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Application of Deep Learning based on a Simulation Model to classify Production Orders

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Abstract

The application of artificial intelligence can support employees in decision-making on highly complex issues. The improving performance of computers in combination with the progress in deep learning makes it possible to answer problems with a very high complexity. The approach presented in this paper demonstrates that production orders of an assembly line can be classified with regard to a chosen key performance indicator using deep learning as a surrogate model for a logistics simulation. Evaluating production orders in advance enables a higher performance of a production system without cost intensive process improvements. The aim of the approach, demonstrated on an exemplary use case, is to utilize deep learning to determine which sequence of individual production orders leads to a high throughput in units. Results gained reveal a significant increase of average throughput and therefore showing the feasibility of the approach. The application of artificial intelligence models enables that such complex questions can be solved in a short time. Consequently, the model is able to classify production orders with an accuracy of 86%.

Keywords: Artificial Intelligence, Classification, Deep Learning, Production and Logistics simulation

1. Introduction

New technologies enable the extensive generation of different data from heterogeneous systems as well as the efficient processing by data-oriented approaches in logistics. This technological progress allows the use of computing-intensive applications at comparatively low costs. However, conventional methods of structured information models or manually written programs are reaching their limits regarding the performance and maintenance effort. In particular, the use of artificial intelligence (AI) as a type of surrogate modeling can help to cope with these new requirements and is already of considerable importance (Wuest et al., 2016; Bárkányi et al., 2021). AI can be used to support people in making time-consuming or difficult decisions within the planning and control of production and logistics systems (Timm and Lattner, 2010). Problems that cannot be solved due to high complexity and extensive connections could be potentially solved by AI (Zafarzadeh et al., 2021).

A frequently mentioned issue regarding planning and control of a production and logistics system is the scheduling and sequencing of production orders (Sun and Xue, 2001; Boysen et al., 2009; Dylewski et al., 2016). Surrogate modeling can be used to provide data on production sequences and consequently the progress of production (Bárkányi et al., 2021). Due to the high complexity of the various possibilities for placing products in the right order, these are often still optimized on experience-based knowledge. This can lead to potentials being wasted regarding the performance capabilities of a system. For example, in terms of a higher throughput in units, which can be achieved by an improved order sequence. A prior validation of the production orders could lead to a higher throughput in units without any other process adjustments such as further resources or longer working times. Hence, costs can be saved this way (Meissner, 2010). In terms of the high complexity of validating production orders, this article aims to answer the following research question (RQ).

RQ: *Can deep learning be used to classify a production order sequence with regard to the system's throughput?*

This article demonstrates the usage of advanced AI techniques (deep learning) to classify production orders. The approach shows the required components and their interactions. For verification, realistic data - generated with a simulation model - is used to train and test an advanced AI model. Through the classification of production orders, the aim is to provide a faster decision support about which sequence will generate a high throughput in units.

2. State of the art

In scheduling and planning a multitude of surrogate model types are used, e.g. (piecewise) linear regression, polynomial function and neural network (Bárkányi et al., 2021). For the following approach the focus is on the application of deep learning as a surrogate model. In this section, the fundamental functionalities of AI are described. Furthermore, the current state of the art and the applications within production and logistics systems are presented. Finally, the research gap for the following approach is highlighted.

2.1. Artificial Intelligence

The term AI can be divided into various techniques. These include machine learning (ML) and deep learning (DL). Reasons for the rising use of ML are the increasing amount of data in higher quality as well as the improved computing power at lower costs. (Goodfellow et al., 2016) ML enables computers to automatically learn patterns in data (Domingos, 2012). A decisive advantage is that a trained ML model can be applied to new data in the same structure without great effort (Goodfellow et al., 2016).

ML is a basic form of applied statistics and can be divided into three categories of *supervised*, *unsupervised*, and *reinforcement learning*. These types of learning differ mainly in the required input information and the way in which models interacts and learns from data. For the following article the primary focus lies on supervised learning. *Supervised learning*, involves learning with different features of a dataset and are additionally provided with a label. The aim is to learn a function by minimizing the discrepancy between real and predicted values within the dataset. In contrast, *unsupervised learning* is used when the input data is not labeled and has no predetermined target values. (Goodfellow et al., 2016)

DL is a method for information processing of large amounts of data based on ML. It describes a deep neural network, where the depth is determined by the different number of layers. There are various definitions about DL so the following section will describe how a neural network operates (Zhang et al., 2018). Objective of artificial neural networks (ANN) is to learn nonlinear relationships of input and output data. ANN consist of different layer types such as input, output, and hidden layers in between, which are interconnected. In the process of training, information is recorded in form of patterns which are finally weighted and evaluated in hidden layers according to their impact. This is repeated until the objective functions are minimized. During forecasting, data is fed through the networks to obtain a prediction. There are more than ten different types of DL techniques, which vary in different ways (e.g. complexity, type of neuron linkage, etc.) (Wang and Wang, 2018). In the following section, three different DL architectures are shortly presented, which will be used to validate the approach.

An often-used advanced technique of DL is the *recurrent neural network* (RNN), with its special implementation *long-short-term-memory* (LSTM). Other architectures are *convolutional neural networks* (CNN) as well as *multiple layer perceptron* (MLP). LSTM works with time series data and uses hidden elements that enable inputs to be stored for a longer period of time. This, allows information from the beginning of the time series to influence a prediction (LeCun et al., 2015). An MLP will feed information only forward through the neural network (Goodfellow et al., 2016). It consists of fully connected layers which are able to process data. If the data is too big to process, filtering is required. This is why CNNs also use different layers such as the convolutional layer and pooling layer. Through these layers the number of connections is limited even with large input quantities (LeCun et al., 2015). Hence, this explains the main application in the field of image recognition.

In addition to other advanced ANNs, there is also the possibility of developing an individual solution by combining different advanced DL techniques. Applications of ML and DL within production and logistics systems is described in the next section.

2.2. Artificial Intelligence in production and logistics systems

The application of AI within production and logistics systems has already been discussed in various literature reviews. (E.g. Woschank et al., 2020) mentions that the presented applications are often conceptual approaches or use cases in early development phase. In the next two sections, the relevant literature is reviewed, which focuses on the application of AI within planning and control of production and logistics systems.

Many articles dealing with AI in production systems focus on the current state of the art using ML to support decision-intensive planning and control tasks (Usuga Cadavid et al., 2020; Wuest et al., 2016; Elbasheer et al., 2022). They often mention similar points like the data sources used for AI application, which are information systems such as enterprise resource planning (ERP) or manufacturing execution systems (MES). Further data sources include data from technical equipment and generated data e.g., through simulation models (Usuga Cadavid et al., 2020). With regard to production planning and control, these include process control and monitoring as well as intelligent planning and scheduling or automated optimization within production systems (Usuga Cadavid et al., 2020). A further key aspect within production or manufacturing processes is predictive maintenance. For example, (Cho et al., 2018) describes an hybrid ML approach for predictive maintenance by combining supervised and unsupervised learning in smart factories. (Ungermann et al., 2019) describe an approach how AI and the implementation of further sensors can be used to monitor and optimize technical equipment based on key performance indicators (KPI).

Articles that focus more on logistics are often used to support planning processes or to predict future scenarios. (Knoll et al., 2016) describe an approach to use ML within logistics planning tasks. The overall objective is to support inbound logistics planning by extracting knowledge of logistics processes to predict future scenarios. Other authors deal with the anticipation of disruptions within production logistics based on relevant KPI. They validate their AI models on a simulation (Vojdani and Erichsen, 2019). Another approach of (Knoll et al., 2019) shows an automated packaging planning approach by using ML to support the rough planning for different parts and load carriers and should help by determining the fill rate. (Uttendorf et al., 2016) describe an approach to automatically generate a layout for the use of automated guided vehicles with AI. Other approaches often focus more on building frameworks, describing abstract concepts for the future as well as review the current state of the art to identify further research activities (Li et al., 2017; Weichert et al., 2019).

Literature shows that a number of AI approaches in the field of production and logistics systems have already been described and partially tested. However, the application of AI for manufacturing and logistics environments is still at an early development phase. Most applications often describe theoretical concepts or approaches that have been prototypically tested. While the following approach is also a prototype, further steps are taken by being based on a real system with dimensioned and described processes. Hence, the following approach is closer to a practical implementation and aims to solve a specific problem. The aim for nearly all procedures is to solve complex problems that can hardly be solved or can only be solved with a great effort. Thus, supporting or automating decision-making processes with regard to planning and control. In addition, self-generated data e.g., from simulations, is often used to test AI models for production- and logistics-specific problems. On the one hand, despite the large amount of data generated in real processes, this is due to the fact that it is not available in the necessary quality or quantity. The use of AI to classify production orders with regard to the system's throughput has not yet been described, although it is to be expected that enormous efficiency potentials can be leveraged in the process of planning sequences of production orders.

3. Approach to classify a production order based on a simulation model with deep learning

In the following section, the approach developed with its components as well as the application within a use case is described. Afterwards the results of the use case and the findings are discussed.

3.1. Key elements of the approach

The required elements of the approach are presented in Figure 1. Key elements are: (1) a validated simulation model, (2) input data for the simulation model, (3) output data of the simulation model containing the desired KPI, and (4) a programming environment with AI clustering, data preparation, and DL. In the next section, the general approach is shortly presented.

The *initial situation* resembles the connection to the real physical world. It is a real production or logistics system that obtains its production or transport orders from an information system such as enterprise resource planning (ERP) system, manufacturing execution (MES) and generates a system output. The *productive operation with AI support* describes the application of the trained AI model in a real production system. The *AI training process* consists of two parts. The simulation model is used to generate training and testing data for the AI model. It is particularly important that the results of the simulation model match the reality, e.g. the actually completed orders of a real production system, as much as possible. With the output data of the simulation, requirements for the AI model shall be defined. In the next step, the input data in form of features and labels are divided into different classes using clustering (e.g. K-Means, etc.). The classes should show how the utilized features influence the desired KPI. The training data generated needs to be preprocessed. Finally, a DL model is trained and if the predefined requirements are met the model is given into the productive operation. Otherwise a

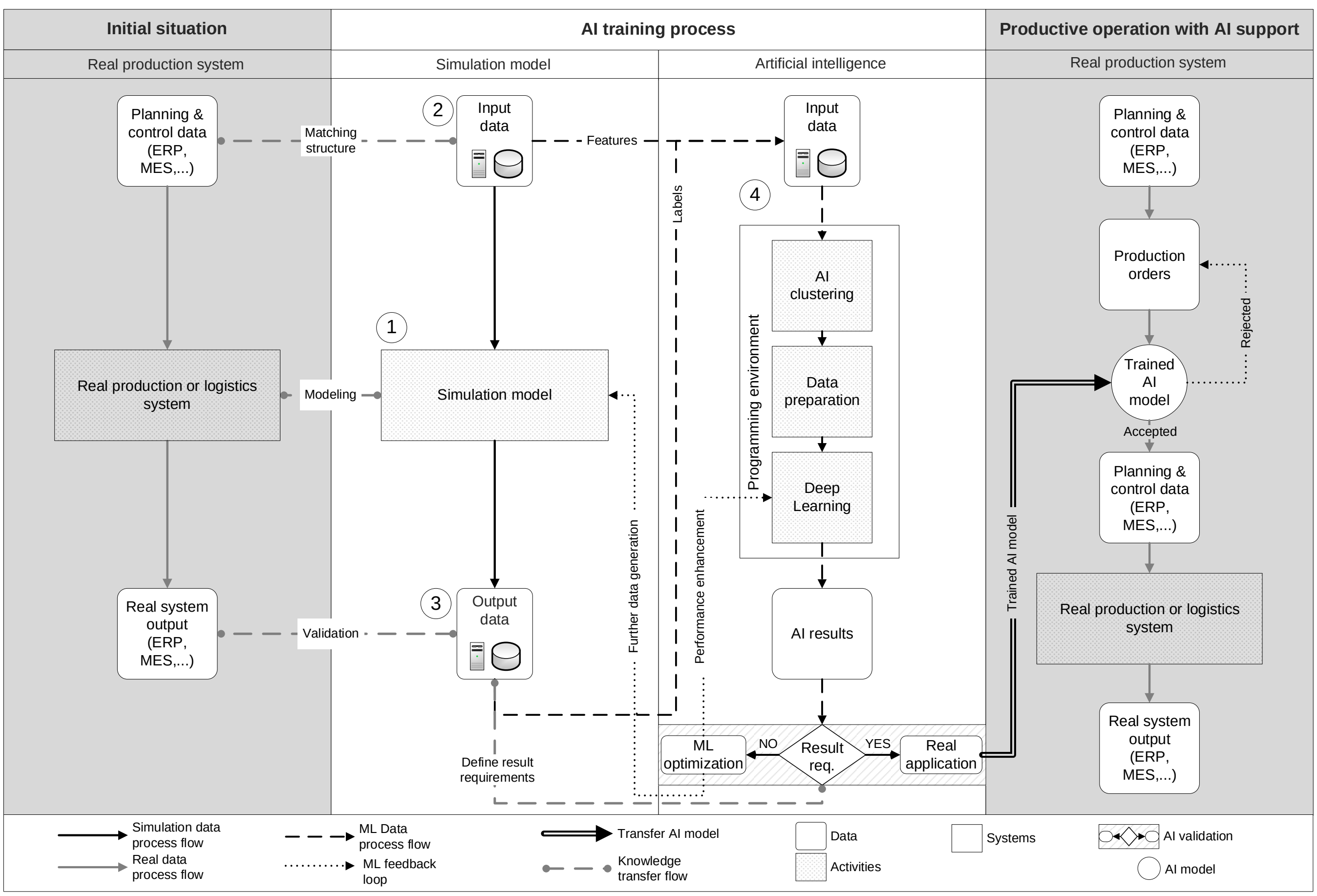

Figure 1. Approach to classify a production order based on a simulation model with deep learning

feedback loop back to the creation of the DL model or even the simulation model is intended. In the following section the approach is explained in detail using an exemplarily use case.

3.2. Use case

In this section the previously mentioned approach is exemplarily implemented using a U-cell assembly line. The objective in this use case is to predict the KPI throughput in units. By classifying production orders into two categories (high and low yield) the aim is to increase the average throughput in units.

The real production system used is a U-cell assembly line of a medium-sized company which is exemplarily set up in the Technology Centre Production and Logistics Systems of the University of Applied Science Landshut (Blöchl and Schneider, 2016). In the considered system, floor rollers in six different variants (three colors and two different frames) are assembled in seven steps (Figure 2).

Figure 2. Representation of the used U-cell assembly line simulation model

As shown in Figure 2, a simulation model is built up in Plant Simulation which contains the entire value-added process. It is based on the real system, from goods reception to storage, transport to assembling, and finally to goods issue. The simulation model was validated with a *Historical Data Validation* by comparison of various KPI from the real system against the simulation model such as throughput in units, cycle time, etc. (Rabe et al., 2008). Due to the fact that the U-cell assembly line at the Technology Centre is used for educational purposes, the conceptual data as well as results of educational production runs are used for the validation of the simulation model. Random generated production orders, using the same structure as the production orders of the U-cell assembly line are used as input variables for the simulation model. The other areas such as goods reception, storage, transport, and goods issue only influence the simulation model indirectly through request of the assembly line.

At the beginning, a set of 5,000 random production orders which corresponds to 5,000 working days is generated through *numpys random.choice algorithm* and prepared to test the functionality of the DL architecture. For this purpose, 4,000 production orders are used for training and 1,000 for testing the model. The variants within a production order are distributed by color as follows: 60% for high runners, 30% for middle runners, and 10% for least runners. All six different variants were randomized, considering their distribution within the production orders. Each production order was limited to 751 units, as this is the maximum output quantity of the assembly line each day. Every simulation run corresponds to one working day with sixteen hours of working time. The resulting amount of possible production order combinations is show below:

$$\frac{751!}{450! * 225! * 75!} \approx 7{,}94 * 10^{289}$$

The initial approach was to use regression algorithms. Probably due to the large number of features (751) classic regression algorithms as well as (deep) neural networks struggle to identify patterns in the data. Due to these findings a two-step procedure that starts with clustering the data and afterwards classify them, was selected. Hence, the results of the simulation model are clustered into five classes using K-Means. Based on the result of the clustering, the label throughput in units is substituted for the classifying task at hand. The four clusters with lower yields are further grouped together. Thus, the classification model has to distinguish between the two classes of high and low yield. This helps to increase the prediction accuracy of the model used in the next step. The separation between high and low yield is found at 722 units with the average throughput in units of 709 and is displayed in Figure 3. As shown in Figure 1 it is necessary to define the requirements for the results in order to evaluate the final AI results. With regard to the present problem, the requirement is to reach an accuracy of 75%. This means that three quarters of the production orders should be correctly classified. The average in the high yield class is at app. 742 units and the low yield class at app. 665 units. With the desired accuracy set to 75% it is expected that the average throughput in units to be at 723 units. This will bring the average throughput over the separating 722 units. Hence, the output in the productive system should always be high yield.

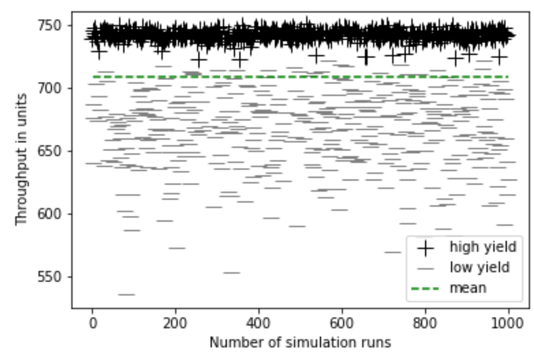

Figure 3. 1,000 randomly sequenced production orders with two classes clustered by K-Means used for testing

In the following step data preparation, different sample and augmentation techniques are used. Furthermore, feature engineering (FE) is conducted. As the original dataset contains 751 features which are seemingly of equal importance feature engineering was applied. During feature engineering the production order was splitted into sets of varying numbers of products. For each set the four following metrics were used: *dominant color*, *longest continuous occurrence of the dominant color*, *dominant frame*, as well as *the longest continuous occurrence of the dominant frame*. The four sets are used because of the following assumptions. The color belonging to products of the least runner category have a negative impact on the target throughput

Table 1. Base datasets used with the resulting number of features

Datasets	Varying numbers of products	Combination of different DS	Prescaled	Number of features
DS 1	*30 units*	*No*	*No*	*55*
DS 2	*15 units*	*No*	*No*	*115*
….	….	….	….	….
DS 5	*1 unit*	*No*	*Yes*	*751*
….	….	….	….	….
DS 13	*1 unit*	*DS 1, DS 2, DS 3, DS 4*	*No*	*1518*
DS 14	*1 unit*	*DS 1, DS 2, DS 3, DS 4*	*Yes*	*1518*

in units. The same applies for frames. A similar impact for a continuous chain of equal products is expected. This was done to improve model performance. As a result, 14 base datasets (DS) were created as shown in Table 1.

Furthermore, combinations of different datasets were utilized to extend the number of available datasets. For selected datasets prescaling was applied. In the process, the original values are manually scaled to a range between 0 and 1 which is more suited to a neural network. The base datasets were consequently combined to generate 84 different datasets. This was done by applying principal component analysis (PCA), scaling and normalization as displayed in Table 2. Afterwards the data is randomly divided into a training and test dataset.

Table 2. The 84 datasets including data preparation

Datasets	PCA	Scaling	Normalization
-	*PCA (0.96)*	*StandartScaler()*	*MinMaxScaler()*
1-14*	*No*	*No*	*No*
15 - 28	*Yes*	*No*	*No*
29 - 42	*No*	*Yes*	*No*
43 - 56	*Yes*2*	*No*	*No*
57 - 70	*No*	*No*	*Yes*
71 - 84	*Yes*	*No*	*Yes*

*Original dataset

As mentioned in section 2.1 there are numerals DL architectures available. For this use case a LSTM architecture was selected due to the information implicitly given by the sequence of production orders. As the data available might contain a lot of unnecessary information filtering can be beneficial, hence CNN are chosen. Furthermore, an MLP was picked for control reasons as it is not as computing intensive and is easier to apply.

Figure 4 shows the best datasets (DS 5) as well as its variations tested against a simple CNN. It can be noted that the lines visible at the beginning at 0.41 as well as 0.59 resemble a neural network prediction of only one class. Exceeding this threshold (0.41 - 0.59) the neural network performs a prediction on both classes.

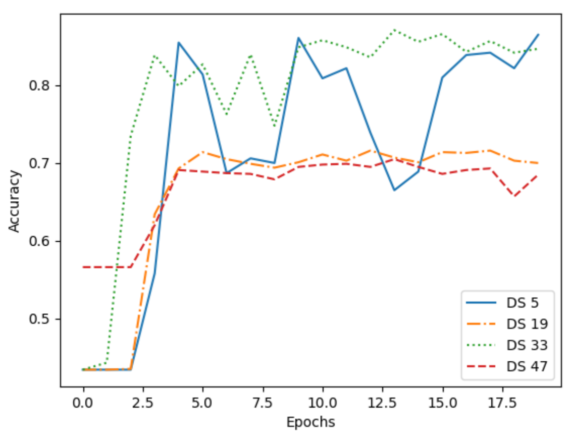

Figure 4. CNN performance on the 14 base datasets

Testing was done for all 84 different datasets, which were compared against numerous variations of the three chosen ANN architectures. The best performing networks for each category (CNN, LSTM, MLP) were selected for further hyperparameter tuning. Furthermore, the best dataset was selected (Figure 4, DS 5).

Final adjustments to the neural network are carried out during "hyperparameter tuning". In this step each component ranging from hidden layers sizes to activation functions and solvers such as "Adam" or "Stochastic gradient descent" (SGD) can be individually fine-tuned.

At this point, the chosen AI model, which has been extensively tuned is trained on the selected dataset. After training, the model is used on the still unknown data contained in the test dataset. To check the AI result, various metrics can be used. The following metrics are important for classification: "recall", "precision", "f1-score", and "accuracy" (Sammut and Webb, 2010). "Precision" value indicates the rate of true and false positive predictions for all positive values. With the "recall" value, the ratio of true positives and false negatives is described. "F1-score" is defined by the balance between "precision" and "recall". "Accuracy" describes the ratio of correctly classified predictions. It is essential that the different metrics for both classes are as equally pronounced as possible. Thus, both classes can be predicted identically. The results applying the approach presented are described in the section 4.

Further, the developed AI model is implemented in the productive operation. Here, a production order sequence is given by the planning and control system of the real production system. The production order sequence is classified by the developed AI model and accepted if a high yield is predicted. If a low yield is predicted the production order sequence is rejected and a new one has to be created.

4. Results

The first approach aims to predict the throughput in units with advanced deep learning models such as LSTM and CNN. It was possible to achieve results with an accuracy of approx. 60% already at the beginning. However, to achieve even better results, the data preparation was optimized with feature engineering and PCA. While the CNN architecture required only scaling of the input data, the MLP architecture additionally required FE for its best score. For the LSTM network scaling, FE, and PCA was necessary. The results for each architecture tested as well as the data preparation used are displayed in Table 3.

A CNN was found to be the best performing. This CNN consists of eleven layers and has 598,421 trainable parameters. A maximum "accuracy" of 86% is obtained with a "precision" of 90% for the high yield class (1). Furthermore, 85% of the given production orders are correctly classified in the low yield class (2). It has to be mentioned that the accuracy reached by the CNN is higher than the LSTM architecture and it requires significantly less data preparation (Table 3).

Table 3. Results of the best deep learning classification models for each type for both classes high (1) and low (2) yield

Architectures	Precision	Recall	F1-score	Accuracy	FE	PCA	Scaling
CNN (1)	*0.90*	*0.86*	*0.88*	***0.86***	*Yes*	*Yes*	*Yes*
CNN (2)	*0.82*	*0.88*	*0.85*				
LSTM (1)	*0.82*	*0.83*	*0.83*	***0.80***	*No*	*No*	*Yes*
LSTM (2)	*0.77*	*0.77*	*0.77*				
MLP (1)	*0.69*	*0.78*	*0.73*	***0.68***	*No*	*No*	*Yes*
MLP (2)	*0.67*	*0.55*	*0.60*				

Based on the results, the approach is able to identify the high and low yield class with a high probability. In order to verify the approach presented, the trained AI model is implemented in the productive operation. 1,000 productions orders (Figure 3) are classified by the AI model. The production orders that are classified as high yield with its corresponding throughput in units are shown in Figure 5. As displayed the average throughput in units is at 736 which is 27 higher than the none AI classified production orders (Figure 3). Furthermore, the desired throughput of 723 units has been exceeded. These results confirm the successful application of the approach to classify production orders with a deep learning architecture.

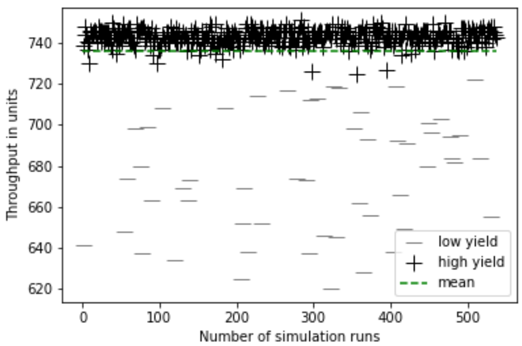

Figure 5. 570 pre-validated production orders with the original classes

5. Discussion

The following section considers the strengths and weaknesses of the approach. The application within a use case demonstrates that production orders can be classified with regard to the resulting throughput in units by using DL. This enables a faster decision on the production orders, which can increase the efficiency of a production system without additional costs by further resources. In a hypothetical scenario between a simulation- or AI-based approach the decisions about the production order can be sped up by a factor of 2,000. This is based on the fact that in the presented use case a complete simulation run of one working day takes 40 seconds while a single classification requires 0.02 seconds. With these results and the stated limitations (e.g. distribution of variants, etc.), the research question can be answered as follows: Within the use case utilizing the approach presented, production orders can be classified by a CNN with an accuracy of 86%. The aforementioned neural network is able to increase the average throughput in units by 27 products per working day. In summary, a DL model is able to classify a production order sequence with regards to the system's throughput.

A significant advantage of the approach is that by using a simulation model the available training data can be increased enormously. In the use case discussed 4,000 working days were simulated. It is important to noted that during these simulated 16 years of work no changes except the production sequence were made. In comparison a real production system continuously encounters changes. By utilizing a simulation model less frequent occurrences can be included in the training data. This allows the AI model to handle such events better.

Nevertheless, there are still some limitations. First of all, it should be mentioned that challenges like overfitting proofed difficult to overcome. It has to be noted that in a real production system the sequence of production orders is not chosen randomly due to different restrictions. However, this should neither influence training nor the application in the productive operation. Further investigations should demonstrate how the developed approach reacts to randomly occurring problems in production and logistics systems (e.g. failures, downtimes etc.). While only the classification of throughput in units was validated, other key performance indicators, such as predicting the completion time of individual units or the throughput time, needs to be tested. For this purpose, the data basis may need to be enlarged.

6. Conclusions and outlook

In this article, an approach is presented to classify production orders with an advanced deep neural network based on a simulation model. The aim is to classify production orders sequences that lead to a higher throughput in units.

For this purpose, production orders were simulated and the corresponding throughput measured. The generated data was clustered with K-Means and used to create a new dataset. This dataset was consequently utilized to train a deep learning classification model. The findings show that artificial intelligence models are capable of solving complex issues with a very high number of different possible combinations, which can only be answered by optimization algorithms with enormous effort. Furthermore, the developed approach in combination with the created AI is able to provide results in a shorter time and with sufficient quality. This is a first approach and further research is needed. In terms of application with a simulation model, future research should emphasize on dealing with the inaccuracies in the simulation model in combination with the AI model. These inaccuracies carry the potential to multiply if combined. With regard to the stated problem, future work should focus on a comparison with existing approaches to production order sequence optimization.

In future research activities, the approach presented should be tested on a production system with real production orders to gain further insights to improve the approach. Furthermore, the approach should be compared to other surrogate modeling techniques.

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