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MODELLING ENERGY CONSUMPTION IN SIMULATION MODELS BY THE USAGE OF DEEP LEARNING

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ABSTRACT

Traditionally, simulation has used data about the real system for input data analysis or within data-driven model generation. Automatically extracting behavioral descriptions from the data and representing it in a simulation model is a weak point of these approaches. Machine learning, on the other hand, has proven successful in extracting knowledge from large data sets and transform it into more useful representations. Combining simulation approaches with methods from machine learning seems therefore promising. By representing some aspects of a real system by a traditional simulation model and others by a model generated from machine learning, a hybrid system model is generated. This extended abstract suggests a specific hybrid system model that incorporates a deep learning method for predicting high-resolution time series of power usage of machining jobs according to the control code the machine is operated on.

1 INTRODUCTION

Traditional simulation modeling approaches are bound to and potentially limited by the chosen modeling paradigm. Machine learning, in contrast to simulation, is a set of algorithms that provide an effective way to aggregate rather big data sets and to find patterns within that data (Goodfellow et al. 2017). Such patterns can then be used to describe the mechanism of the system of interest that emitted the original data points. Applications of machine learning are not limited to sets of static data, as in the most prominent picture classification tasks, but can also be applied to dynamic data sets such as time series data. This duality results in machine learning methods being a promising match for hybrid systems modeling (HSM), since a chosen simulation methodology can be complemented by a machine learning method with a different methodology and vice versa.

Here we propose such a HSM that combines discrete event simulation (DES) with Sequence-to-Sequence neural networks. This newly proposed HSM focuses on the realistic depiction of power usage of a job in a manufacturing cell.

The aim of the proposed method is to be able to predict time series for the power usage of unknown jobs by means of appropriately trained artificial neural networks (ANN). The basic idea here is to train an ANN with relevant control information, such as the numerical control codes of production jobs of a machine tool, and the high-resolution time series of power consumption measured for these jobs.

2 SEQ2SEQ AS A CONSTITUENT OF DISCRETE EVENT SIMULATION

Artificial neural nets are used to identify patterns in complex data structures. If patterns change over time, this temporal sequence of patterns is understood as a sequence. If the inputs and outputs of a deep learning method are sequences, this is referred to as Sequence2Sequence (Seq2Seq) architectures. If the input sequence is encoded into a specific neuronal layer or decoded therefrom, those parts of a network topology are called encoder resp. decoder (Goodfellow et al. 2017). If the task of a Seq2Seq model is to map asynchronous sequences to one another, such structures are generally referred to as encoder-decoder networks (Goodfellow et al. 2017). Further explanations of the encoder-decoder implemented here can be found in (Cho et al. 2014; Sutskever et al. 2014; Goodfellow et al. 2017).

For testing the applicability of Seq2Seq architectures, two input and output sequences from the same temporal and spatial domain were monitored and used. Specifically, we used a job's time series of energy consumption as well as the numerical control code of the same job. The numerical control (NC) code describes the sequence of necessary technological process steps up to the completion of a job. This NC code must first be translated into a sequence of numerical values, that retains the structure of the targeted input sequence. A *tokenizer* assigns such numeric value to each symbol or set of symbols present in the numerical code, e.g. on the basis of the frequency of the symbol concerned. The NC code is then trained to the time series data of the machine tool's usage of energy within a Seq2Seq neural net.

Once the training is finished, the trained neural net is used in the machine tool's DES-model to predict the time it takes to finish a job and the quasi-continuous energy usage while a job is manufactured.

3 CONCLUSION AND FUTURE WORK

The basic functionality of the described approach was confirmed in the test scenario. However, the generated time series still have to be critically questioned and validated in further research work. On the one hand, there is still a lack of evaluation methods for generative models of machine learning to check the generated time series entries for the meaningfulness of their entries. At the moment this is done by the observation and comparison of the generated time series through an expert of the application. However, a general suitability of the methods used is assumed, since the system exhibits a plausible learning behavior at a high level of abstraction, even if the result of what was learned still has to be considered critically.

For a final evaluation of the methods used, it is advisable to increase the qualitative and quantitative data basis of the Seq2Seq model. Furthermore, a suitable evaluation method must be added to the proposed solution. The further development of the machine learning method described above and its use for hybrid simulation models is currently the subject of ongoing research.

Also, once the method is successfully established and validated, a solution could be developed that produces plausible power consumption forecasts for unknown jobs based on their numerical control codes. This would have a high practical potential and would also be a breakthrough from a scientific point of view.

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