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Predicting Failures in Plastic Pipe Production Line Using LSTM Neural Network Enhanced with Penguin Algorithm

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Abstract: Plastic pipe production involves multiple interconnected stages, such as extrusion, cooling, and cutting. Each of these stages is prone to various types of failures, whether mechanical or environmental, which can disrupt workflow, reduce product quality, and lead to economic losses. Traditional maintenance methods, including reactive and preventive approaches, are often costly and inefficient. In this study, a predictive maintenance approach is proposed using a Long Short-Term Memory (LSTM) neural network optimized with the Penguin Search Optimization Algorithm (PeSOA). LSTM networks are particularly suited for analyzing time-series data from sensors due to their ability to learn long-term dependencies. PeSOA is applied to optimize key hyper-parameters such as learning rate, dropout rate, and number of LSTM units. Experimental results demonstrate that the LSTM + PeSOA model outperforms both the baseline LSTM and the LSTM optimized using Particle Swarm Optimization (PSO), achieving higher accuracy and reliability. This model shows promise in enabling early failure prediction and reducing unplanned downtime, offering a more intelligent and efficient maintenance solution for plastic manufacturing environments.

Keywords: plastic pipe production; LSTM; PeSOA; long-short-term memory; Penguin Search for Achievement optimization algorithm.

INTRODUCTION

The plastic pipe production process is complex, encompassing multiple stages, including extrusion, cooling, and cutting. Each stage contains multiple failure modes that can disrupt production, reduce product quality, and cause significant financial losses. Failures can be mechanical (such as mold blockages, motor failures, etc.) or environmental (such as temperature fluctuations), which can hamper production. (Büchi, G. *et al*., 2020)

Most traditional maintenance practices in the industry are either reactive or scheduled. Reactive maintenance occurs when equipment suddenly stops and is extremely costly. Scheduled maintenance, on the other hand, is performed even if the equipment is operating properly according to a predetermined schedule, to avoid future maintenance costs.

These strategies result in imperfect resource allocation and inefficiencies. This has led to the emergence of a new strategy based on predictive maintenance, which relies on machine learning (ML) to reduce wasted downtime and optimize maintenance scheduling.

Importance of Predictive Maintenance in Plastic Pipe Production

The ability to predict failures in the plastic pipe industry in real time impacts profitability, quality, and efficiency. Using historical sensor data, virtual models can be trained using machine learning and leveraged to identify failure paths within production lines. These steps reduce maintenance time and extend equipment lifespan by allowing for timely intervention and proactive maintenance. (Werth, J. 2021)

OBJECTIVE OF THE STUDY

Using a long-short-term memory (LSTM) neural network and an optimization algorithm called Penguin Search for Achievement (PeSOA), we present a novel method in this paper for predicting failures in a plastic pipe production line. By examining temporal sensor data, the primary objective is to create a reliable predictive maintenance model that can precisely forecast failure events. LSTM networks are especially well-suited to time series data because of their capacity to identify long-term dependencies in sequential data. Nevertheless, these models necessitate adjusting hyper-parameters, which is computationally costly. Consequently, the Penguin algorithm is presented to enhance the performance of an LSTM model by optimizing its hyper-parameters. (Sensors, 2021)

BACKGROUND AND LITERATURE REVIEW

Plastic Pipe Production Process

To achieve the desired quality of pipes, controlling the temperature of the plastic melt and the extrusion process requirements, such as the speed and force of the plastic through the pipe forming die, are vital issues. Die blockages, irregular speeds, or temperature fluctuations can lead to product defects. (Decis. A. J. 2023)

The cooling process, which solidifies the pipes to their final shape and cuts them into suitable

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lengths, is also an important product finish; failure to do so can affect product quality (Fig. 1). (Decis. A. J. 2023)

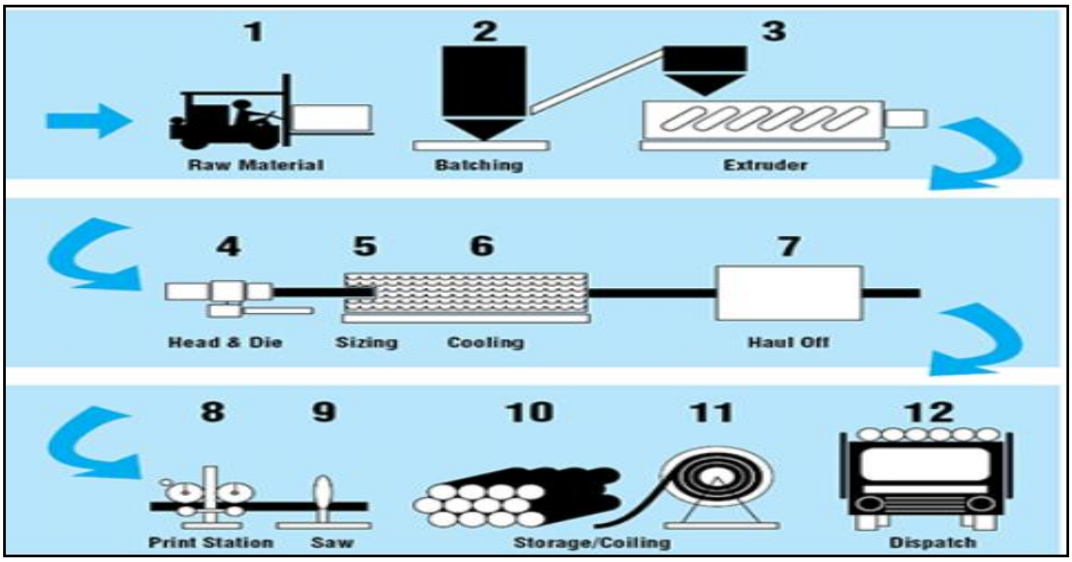

Fig. 1: Multiple Stages in the Manufacturing Process of Pipes Prone to Failure.

Traditional Maintenance Approaches
Traditionally, maintenance in plastic pipe production falls into three categories:

- Reactive maintenance: This occurs after an equipment failure. Unplanned downtime following an equipment failure often results in significant production losses.
- Preventive maintenance: This occurs at regular intervals, but can be costly if unnecessary maintenance is performed, despite its importance in reducing unexpected breakdowns. (Comput. Ind. Eng, 2022)
- Predictive maintenance: This reduces downtime and maintenance costs and is considered more cost-effective. This method schedules maintenance only when necessary, using real-time data to predict when a breakdown will occur.

Machine Learning in Predictive Maintenance
Machine learning has revolutionized predictive maintenance by enabling systems to learn patterns from historical data and predict future failures. LSTM networks, a type of recursive neural network (RNN), have gained popularity for their ability to learn from time series data. They can model sequential dependencies in data, making them particularly effective in predicting failures in industrial processes (Fig. 2). (Malawade *et al.*, 2021)

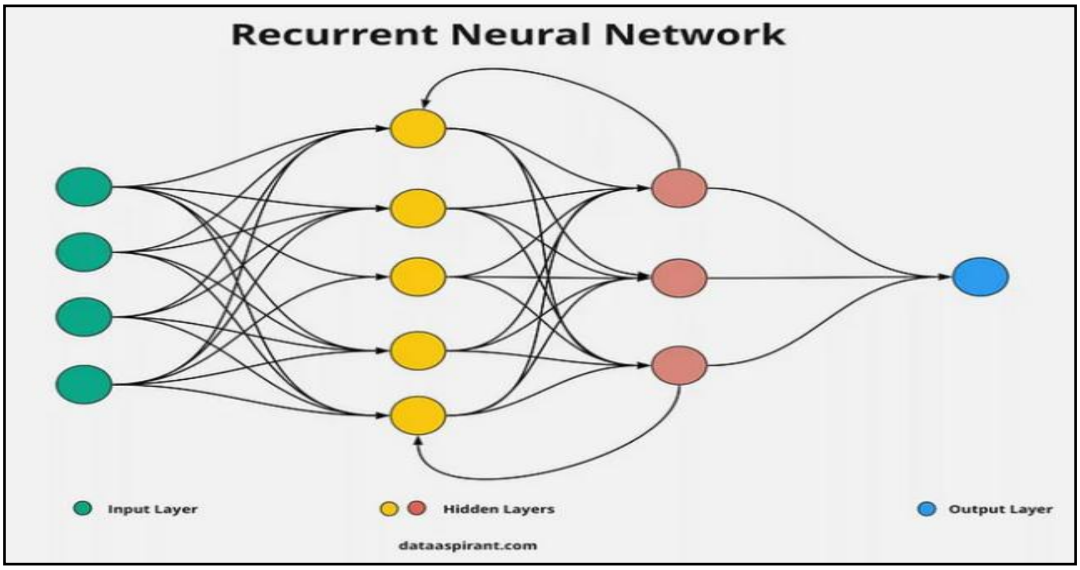

Fig. 2: Recurrent Neural Network (RNN).

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In addition to recurrent neural networks (LSTMs), optimization algorithms are commonly used to tune the hyper-parameters of machine learning models. Common optimization algorithms include particle swarm optimization (PSO), genetic algorithms (GA), and ant colony optimization (ACO). These algorithms help navigate the hyper-parameter search space, improving model accuracy. (Int. J. Prod. Res, 2023)

Penguin Search Optimization Algorithm (PeSOA)

The Penguin Search Optimization Algorithm (PeSOA) is a relatively recent optimization technique inspired by the foraging behavior of penguins. Penguins dive in groups to search for food, taking turns to find the best food source. (Comput. Ind. Eng, 2022) Similarly, in the context of optimization, PeSOA uses multiple "penguins" (candidate solutions) to explore the search space and converge toward optimal solutions. The algorithm is particularly useful for optimizing deep learning models, where the hyper-parameter search field is large and complex. (Zhou, Y. *et al*., 2020)

Problem Statement

The plastic pipe production process is susceptible to various failures that are difficult to predict using traditional methods. Current predictive maintenance models struggle with hyper-parameter tuning, resulting in suboptimal performance. This study aims to bridge this gap by integrating LSTM with PeSOA to improve failure prediction in a plastic pipe production line. Specifically, the study will: (Serradilla, O. *et al*., 2020)

• Improve the accuracy and reliability of failure predictions.

• Optimize the LSTM model using PeSOA to avoid local minima and ensure better hyper-parameter selection.

• Provide real-time predictive maintenance solutions that can be implemented in operational environments.

METHODOLOGY

Data Collection and Preprocessing

The dataset used in this study consists of sensor readings collected from a plastic pipe extrusion production line. These sensors monitor various parameters such as temperature, pressure, vibration, motor speed, and other operational features. Data is sampled every 5 seconds over a period of 6 months, yielding millions of data points. (Büchi, G. *et al*., 2020)

Data preprocessing includes:

- Missing data handling: Missing values are filled using interpolation or forward/backward bagging methods. (Al-Taie, M. *et al*., 2024)
- Normalization: All sensor readings are normalized to ensure uniformity across features, which helps speed up convergence during model training.
- Time series segmentation: The data is segmented into fixed-length sequences (such as 30-second windows) to train the LSTM model.

LSTM Model Architecture

The layers that make up the LSTM model are as follows:

- Input layer: This layer takes pre-processed sensor data as input. (M. Bogojeski *et al*., 2020)
- LSTM layer: This layer uses multiple LSTM units to capture temporal dependencies in the data; the number of units is a hyper-parameter optimized using PeSOA.
- Dense layer: This fully connected layer has a single output neuron and uses a sigma activation function to predict the likelihood of a failure.
- Dropout layer: Prevents overfitting by randomly setting some neurons' outputs to zero during training.

Penguin Search Optimization Algorithm (PeSOA)

PeSOA is used to optimize the following LSTM hyper-parameters: (Energies, 2024)

• Number of LSTM units: The number of neurons in each LSTM layer.

• Learning rate: Controls the step size during gradient descent.

• Batch size: Specifies the number of samples used in each gradient update.

• Dropout rate: Reduces overfitting by randomly disabling neurons during training.

The Optimization Process Includes the Following Steps:

1. Initialization: A population of penguins (candidate solutions) is randomly generated, each representing a set of hyper-parameters.

2. Fitness Evaluation: The fitness of each penguin is evaluated by training an LSTM model using the corresponding hyper-parameters and calculating the validation loss.

3. Exploration and Exploitation: The penguins update their positions based on their own fitness

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and the collective behavior of the group. The algorithm explores the search space to find the globally optimal solution.

4. Convergence: The process continues for a predetermined number of iterations or until convergence is reached.

EXPERIMENTAL RESULTS

Experimental Setup

Experiments were conducted on a device with the following specifications:
1. Hardware: 8GB RAM, AMD Ryzen 5 5500 U with Radeon Graphics 2.10 GHz.
2. Software: Python 3.11.8, amd64.

The dataset consisted of over a million data points, with 10 input features and one output feature (failure or normal). The data was divided into two sets: training and validation, with 80% used for training and 20% for validation.

Results Comparison

We compared the performance of the following models:
1.Baseline LSTM model: An LSTM model with default hyper-parameters.
2.LSTM + PSO model: An LSTM model optimized using particle swarm optimization.
3.LSTM + PeSOA model: An LSTM model optimized using the Penguin Search optimization algorithm.

Table 1: Comparison of model performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LSTM (Baseline)	87.2	85.9	84.3	85.1
LSTM + PSO	89.4	88.2	87.5	87.8
LSTM				

The results show that the LSTM + PeSOA model significantly outperforms both the baseline LSTM and LSTM + PSO models. This demon-strates the effectiveness of PeSOA in improving LSTM hyper-parameters and improving prediction accuracy.

Analysis

LSTM + Pesoa guarantees the model's ability to predict errors, guarantees initial identity and intervention, exhibited by increased accuracy, accuracy and recall values. Because it reflects the low probability of the events with the lack of error in the model, the better degree of recall is especially important.

DISCUSSION

Challenges and Limitations

Despite the promising performance that LSTM shows combined with the Pesoa adaptation algorithm, the model is still facing several important challenges that can affect its general efficiency. One of the most important concerns is data quality, because the model's future accuracy is very high, depending on the integrity and reliability of input data. Problems such as sensors noise, lack of values and data collections such as deviations can greatly reduce the performance if they are properly addressed through appropriate passion and data cleaning techniques. Another major challenge is overfit, which LSTM models are exclusively exposed to, especially when trained on small or unbalanced datasets. This can lead to poor normalization of unseen data. To reduce this risk, regularization methods such as dropout and early stops have been used. Finally, calculation costs are associated with training deep learning models and performing population -based adaptation algorithms such as PESOA relatively higher. This is especially true when working on large-scale datasets, where high processor power and memorial resources are required, and present a limit for real-time or resource interaction applications.

Practical Implications

The successful implementation of the LSTM + PeSOA approach holds substantial potential for the plastic pipe manufacturing industry. By enabling accurate predictive maintenance, this method can significantly reduce unplanned downtime, enhance operational efficiency, and lower overall maintenance costs. Moreover, the model's ability to be integrated into real-time monitoring systems allows for continuous performance forecasting and early fault detection, thereby supporting more informed and timely decision-making processes on the production line

Future Work

Future research will focus on the following areas:

- Model certification: Integration of the model with current future maintenance platforms and puts it in a real -time production environment.
- Hybrid model: To increase the extraction function, LSTM is combined with other sophisticated models, such as transformer

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models or conversion of neural networks (CNN).

- Edge Computing: Use the model on the Edge device instead of cloud computing to provide real -time predictions.

CONCLUSION

In order to predict errors in the plastic pipe production line, this study showed how well the LSTM nerve network can be integrated with Penguin Search Optimization -algorithm (pesoa). By using Pesoa's ability to effectively adapt the hyperparameter, the proposed model improved the traditional LSTM model. This type of future maintenance solution has the ability to significantly increase the operational efficiency of the production environment.

REFERENCES

1. Büchi, G., Cugno, M. and Castagnoli, R. “Smart factory performance and Industry 4.0.” *Technol. Forecast. Soc. Change*, 150 (2020): 119790,
2. Werth, J. “LSTM for Predictive Maintenance on Pump Sensor Data.” *Towards Data Science*, 10 (2021).
3. Malawade *et al.*, "Neuroscience-inspired algorithms for the predictive maintenance of manufacturing systems." *IEEE Transactions on Industrial Informatics* 17.12 (2021): 7980-7990.
4. Jiang, Y., Dai, P., Fang, P., Zhong, R. Y., Zhao, X., & Cao, X. "A2-LSTM for predictive maintenance of industrial equipment based on machine learning." *Computers & Industrial Engineering* 172 (2022): 108560.
5. Bampoula, X., Siaterlis, G., Nikolakis, N., & Alexopoulos, K. "A deep learning model for predictive maintenance in cyber-physical production systems using lstm autoencoders." *Sensors* 21.3 (2021): 972.
6. Decis. A. J. “A predictive maintenance model using Long Short-Term Memory Neural Networks and Bayesian inference.” 6 (2023): 100174,
7. Shoorkand, H. D., Nourelfath, M., & Hajji, A. "A hybrid CNN-LSTM model for joint optimization of production and imperfect predictive maintenance planning." *Reliability Engineering & System Safety* 241 (2024): 109707.
8. Serradilla, O., Zugasti, E., Rodriguez, J., & Zurutuza, U. "Deep learning models for predictive maintenance: a survey, comparison, challenges and prospects." *Applied Intelligence* 52.10 (2022): 10934-10964.
9. Bogojeski, M., Sauer, S., Horn, F., & Müller, K. R. "Forecasting industrial aging processes with machine learning methods." *Computers & Chemical Engineering* 144 (2021): 107123.
10. Zhou, Y., Hefenbrock, M., Huang, Y., Riedel, T., & Beigl, M. "Automatic remaining useful life estimation framework with embedded convolutional LSTM as the backbone." *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*. Cham: Springer International Publishing, (2020).
11. Bampoula, X., Nikolakis, N., & Alexopoulos, K. "Condition monitoring and predictive maintenance of assets in manufacturing using LSTM-autoencoders and transformer encoders." *Sensors* 24.10 (2024): 3215.
12. Wang, H., Huang, S., Yin, Y., & Gu, T. "Short-term load forecasting based on pelican optimization algorithm and dropout long short-term memories–fully convolutional neural network optimization." *Energies* 17.23 (2024): 6115.

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