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APPLICATION OF LSTM MODEL FOR FORECASTING PRODUCTION ORDERS

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Abstract: *Production planning is critical in modern industry, especially in custom machine manufacturing, where efficiency and meeting deadlines are essential. Time series analysis has become pivotal in optimizing production systems in recent years. This study presents the application of LSTM neural networks for production scheduling predictions, modelling temporal patterns and seasonal fluctuations based on historical data. The goal is to enable more efficient planning and accurate delivery times, thereby improving overall production performance. Preliminary results suggest that LSTM can outperform traditional statistical models, such as linear regression. It is crucial to tailor the model to the company's specific needs and relevant data.*

Keywords: *production planning, LSTM, time series analysis, efficiency optimization*

1. INTRODUCTION

With the growth of the economy, optimization and forecasting are playing an increasingly important role in production logistics. In a competitive market, those with more accurate forecasts gain an advantage. Within production, the coordination of transportation tasks with manufacturing is becoming increasingly critical. Production planning plays a key role in modern industrial systems, as it directly impacts efficiency, costs, and the optimal use of resources. The constant changes in globalized markets and fluctuating demand place increasing pressure on the development of forecasting methods.

Traditional forecasting techniques, such as time series analysis or linear regression, often struggle with limited accuracy when facing complex, nonlinear patterns observed in manufacturing and logistics systems. The main challenge is that tasks requiring solutions are often too complex for simple dynamic algorithms. In our rapidly evolving world, production scheduling is a field fraught with challenges, requiring greater attention to coordination, including communication between machines as robots become more prevalent. In a dynamic environment, with numerous human factors, adopting a flexible problem-solving approach is essential. Large companies process vast amounts of data within enterprise resource planning systems, ensuring that everyone works within a unified platform and has real-time information on internal and external factory changes. Forecasting plays a crucial role in ordering components ahead of customer requests, anticipating future needs. This allows for more efficient planning and preparation for upcoming demands. Securing a competitive advantage often depends on completing orders earlier than rival companies.

In recent decades, significant advancements in artificial intelligence and machine learning have opened new opportunities for optimizing production planning. LSTM (Long Short-Term Memory) neural networks have proven particularly effective in time series forecasting, as they can manage long-term temporal dependencies critical for understanding the dynamic patterns of manufacturing processes. The deep neural architecture of LSTM models enables

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the detection of complex trends and seasonal effects that are challenging for traditional methods to capture. Implementing LSTM-based forecasting methods is especially beneficial when production systems require not only predictions of current demand or production volumes but also more accurate estimates of future inventory needs and resource utilization. The model's flexibility and learning capabilities offer a significant advantage in Industry 4.0 environments, where real-time data processing and adapting to dynamically changing production conditions are essential for maintaining competitiveness [1, 2].

The aim of this study is to present the advantages and challenges of applying the LSTM model in production planning and customer order forecasting. Forecasting based on time series data enables the fine-tuning of manufacturing processes, thereby reducing inventory costs and increasing productivity. The research focuses on examining the accuracy and robustness of the LSTM model, with particular emphasis on production data characterized by long-term dependencies and nonlinear patterns.

2. Literature review

The exploration of integrating artificial intelligence (AI) techniques and applications in industrial production and logistics has advanced significantly in recent years. Special attention is given to optimizing production systems, demand forecasting, developing decision support systems, and applying various algorithms and models to effectively predict electricity consumption, highlighting the comparison of model performance using real-world data [3-5]. In the rapidly evolving field of logistics, particularly in e-commerce, efficient task scheduling and resource allocation have become critical factors for operational success. Advanced AI techniques, especially deep learning models such as LSTM networks, are increasingly recognized as viable solutions for addressing complex challenges in intelligent logistics systems.

Since the late 2010s, the examination of LSTM models has become widespread due to their success in delivering accurate forecasts. Models incorporating state-of-the-art technologies began to emerge, emphasizing AI-based solutions. These models focus heavily on deep learning [4, 6-8]. The LSTM model is increasingly recommended over ARIMA (autoregressive integrated moving average) [9-11]. According to [10], the LSTM model operates with a 22% error rate, while ARIMA shows a 34% deviation on the same dataset.

The study by Changchun L. et al. (2022) emphasizes the necessity of innovative logistics models that enhance efficiency through intelligent scheduling systems. These models not only optimize resource management but also improve service quality, addressing the growing demand for accurate and reliable deliveries [12]. Similarly, the research by Issaoui Y. et al. (2021) supports this need for efficiency by proposing an LSTM-based approach that enables dynamic scheduling and efficient resource allocation, ultimately improving customer satisfaction and operational performance in smart logistics frameworks [13].

Ketan R. (2020) highlights the importance of employing AI-driven strategies to optimize logistics processes and support sustainable practices. Their findings advocate for the development of intelligent scheduling algorithms that can adapt to changing market demands, ensuring that logistics systems remain agile and responsive [14]. Likewise, the work of Salah B. et al. (2018) underscores the importance of optimizing logistics activities through machine learning techniques, demonstrating significant improvements in task scheduling and resource efficiency [15].

Together, these studies shed light on the transformative potential of LSTM and other AI methods in reshaping logistics operations, paving the way for smarter, more efficient systems that not only meet but exceed the ever-evolving expectations of customers and businesses alike [16, 17].

3. EXPLANATION OF LSTM MODEL

LSTM networks are a specialized type of recurrent neural networks (RNNs). RNNs were originally developed to account for temporal sequences in problems such as speech recognition, language modelling, or time series forecasting. However, RNNs were limited in their ability to effectively handle long-term dependencies due to the so-called "vanishing gradient" problem, where the significance of information from earlier steps gradually diminishes during training. LSTM networks addressed this issue with their unique architecture.

We chose this model because research has demonstrated its success across various fields in generating accurate forecasts on large datasets. Additionally, it is well-suited for identifying the long-term dependencies necessary for production planning. In industry, numerous periods or factors need to be considered, such as planting, harvesting, Easter, Christmas, New Year's Eve, economic trends, and different weather conditions [18, 19].

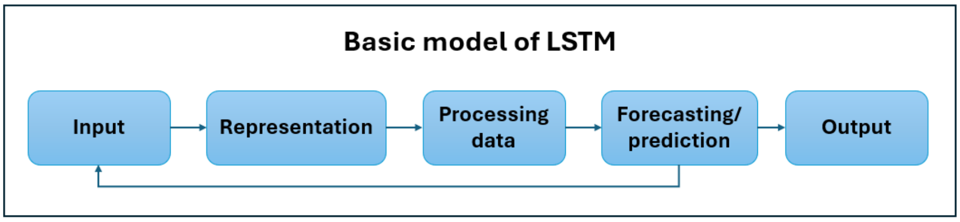

Figure 1. *Basic model of LSTM*

Fig. 1 illustrates a feedback loop, where the calculated forecast is fed back into the system to enable processing based on these calculated data points. This feedback mechanism is crucial as it allows the system to account for data that are not yet available at the time of forecasting. Based on this, the key components can be defined as follows:

1. Input
The input typically consists of time series data, where temporal order and historical data significance are critical. Time series data generally comprise timestamped measurements, such as production volume, resources, capacity, or delivery dates recorded during a manufacturing process. The input can be visualized as a multidimensional matrix, where observations corresponding to different time points are used in the modelling process. It is essential to arrange the data in chronological order before use, as the model relies on indexing to process data according to their respective timestamps [20].

2. Representation
The internal structure of LSTM models is complex, representing input data through specialized memory cells. These memory cells are capable of retaining long-term temporal dependencies while filtering out irrelevant information from noisy data:

- Input Gate: Controls how much of the current input influences the memory cell's state.
- Forget Gate: Determines which past states should be forgotten or retained.
- Output Gate: Regulates how much of the current state contributes to the output and what information flows into the next steps.

The data representation within LSTM is a dynamically evolving memory state that captures long-term patterns while eliminating short-term noise [12, 21, 22].

3. Processing of Data
Data are processed step by step in temporal order. At each time step (e.g., a day, hour, or minute), the LSTM cell receives a new input and updates the state of its memory cells. This process is governed by the LSTM's gates, which filter the data and enable the model to learn which patterns are critical for forecasting and which can be disregarded.

The primary advantage of LSTM over other neural networks is its ability to handle long-term dependencies. This is particularly important for production data, where the production volume of a specific month may depend on processes spanning longer periods, not just recent results [9, 23].

4. Prediction
After processing the inputs, the model transitions to the prediction phase. The output layer can be a fully connected neural layer that forecasts the next value or values in the time series. Prediction possibilities include:

- Single Data Point Prediction: Forecasting a specific future time point, such as the production volume for the next week or month.
- Multi-Step Prediction: Using the LSTM model to predict several steps ahead, such as daily production volumes for the next month or estimated production capacity/product quantities over multiple months.

The forecasts are generated based on learned patterns and the information retained in the memory cells. Predictive performance is critical for industrial applications such as production process optimization, inventory management, or demand forecasting [24-27].

5. Output
Finally, the LSTM model delivers the prediction through the output layer. The output can be a scalar value, such as the production volume for a specific day, or a sequence if multiple future points need to be forecasted. The following figure details how the LSTM model generates predictions [28].

Fig. 2 illustrates how temporal dependencies are divided into seasons based on the source of the data. All incoming data are aggregated into an "i-th hour" table, which then moves to a decision-making phase. At this point, the system receives an instruction either to stop, as the desired value has been reached, or to return to the beginning of the LSTM model.

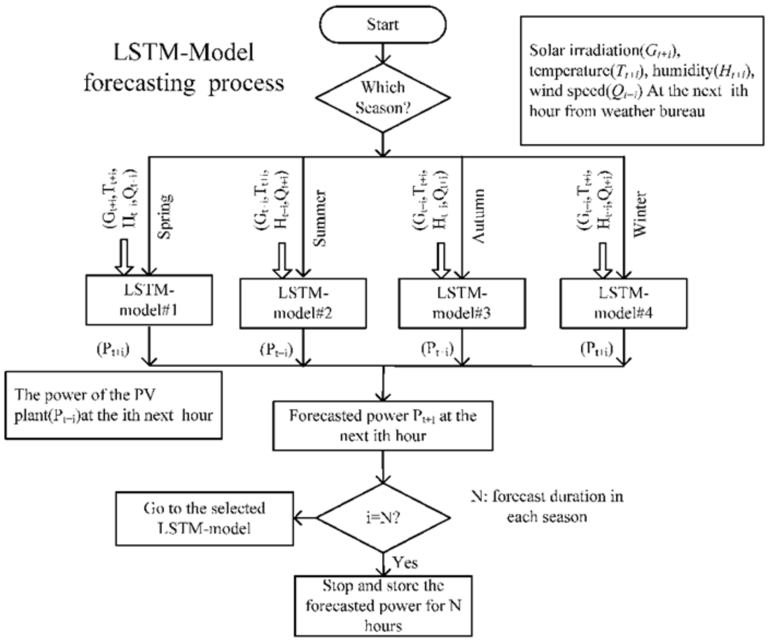

Figure 2. *LSTM Model Forecasting Process [21]*

4. TESTING THE LSTM MODEL

For testing, we used a standard home computer with the following specifications:

- Processor: AMD Ryzen 7 5700X3D
- Graphics Card: RTX GeForce 4070 Ti 12GB GDDR6X
- RAM: 32 GB GDDR4

We successfully built a functioning model in which the program was tested based on various parameters, achieving successful predictions. The program was developed in Python, following the aforementioned research [29].

The base dataset is defined as follows.

```
# Data setup (already sorted by date) Sorbarendezett tételek
data = {
    'Dátum': ['2023.01.01', '2023.02.01', '2023.03.01', '2023.04.01', '2023.05.01',
              '2023.06.01', '2023.07.01', '2023.08.01', '2023.09.01', '2023.10.01',
              '2023.11.01', '2023.12.01'],
    'Mennyiség': [0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89]
```

Figure 3. *Main part of testing dataset*

Fig. 3 depicts yearly shipments, where Fibonacci numbers were used for simplicity. The test dataset contains far more data and spans more than one year.

The data represent the production or shipment dates of a product. For instance, "Item A" can be represented as having 0 shipments in January 2023, 1 in February, and so forth. The following results were obtained for the (1-6) time series:

Table I.

Sampling and Results

Sampling Size (pcs)	13th Element	14th Element	15th Element	16th Element	17th Element	18th Element	Average Execution Time (s)
30	144	233	376	601	966	1512	17
300	144	233	377	610	985	1590	19
3000	144	233	377	610	987	1597	65
30000	144	233	377	610	987	1597	645

In Table I., discrepancies are highlighted in orange, indicating areas where the model's accuracy can be assessed. It is evident that for forecasting 6 time series, a sample size of 3,000 was sufficient. However, when forecasting more time series, discrepancies began to appear—this was tested on the 7th element, where accurate results were not always obtained. With a sample size of 30,000, we successfully analysed up to 12 time series.

The system produces more accurate forecasts as it processes more samples. Data rounding was implemented within the program code, where values above 0.5 were rounded up and those below were rounded down. Regarding the volume of data examined on the time axis, we concluded that setting at least 2 time points was sufficient for this simple model; further increases did not improve the forecast.

The depth of the neural network was tested with between 1 and 200 neurons, but no significant changes were observed. A definitive conclusion is that increasing the number of neurons should be paired with an increase in sample size.

For the forget gate, a 10% value was set, meaning the model "forgets" 10% of the data. This is a random algorithm that could be further optimized. Guidelines for setting the main parameters are provided in [30], but these configurations did not perform adequately in our model.

Table 1. LSTM parameter setting.

Parameter	Setting Values
Time step	1
Batch size	1
Loss function	MSE
Activation function	Sigmoid
Neurons	1
Hidden layers	4
Epochs	100
Optimizer	Adam

Figure 3. *Settings of LSTM parameters [30]*

4.1 Advantages and Disadvantages of the LSTM Model

This chapter presents the advantages and disadvantages of the LSTM model, highlighting various factors that influence its applicability and efficiency in different forecasting tasks.

Advantages:

1. Handling Time-Dependent Data and Long-Term Trends: One of the key benefits of the LSTM model is its ability to connect multiple years of data and draw

parallels between two datasets, ensuring long-term dependencies. The model performs exceptionally well in managing time-dependent, sequential data, making it ideal for production scheduling, where past production patterns may influence future outcomes [31-33].

2. Modelling Nonlinear Relationships: LSTM models are effective in handling complex, nonlinear relationships, which are common in production planning, such as the interplay between production cycles and demand fluctuations.
3. Handling Incomplete Data: LSTM models can process incomplete or noisy datasets, which are often encountered in manufacturing environments. It is important to note, however, that care should be taken when setting missing values to zero, as this does not necessarily indicate the absence of data [33, 34].

Disadvantages:

1. Data Intensity: The primary drawback, which we experienced firsthand, is that a relatively large amount of data is required to achieve accurate results. This can be a challenge if sufficient data is unavailable. Incorporating experiential insights into analyses can help address this issue [35, 36].
2. Slow Learning Process: The training process can be time-consuming, particularly with large datasets or complex models, potentially delaying design cycles. As seen in our example, even with relatively small data, many samples were needed. For datasets containing millions of records, training could take an estimated 1-2 weeks [21, 5].
3. Risk of Overfitting: Due to its ability to detect complex patterns, there is a significant risk of overfitting the existing data, leading to inaccurate forecasts if future patterns differ from historical data [30, 37, 38].
4. Operational Complexity: Operating and fine-tuning LSTM models can be complicated, especially in environments lacking appropriate technical expertise. It is important to note that this procedure requires a properly trained professional [9, 20, 39].

5. DEVELOPMENT SUGGESTIONS

One of the key areas of focus for us is how to accelerate computations without involving additional resources. Hybrid models that combine convolutional neural networks with LSTM models exist, and our research suggests that with appropriate parameter tuning, faster results can be achieved [11, 14, 40, 41].

There is no specific guideline on how to perform sampling with our data. Determining the model's reliability relies on experience and experimentation, but optimization can be cumbersome and time-consuming, especially when only a three-month forecast is required. [42, 43].

Initially, when the model was operational but not fully developed, we were unable to effectively verify whether the program was functioning as expected. We also encountered issues with faulty sample handling, where an input error resulted in inaccurate data. Configuring adjustable and customizable parameters required considerable effort and experimentation.

We had to abandon the random selection algorithm at the forget gate to ensure no data was removed. The model is not yet considered fully optimized, as hybrid models have already shown advancements, demonstrating that further optimization of predictions is possible. However, achieving this requires sufficient high-quality data [12, 18, 28, 29, 30, 5].

In our opinion, hybrid models such as CNN-LSTM (Convolutional Neural Network - Long Short-Term Memory) and ARIMA-LSTM represent promising directions for enhancement. CNN-LSTM combines the strengths of convolutional neural networks and LSTMs, improving the model's ability to simultaneously manage both local dependencies and long-term temporal patterns. Meanwhile, ARIMA-LSTM integrates statistical methods with neural networks, offering superior accuracy in forecasting complex and nonlinear trends. These hybrid approaches could address some of the existing limitations while unlocking new possibilities for robust and efficient predictive modelling in production and logistics contexts [43].

Reinforcement Learning can also be utilized for tasks involving dynamic optimization, offering a way to improve decision-making in production planning through trial-and-error interactions with the system. This adaptive approach allows the model to learn optimal strategies over time by directly interacting with the environment and observing the results of its actions. However, this method is not without challenges, as it requires a well-designed simulated environment to test and train the system effectively. Creating such an environment is computationally intensive, demanding significant resources, which may limit its practicality in some scenarios. Furthermore, ensuring that the simulated environment accurately mirrors real-world conditions is essential to avoid discrepancies in performance when applied in practice.

In addition, we are also considering two simpler machine learning models that could deliver comparable results while being less resource-intensive [44]:

- *Gated Recurrent Units* (GRUs): As a more straightforward alternative to LSTMs, GRUs retain the ability to model sequential data effectively while requiring less computational power. Their streamlined architecture makes them particularly appealing for applications where efficiency and speed are critical, and their simpler design often leads to faster training times without a significant loss in accuracy.
- *Bayesian Neural Networks* (BNNs): These models stand out for their ability to incorporate uncertainty into predictions, making them especially well-suited for highly volatile and uncertain environments, such as those found in production and logistics. By quantifying the confidence of predictions, BNNs offer an additional layer of robustness, which can be invaluable when making decisions based on incomplete or noisy data.

Both of these approaches hold promise for improving predictive performance in production planning scenarios, particularly where computational resources or data availability may be limited. Their respective strengths also make them strong candidates for integration into hybrid modelling strategies, potentially enhancing the adaptability and precision of forecasting systems even further.

Lastly, there are additional helper algorithms rather than standalone models that can significantly improve solution generation and enable faster convergence. These include [45]:

- *Gradient Boosting Models* (e.g., XGBoost, LightGBM): These tree-based ensemble models are highly effective for structured data and serve as an excellent alternative for non-sequential datasets. Additionally, they can be combined with neural networks to create hybrid models, leveraging their strengths for enhanced performance in specific tasks.
- *Kalman Filters*: A traditional yet powerful tool, Kalman Filters remain useful for dynamic systems requiring sequential prediction, particularly in real-time

applications. Their ability to handle noisy and incomplete data makes them an enduring choice for real-world implementations.

- *Attention Mechanisms*: By focusing on the most relevant parts of the input sequence, attention mechanisms significantly enhance the performance of both Recurrent Neural Networks (RNNs) and Transformer architectures. This targeted approach improves predictive power, especially for tasks involving complex patterns and long-term dependencies.

These algorithms, while not standalone models, can be integrated into broader AI systems to augment their efficiency, accuracy, and adaptability in solving challenging predictive tasks.

In logistics and production scheduling and procurement, leveraging advanced AI techniques like LSTMs, GRUs, and hybrid models such as CNN-LSTM can greatly enhance predictive accuracy and operational efficiency. These methods effectively handle temporal dependencies, nonlinear relationships, and volatile data, making them ideal for dynamic environments. Helper algorithms like Gradient Boosting Models and Kalman Filters, combined with mechanisms like attention, further optimize solutions by refining data handling and focusing on critical inputs. Despite challenges such as computational intensity and data requirements, these tools pave the way for more precise demand forecasting and resource planning. Ultimately, adopting these innovations can streamline operations, reduce costs, and ensure a competitive edge in modern production and logistics systems.

6. CONCLUSION

Based on the work presented, it can be concluded that LSTM models are promising tools for analysing and forecasting temporal data, particularly in production processes where long-term trends and patterns need to be considered for efficient planning. Both theoretical and practical examples of this have been provided.

Continuing this research and further developing the models could contribute to improving predictive performance and increasing production efficiency. Development suggestions include exploring ways to accelerate computations, such as implementing hybrid models that combine convolutional neural networks with LSTM architectures. It is also important to address the challenges of optimization, as customizable parameters and issues with faulty sample handling can significantly impact the model's performance. As a continuation of this research, advanced AI models and helper algorithms, such as LSTMs, GRUs, hybrid CNN, Gradient Boosting, and attention mechanisms, can enable precise demand forecasting, efficient resource planning, and streamlined operations, effectively addressing the complexities of logistics, production scheduling, and procurement in dynamic environments.

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