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A SIMULATION METAMODELLING BASED NEURAL NETWORKS FOR LOT-SIZING PROBLEM IN MTO SECTOR

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Abstract

Simulation is essentially a trial-and-error approach, and is therefore, time-consuming and does not provide a method for optimization. Metamodelling techniques have been recently pursued in order to tackle these drawbacks. The main objective has been to provide robust, fast decision support aids to enhance the overall effectiveness of decision-making processes. This paper proposes an application of simulation metamodelling through artificial neural networks (ANNs). The building of the appropriate ANN model over second-order linear regression model and the reverse simulation metamodelling as simulation-optimization are assisted by the Neuro® Software. To validate the proposed approach, a case study which is adopted from literature, deals with a lot sizing problem in make-to-order supply chain. The optimal solution is to determine the fixed lot size for each manufacturing product type that will ensure order mean flow time target. The comparative results with others metamodels techniques; illustrate the efficiency and effectiveness of the proposed approach.

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Key Words: Simulation Based Metamodel, Neural Network, Multiple Criteria Optimization, Lot-Sizing Problem, MTO, Supply Chain Management, Case Study

1. INTRODUCTION

Today, simulation is a popular tool for the analysis and/or design of existing or proposed complex systems. This popularity is partly due to its flexibility, and to its ability to model real-world systems in some detail, which, in turn, leads simulation to be used as a decision support tool in supervising and controlling the underlying system. Though, simulation models require fewer restrictive assumptions than mathematical models when representing complex, dynamic systems, these models themselves are usually fairly complex and of relatively high dimensionality. That is, the performance of a simulation model mostly depends on a large number of parameters or factors that act and interact in a complex manner. However, with simulation modelling, the relationships between the design parameters and their resulting performance measures are not explicitly known. Therefore, simulation modelling becomes a trial-and-error process in which a set of input factors is used to predict a set of output performance measures. If the desired performances are achieved, a good system design has been attained; otherwise the process is repeated until a satisfactory set of performance measures is obtained. Unfortunately, the iterative nature of this process can result in both high computing costs and difficulties in interpretation and prediction of the results. In order to overcome these problems, there is a significant body of literature devoted to the problem of simulation metamodelling. A metamodel, or model of the simulation model, simplifies the simulation optimization in two ways: the metamodel response is deterministic rather than stochastic, and the run times are generally much shorter than the original simulation.

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