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A neural network model for solving the lot-sizing problem

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Abstract

Artificial neural network models have been used successfully to solve demand forecasting and production scheduling problems; the two steps that typically precede and succeed Material Requirements Planning (MRP). In this paper, a neural network model is applied to the MRP problem of lot-sizing. The model's performance is evaluated under different scenarios and is compared to common heuristics that address the same problem. Results show that the developed artificial neural network model is capable of solving the lot-sizing problem with notable consistency and reasonable accuracy. © 2000 Elsevier Science Ltd. All rights reserved.

Keywords: Neural network models; Lot-sizing; Heuristics; Design of experiments

1. Introduction

This paper investigates the applicability of artificial neural networks (ANNs) to the problem of lot-sizing in Materials Requirement Planning (MRP) for the case of a deterministic time-varying demand pattern over a fixed planning horizon. Specifically, we are interested in the ANN's ability to generate the optimum order pattern as compared to other commonly used heuristics. Although an algorithm to obtain the optimum solution to this problem has been developed by Wagner and Whitin [1], our motivation in developing a neural-network-based solution is due to the fact that ANNs are successfully being used in demand forecasting and production scheduling; the two steps that usually precede and succeed MRP, respectively [2–9]. Thus, extending the use of ANNs to the MRP lot-sizing problem will permit the integration of the production information system, a key requirement for its success. With ANNs supporting all major functions in production planning, historical data and other inputs may be directly converted into planned order releases or production schedules in a transparent way. Some benefits of such integration have been documented in the literature [10].

The ANN solution developed in this paper is compared to the optimum solution, as well as to solutions developed using other heuristics including Periodic Order Quantity (POQ), Silver-Meal (SM), and MINS [11]. POQ and SM are based on the EOQ approach, which minimizes the total inventory cost per unit, in different ways. The POQ determines the average number of periods covered by the EOQ and then orders the exact quantity to cover the demand for those periods. The SM finds the number of periods for which the total inventory costs per period is minimized and then orders the exact quantity to cover the demand for those periods. Details of these two heuristics may be obtained from standard production planning textbooks (e.g., [12,13]). On the other hand, MINS is a mnemonic that indicates the method's repetitive selection of the period with minimum demand

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to explore the benefit of accelerating the delivery of its requirements.

The chosen heuristics are simple, and on average, provide close to optimal solutions [11]. Therefore, comparing an ANN-based approach to these heuristics provides a good indication of its performance. For comparison purposes, POQ was chosen to provide a bottom line of acceptable performance as it is known to be the least accurate of the three methods, but the most simple at the same time. SM was chosen because it is one of the most commonly used methods with reasonable accuracy. Finally, MINS was chosen as one of the most recently developed methods with reasonable simplicity and notable accuracy. These choices were made to evaluate the ANN model against common algorithms to assure acceptable performance in support of the main objective of extending the use of ANNs to the lot-sizing problem for production planning integration. Zhiwei et al. [11] provide a simplicity/accuracy scale comparing various approaches to the lot-sizing problem that justifies our choices.

2. Literature review

2.1. Lot-sizing

This paper addresses the problem of determining the optimum quantities (lot sizes) to order in discrete time periods of a single item over N periods to satisfy a certain demand pattern D while minimizing the sum of ordering and carrying costs. It is assumed that demand of variable quantities occurs in each of the N consecutive periods. The demand that occurs in a given period may be satisfied by an order during that period or during an earlier period, as inventory is carried forward in time. This problem has received significant interest in the literature with hundreds of papers addressing various aspects of the problem [14]. The optimum solution developed by Wagner and Whitin [1] has been criticized as being hard to understand and computationally complex [15,16]. Simpler algorithms that provide reasonable solutions have been developed over the past three decades. Two of the most common algorithms are the PPB algorithm developed by DeMatteis [17] and the SM algorithm developed by Silver and Meal [18]. Both algorithms have received many modifications (e.g., [15, 19–22]). Other algorithms include TOPS [23] and MINS [11]. Comparative studies have shown that many of these algorithms are good alternatives to the Wagner–Whitin algorithm, and may even outperform it in certain cases [24,25].

2.2. Artificial neural networks

Artificial neural networks (ANNs) are alternative computational tools that consist of a large number of simple processing elements, all interconnected, and in parallel. The design of these networks was inspired by the biological neural network (the mammalian cerebral cortex). ANNs have a number of features that have caused them to be successfully implemented, with significant economic benefits. First, they are massively parallel and interconnected, and thus, hardware and software implementations are much easier [26]. Second, ANNs have a high tolerance to noise [27]. Knowledge and information are generally stored throughout the network in the form of weights rather than in a complex-structured central processing unit. It is for this reason that ANNs typically exhibit graceful degradation to noise. Third, ANNs provide a means for modeling arbitrarily complex non-linear functions. A collection of processing elements with weighted interconnections realizes a powerful modeling capability. In fact, some ANNs are capable of modeling arbitrarily complex functions to an arbitrarily degree of accuracy [28]. These are often called universal approximators. Lastly, a fourth feature of ANNs is the existence of general purpose learning rules [29]. These are rules that enable a neural network to adjust to new changes in the behavior of the system that is being modeled.

A production planning problem, as mentioned earlier, spans three sub-problems; the demand forecasting problem, the material requirements planning/lot-sizing problem, and the production scheduling problem. The literature is saturated with successful applications of neural network models in time-series demand forecasting [2–5].

Applying neural network models to solve job-scheduling problems has been recently gaining some momentum. Ntuen [8] used neural networks to map production elements such as lead-time, time between orders, service rate, and order release time to the demand patterns. Laarhoven et al. [7] used simulated annealing to minimize the makespan in a job shop. Yih et al. [9] trained a backpropagation feed-forward neural network to act as a decision making tool in job scheduling. Kim et al. [6] trained a neural network to predict several parameters that were then used in computing priority indices for jobs to be sequenced.

Empirical work on using ANNs in lot-sizing problems is sparse. Ezziane et al. [30] used a neural network approach in deciding whether or not to place an order for raw material in an inventory control management system. Zweitering et al. [31] demonstrated that a properly trained neural network could outperform the traditional algorithms in solving the lot-sizing problem for specific ordering and carrying costs. Their work was later extended by Stehouwer et al. [32] to include the overtime cost. Our research is yet another extension to the latter work in that the developed neural network model is based on thousands of lot-sizing pro-