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A review on simulation metamodeling for decision support systems using artificial neural networks

Ein Überblick über die Simulationsmetamodellierung für Entscheidungssysteme unter Verwendung künstlicher neuronaler Netze

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Abstract: Flexible and agile manufacturing systems can benefit from computer-aided tools that improve and speed-up the decision-making process. The combined use of discrete event simulation together with decision support systems enables manufacturers to test different control alternatives, scheduling and sequencing strategies for a specific planning horizon. Because multiple runs are typically necessary for this, computational effort of simulation models is a key limiting factor that contrasts with the need for quick planning decisions. A popular method for reducing that computational time is the use of Artificial Neural Networks (ANN) metamodels that approximate the simulation in a cheaper-to-compute functional model. This paper aims to review recent cases of simulation metamodeling through ANN for manufacturing and logistics systems in order to understand the current state of the art in simulation metamodeling. A theoretical framework of a possible solution for two identified problems will also be presented.

1 Introduction

Recent years have shown the emergence of new challenges for manufacturers; they need to improve their flexibility, efficiency, and have to adapt to an increasing demand for customizable products (Dalmarco et al., 2019). This is made possible with the use of computer-aided tools and methods. Recognized as a key aspect of the digital factory, Discrete Event Simulation (DES) is widely used as an analysis tool for manufacturing or logistics systems (Bangsow, 2020). It enables a complex analysis of the dynamics of a manufacturing system and the evaluation of different alternatives in order to adopt an appropriated strategy. Mainly used during the planning phase, companies use DES in order to optimize a manufacturing system before transferring these changes reality.

With the emergence of Industrie 4.0, information and communication technologies are enabling companies to manipulate large amounts of real-time data. Thus, DES can be used during production in order to evaluate new scenarios and changes in the production system in real time (Heilala et al.). These simulation models are often integrated into more or less complex Decision Support Systems (DSS), in order to assist decision makers into taking the best possible decision in a complex environment (Kasie et al., 2017).

Even if recent years have shown a continuous expansion of computational power, DES is still computationally expensive. For users of simulation-based DSS, it is important to reduce this computational time in order to be able to quickly analyse many different decision-making scenarios. For Sobottka et al. (2019), computational effort is a key limitation of simulation-based optimization that contrasts with the need for quick planning decisions. To address this problem, a cheaper-to-compute metamodel of the simulation model can be created. The most promising technique for is the use of Artificial Neural Networks (ANN) (Sobottka et al., 2019).

The goal of this paper is to review cases of DES metamodeling using ANN in literature. Simulation engineers often do not have a machine learning background and could be interested in learning how different metamodels were created in order to reduce computational time and how well they performed.

The first part will address DES in the manufacturing field. The second part will focus on DSS for manufacturing and their limitations. After a small introduction about ANN, a review of current literature about the usage of ANN for the metamodeling of DES will be presented. The sixth part will present current problems for simulation metamodeling and a possible solution approach to them. The last part will focus on the conclusions of the review and how further research can be needed.

2 Discrete Event Simulation for Manufacturing

DES is a simulation method used in order to represent a manufacturing system using a distinct sequence of state changes occurring in time (Omogbai and Salonitis, 2016). Because of its flexibility and simplicity in understanding the dynamics and behaviour of manufacturing systems, DES is one of the most commonly used simulation techniques today (Negahban and Smith, 2014).

The traditional goal of DES is to model and analyse a manufacturing system during its planning phase. Performance, bottlenecks, utilization rate and standby times, can be analysed for different control and planning strategies (Bangsow, 2020).

DES can also be used during the operational phase throughout production. In order to do this, manufacturers need to synchronize real-time data from the manufacturing system with the simulation. In literature, they are referred to as adaptive simulation models (Denkena et al., 2017). Heiko et al. (2008) defined the association of a simulation system and a physical system as a symbiotic simulation system: the simulation model benefits from the physical model by obtaining the necessary data in order to initialize itself and the physical system benefits from the optional control feedback from the simulation. If failures or plan deviations occur, the DES model can be used in order to predict the impact on production and assist decision makers in taking tactical and operational decisions (Heilala et al., 2010; Jahangirian et al., 2010).

3 Decision Support Systems for manufacturing

DSS are interactive computer-based systems that enhance the ability of decision-makers to solve problems (Sprague and Carlson, 1982). They are intended to improve and speed-up the decision making process (Power, 2001). It is possible to classify DSS in five categories: data-driven, communication-driven, document-driven, knowledge-driven and model-driven DSS. Power (2001) provides more information on this topic. Model-driven DSS are widespread in the manufacturing field. They facilitate access and manipulation of a model in order to analyse different decision scenarios and discover the most favourable alternatives under a given situation (Felsberger et al., 2019). The model used in a model-driven DSS can be analytical or a simulation model. In the case of decision making for manufacturing systems, DES is commonly used because of its ability to represent complex and dynamic systems on a global level in a visually interactive model.

Heiko et al. (2008) differentiated decision support systems from decision control systems. For them, a DSS only supports an external decision maker by helping him in taking a decision whereas a decision control system can implement decisions directly. In literature, they can also be referred to as passive and active DSS (Felsberger et al., 2019).

Kunath and Winkler, 2018 defined different use cases for DSS and manufacturing systems. The first use case is dynamic scheduling. Using operational data from the manufacturing system, the DSS can test different control alternatives in order to create scheduling and sequencing strategies for a specific planning horizon. It can also be possible to integrate suppliers as external resources into the dynamic scheduling system. The second use case concerns the offer-making process. For a make-to-order production system, a DSS can be used in order to predict delivery dates and prices by using the configuration of the product and the current state of the manufacturing system as input. This can also be done if the customer wants to change an existing order. In the future, an active DSS could be integrated into the product configurator and automatically suggest prices according to available delivery dates to the customer.

Manufacturers that benefit the most from simulation-based DSS have flexible and highly variable manufacturing systems with dynamic situations and unforeseen events where it is necessary to respond quickly in an appropriate way. (Prajapat et al., 2020)

DSS capable of suggesting optimal scheduling decisions typically require multiple simulation runs in order to find the most appropriate decision. Because DES is a computationally expensive tool, calculation time can often be a limiting factor (van Gelder et al., 2014; Dunke and Nickel, 2020; Kasie et al., 2017). In order to reduce computational time from simulation models, metamodels, also known as surrogate models, can be considered. In this case, a cheaper-to-compute functional model approximates the unknown input-output function of the time-consuming simulation model (van Gelder et al., 2014). Out of all the different metamodeling techniques, the use of Artificial Neural Networks (ANN) has been found to be the most appropriate and popular method (Fonseca et al., 2003; van Gelder et al., 2014; Negahban and Smith, 2014; Sobottka et al., 2019).

4 Artificial Neural Networks

ANN are known as universal function approximators. They are made of different layers of interconnected units called neurons. Cybenko (1989) and Hornik et al. (1989) mathematically proved three decades ago that a neural network with one hidden layer could approximate any continuous function to a reasonable accuracy. Figure 1 presents an example of an ANN with 3 input neurons, 2 hidden layers (5/3 neurons) and 1 output neuron. It approximates an unknown function with 3 inputs and 1 output.

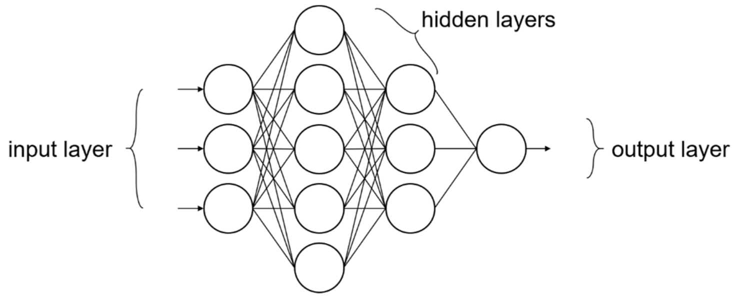

Figure 1: *Example of a feed forward Artificial Neural Network*

ANN use hyperparameter in order to describe their architecture and behaviour. A hyperparameter can, for example, be a number of hidden layers or a type of activation function. For more understanding about ANN in general and about their architecture, see Nielsen (2015). There are different types of ANN; for the metamodeling of DES models, the most frequently used type of neural network is the feedforward ANN, sometimes referred to as a multilayer perceptron, which is typically used in classic regression problems with tabular data.

After training an ANN, it is possible to measure its accuracy using the coefficient of correlation R. It measures the correlation between output and target values on a scale from 0 to 1 (Nuñez-Piña et al., 2018). It is also possible to use the Mean Absolute Percentage Error (MAPE), which calculates the accuracy of the predictions.

5 Review

A literature review was carried out in order to identify different cases of Simulation metamodeling using ANN. The data collection process was conducted on April 8, 2021, by searching *neural networks "discrete event simulation" manufacturing metamodel* in Google Scholar. Only papers published after 2015 and results from the first 10 pages were shown, except for Senties et al. (2009) and Azadeh et al. (2013). After filtering the results by “relevance”, the authors proceeded to select accessible papers presenting interesting manufacturing or logistics use cases of simulation metamodeling through ANN with enough information in the employed method and results. Every reviewed paper concern DSS capable of finding optimal scheduling parameters for a specific planning horizon: analysing the Buffer Allocation Problem (BAP), finding optimal Priority Dispatching Rules (PDR) and generating an Optimal Production Plan (OPP).

Table 1 gives a quick overview of the reviewed papers, their objective and results.

***Table 1:** Reviewed papers*

Authors	Objective	ANN Results
Kłos and Patalas-Maliszewska (2019)	BAP	93% accuracy
Nuñez-Piña et al. (2018)	BAP	R=0,99
Azadeh et al. (2013)	PDR	95% accuracy
Azadeh et al. (2015)	PDR	Satisfying
Xanthopoulos and Koulouriotis (2018)	PDR	R=0,99
Dunke and Nickel (2020)	PDR	95% accuracy
Senties et al. (2009)	OPP	Satisfying
Sobottka et al. (2019)	OPP	R=0,90
Jackson et al. (2019)	OPP	Limited

5.1 Analysing the Buffer Allocation Problem

Kłos and Patalas-Maliszewska (2019) studied the BAP and presented a metamodel of a DES model created in Plant Simulation. Its goal was to study the impact of buffer capacity on the average throughput of a manufacturing system. In order to train an ANN, 100 random permutations of buffer allocations were created using the simulation. The created ANN had two hidden layers (9/3 neurons) and a hyperbolic tangent activation function. The accuracy of the metamodel was around 93%.

An ANN for studying the BAP was also created by Nuñez-Piña et al. (2018), using 360 training samples. The authors compared 780 different ANN architectures and found that the best performing one (R=0,9996) had 4 hidden layers (8/8/10/10 neurons) and a hyperbolic tangent activation function.

5.2 Finding Optimal Priority Dispatching Rules

Azadeh et al. (2013) presented a DSS for the dynamic scheduling of a job shop. Their objective was to find the optimal PDR for each machine. An ANN was trained using data from a DES model. The authors used the following methodology: N dissimilar training samples are created using the DES model. If the desired error percentage after training is not acceptable, the level of N is increased by 10% and the training starts again. An ANN with 3 hidden layers and a log-sigmoid transfer function was trained. By choosing an acceptable MAPE of 5%, it was necessary to generate 200 training samples.

Azadeh et al. (2015) presented another DSS for dynamic scheduling, this time for a production system for different types of canned fruits. The goal was also to calculate every permutation of PDR. A DES model was created in AweSim and generated 100 random permutations, used as training samples for an ANN. For every new planning horizon, every permutation of PDR was calculated through the ANN in order to find the most efficient ones (total of permutations: 2401). The results seemed satisfying for this particular use case.

Xanthopoulos and Koulouriotis (2018) developed an ANN in order to dynamically choose PDR in a flexible manufacturing line. A DES model was created in order to generate 192 training samples. The ANN was made of one hidden layer of 8 neurons and a hyperbolic tangent transfer function. The coefficient of correlation R was 0,99, indication a strong linear relationship between output and target values.

Dunke and Nickel (2020) developed an ANN for dynamically choosing control strategies in an order picking system. Its goal was to determine in real time which order consolidation and picker routing strategies were the most appropriate for the current state of the system. A DES model created using AnyLogic was used to train the ANN. The authors tested different ANN hyperparameter and the best results were obtained with 2 hidden layers (14/10 neurons) and a hyperbolic tangent transfer function. The accuracy of the metamodel was around 95%. The authors suggest using an ANN for a quick first impression on what the outputs might be.

5.3 Generating an Optimal Production Plan

Senties et al. (2009) developed an ANN for the scheduling of a semiconductor wafer fabrication system. Its purpose was to generate planning decisions for the next planning horizon. A DES model of the system was created using MELISSA and used as input, decision variables, that can be optimized and order specific data concerning the next planning horizon. Out of the 2400 generated training samples, 66% were used for training the ANN and 33% for its testing. The authors used an ANN with one hidden layer of 15 neurons and a hyperbolic tangent activation function. The ANN was able to generate planning decisions 100 times faster than the DES model and approximated the simulation with a high accuracy.

Sobottka et al. (2019) studied the feasibility of creating an ANN for the dynamic scheduling of an industrial bakery. The objective was to create an optimal production plan for the next planning horizon. The manufacturing system was modelled using a DES software in order to create training samples for the ANN. If 9 variables needed to be optimized, the authors found that 5000 training samples where enough for a coefficient of correlation R of 0,9. If the number of variables increased to 25, 2 million samples would be necessary.

Jackson et al. (2019) presented a solution for an inventory control problem. Because of the scale and dimensionality of the inventory control problem, optimizing specific decision variables in the simulation model would take too much time. For that reason, the authors trained an ANN using training samples from a DES model. An ANN was created using a rectified linear unit activation function, 3 hidden layers (30/30/10 neurons) and was trained with 5 datasets of 1000 samples. Stochastic noise reduced the accuracy of the model. The authors suggested that increasing the number of simulations runs and changing the architecture of the ANN could improve its accuracy.

6 Solution Approach

The literature review presented in this paper was able to identify problems in the current metamodeling process. A possible theoretical framework for a solution addressing these problems will be presented.

6.1 Research Gaps

The first problem is the technical knowledge needed for the implementation of a simulation metamodel. Simulation engineers are often domain experts, not necessarily computer scientists or programmers. They have deep knowledge of the domain-specific notations used in their domain (Lara et al., 2014). Creating, training, testing and validating an ANN requires complex machine learning skills, which simulation engineers often do not have. Thus, the lack of available qualified resources can be an obstacle for the implementation of such a metamodel.

The second problem concerns the inexistence of a universal methodology for the creation and training of an ANN. The review presented in this paper showed that researchers used almost all the time different ANN hyperparameters: number of hidden layers, number of neurons per hidden layer, activation function and amount of training samples. In some cases, researchers tried different ANN configurations and selected the best ones, see (Nuñez-Piña et al., 2018). Because an ANN is essentially a black-box, it can be difficult to understand and improve the efficiency of the model. Reducing that complexity could make simulation metamodeling more accessible while reducing its average error.

6.2 Framework

A theoretical framework of a possible solution is presented in Figure 2. The goal is to automatically be able to approximate a DES model into a cheaper to compute ANN model. The whole metamodeling process should be automated in a way that no machine learning skills are required from the user. In this case, a specific plugin could be implemented into an existing simulation software in order to simplify the process.

This implies that a DES model has already been created. The verification and validation process should be done using the DES model before starting the metamodeling.

The proposed framework enables any simulation user to configure and start an automatic neural network architecture search for the metamodeling of a validated simulation model. The different inputs and outputs of the simulation would first need to be highlighted by the user so that the algorithm can automatically create the necessary training samples for the ANN. Since most of the existing DES software do not include the tools necessary to create a neural network, an external ANN-capable platform will have to be used. An algorithm integrated into the platform will use the generated training samples from the simulation in order to train different ANN models using specific hyperparameters.

When training a metamodel, a small amount of training samples will only be used for its validation. These samples have never been seen by the metamodel. Accuracy can be calculated by analysing the difference between the validation data and the predicted values from the metamodel. If the desired accuracy is achieved, the metamodel is validated.

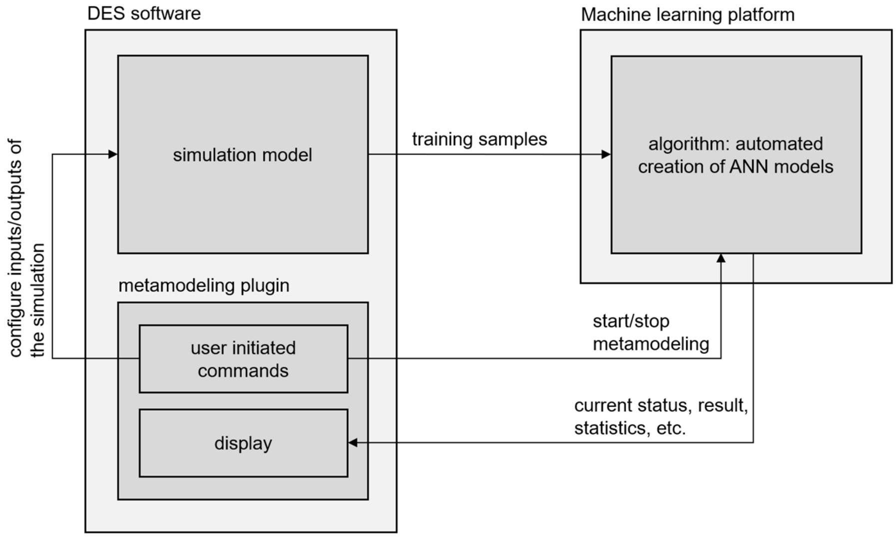

Figure 2: *Proposed framework for automating the metamodeling process*

6.3 Next Steps

The next research steps for the authors are to implement the theoretical framework in an existing simulation software in order to investigate its feasibility and efficiency. In order to search the best performing ANN architecture, the algorithm will have to train many different ANN. This could lead to high computational time. The algorithm should also be tested with different types of manufacturing systems and different levels of simulation complexity.

7 Conclusion

This paper presented a review of recent literature concerning the metamodeling of DES using ANN for the reduction of computational time. The use cases, methods, metamodeling parameters and results of the reviewed papers have been specified in this paper in order to have a better overview of the current state of the art in simulation metamodeling. The use of Google Scholar for selecting the papers can be criticised, because of the unclear prioritization of the large number of results. This could potentially lead to relevant papers being overlooked. Using a Database like Scopus or the archives of Simulation conferences like the Winter Simulation Conference or the ASIM Dedicated Conference could lead to fewer, but more relevant results.

The review was able to highlight the absence of a clear method for the metamodeling of simulation models and emphasized the complexity of the process. In order to simplify the whole metamodeling process, a theoretical framework was presented. The idea would be to implement an algorithm inside an existing DES software, that would automatically train an optimal ANN for the metamodeling of a specific simulation model inside the DES software. This theoretical framework will need to be implemented, tested and validated using different use cases and levels of complexity.

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