optimal solution. In literature, it can be seen that the SA has been appeared in several simulation optimization applications. Some of them are: Bulgak and Sanders (1988), Haddock and Mittenthal (1992), Ahmed et al. (1997), Lacksonen (2001), Alabas et al. (2002).

In this study, a solution was coded as integer numbers. Each number represents buffer size between a pair of stations. The initial solution was obtained in randomly. A move in SA was realized using following scheme: a number was randomly selected between 1 and number of stations in AAS. This number represents selected a pair of stations. Next, a new buffer size for the selected pair of stations was randomly generated between 1 and 15 excepting its current type. After changing the current buffer size to new the buffer size, the new solution becomes the current solution. T_o was determined using the empirical rule of Kirkpatrick et al. (1983) to be 0.02 resulting in the initial fraction of accepted downhill moves of approximately 0.85. As a cooling schedule, a single iteration at each temperature, as per Lundy and Mees (1986) was used. The temperature at each iteration is determined by $T_{k+1} = T_k/(1+\beta T_k)$, where$T_k$ is the temperature at the k^{th} iteration and β is the cooling ratio which is calculated using $[T_o\text{-}T_f /(f\text{-}1)\ T_o\ T_f\ ]$. The final temperature, T_f and f were set to 0.001 and 2000, respectively.

5 EXPERIMENTAL RESULTS

To investigate the performance of ANN/SA procedure, three ASSs having different jam rates were selected. Since SA is a stochastic search method, it was run with different 10 seeds for each problem. While Table 2 gives the jam rates for the ASSs, the best configurations of 10 runs are given in Table 3. In addition, the simulation model was run to predict %95 confidence interval (CI) of production rate for each best configuration. In Table 4, estimation of production rate with ANN metamodel, simulation model and CI for each best configuration can be seen. As it is seen that the CIs contain the results predicted by the ANN metamodel. This result is an another way to represent of ANN metamodel validation.

Table 1. Comparison of Exponential and ANN Metamodels.

Metamodel	RMSE	MAD	MAX	%Error
Exponential	0,003818	0,00307	0,00855	2,16114
Artificial Neural Network	0,002289	0,00174	0,00753	1,23587

Table 2. Jam Rates for Workstations in AASs

ASS	ws_1	ws_2	ws_3	ws_4	ws_5	ws_6	ws_7	ws_8	ws_9	ws_{10}	ws_{11}	ws_{12}	ws_{13}	ws_{14}	ws_{15}
1	0	3.5	0	3.5	0	3.5	0	3.5	3.5	0	3.5	0	0	0	0
2	0	0.5	0.5	0.5	0	0.5	0.5	0	0.5	0.5	0	0.5	0	0	0
3	0	0	0	2	2	2	2	2	0	0	0	2	2	2	0

Table 3. Optimum Buffer Sizes for AASs

ASS	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	b_{11}	b_{12}	b_{13}	b_{14}	b_{15}
1	1	6	3	1	8	5	6	3	6	9	1	2	1	11	4
2	1	4	7	1	3	8	2	5	14	3	2	7	3	1	3
3	4	2	2	8	3	11	7	1	2	1	5	9	4	1	9

Table 4. Estimation of Production Rate with ANN Metamodel and Simulation Model

	Estimation of Production Rate			
ASS	ANN Metamodel	Simulation Model	Lower 95% CI	Upper 95%
1	0,1350	0.1342	0,1328	0,1355
2	0,1588	0.1581	0,1569	0,1595
3	0,1397	0.1416	0,1396	0,1436

6 CONCLUSION

In this study, ANN metamodel together with SA was used to find the best buffer size configuration for the AASs with 15 station. Based on the results obtained, we conclude that these complex stochastic combinatorial engineering problems can be solved with reasonable accuracy. Comprehensive comparisons of the performance of the search algorithms combined with metamodels on the AASs can be made as a future research.

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