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Failure Prediction of Automated Guided Vehicle Systems in Production Environments through Artificial Intelligence

Li Li*, Lothar Schulze

Abstract: Modern industrial systems demand intricate connectivity and automation, especially in the realm of shop floor processes and intralogistics. Automated Guided Vehicle (AGV) systems are characterized by their potential for seamlessly networking value creation areas. However, failures and disruptions in AGV systems and adjacent facilities can lead to production halts, adversely affecting delivery reliability and quality. A substantial portion of the downtime stems from manual troubleshooting, underscoring the pivotal importance of the response time from maintenance staff. This paper introduces an approach employing a neural network with long short-term memory for forecasting and predictive maintenance to enhance AGV system reliability and availability in production environments. By analysing historical data, identifying patterns, and predicting potential failures or maintenance needs in AGV components and neighbouring facilities, the proposed AI-based forecasting ensures timely preventive measures. A case study shows the effectiveness of this approach in significantly improving AGV system performance, minimizing disruptions, and enhancing operational availability. This research contributes to smart manufacturing by providing a practical solution for optimizing availability of the concerned AGV system through advanced AI-based forecasting strategies.

Keywords: Artificial Intelligence; Automated Guided Vehicle; Long Short-Term Memory; TensorFlow; Time-Series Analysis and Forecasting

1 INTRODUCTION

Since decades the advantages and challenges of implementing automated guided vehicle (AGV) systems as well as worldwide growing importance of such systems for optimizing logistics and production processes have been highly concerned [1]. As key components of smart factories, automated guided vehicle systems play a critical role in optimizing material handling, logistics and transportation. Their autonomous navigation capabilities facilitate the smooth movement of goods and increase operational efficiency and productivity in industrial environments. Additionally, an AGV system should be seamlessly integrated with surrounding smart devices and systems to enable real-time data sharing and automated intelligent system control.

Despite numerous advantages of AGV systems, they may encounter numerous challenges during their operations, particularly the challenges of unexpected disruptions and stops due to failures. In many cases, it is required to fix errors and failures through manual intervention. However, the availability of technicians is not always guaranteed in a timely manner, which results in lower availability of AGV systems, more production interruptions and loss of productivity of the entire production system. To address this challenge, a proactive approach, particularly the use of predictive analytics models based on deep learning techniques, could be promising. By predicting potential disruptions in AGV operations, these models can pre-emptively mitigate problems, reduce the need for manual intervention, and increase overall productivity in Industry 4.0 environments.

The main aim of the paper is to analyse failure patterns in AGV operations and develop strategies to mitigate manual interference, enhance availability of AGV systems and hence increase productivity of highly automated production systems in Industry 4.0 environment. By understanding these patterns, it is expected to improve failure identification and rectification, minimizing operational disruptions of the systems. Given the significance of AGV systems in modern manufacturing and logistics, this research is crucial for optimizing their performance and reducing downtime through predictive failure prediction.

The rest of the paper is organized as follows. In the second section, a literature review of methods for ensuring and increasing availability of production and logistics systems is given. The focus of the review is placed especially on time-series analysis and forecasting by using artificial intelligence. The third section presents mainly the considered automated guided vehicle system of a food manufacturer and the historical data of the system especially failures recorded in the AGV controlling software as well as the pre-processing of data for the deep learning models used in the paper. In the fourth section, the first deep learning model, i.e. a long short-term memory (LSTM) model and the results obtained by this model are presented. Conclusion and outlook are given in the last fifth section.

2 LITERATURE REVIEW

In this section a brief review of models and methods especially based on deep learning for time series forecasting is given, including the applications of time series in the field of AGV failure prediction.

As a subdomain of time series analysis, time series forecasting involves developing a model that describes the underlying characteristics of historical data and extrapolating the model into the future [2]. Over the last decade, many machine learning and deep learning models have been developed to analyze time series. Multivariate Time Series (MTS) has received much attention. Deep learning models based on recurrent neural network (RNN) and convolutional neural network (CNN) haven been developed for MTS forecasting.

Athanasopoulos et al. demonstrate the utility of multivariate statistical models and machine learning techniques for predicting air quality parameters in the realm of environmental science with high accuracy [3]. The study introduced by Bai et al. explores the effectiveness of Graph Neural Networks (GNNs) in capturing temporal dependencies and relationships between variables in MTS data and shows promising results in various areas, including finance and healthcare [4].

Borovykh et al. explore the application of CNNs for time series forecastingby treating the time series as a one-dimentional signal [6]. According to their research and observations, CNNs are proficient in capturing local patterns and could be applied in fields such as sensor data analysis and medical signal processing. Bai et al. have specifically designed Temporal Convolutional Networks for sequential data modeling and applied CNNs to various time series forecasting tasks, including electricity load forecasting and traffic flow prediction due to the ability of CNNs to capture long-range dependencies [7].

Shubyn et al. explores how federated learning techniques can be utilized to train predictive models using data distributed across multiple AGVs [8]. As signal for prediction energy consumption has been selected. The results of their experiments based on federated learning let to better signal priction results than the results of just using single LSTM model. Zahng et al. [9] introduce a novel approach that combines the Transformer model a type of neural network architecture commonly used for sequence modeling, with the K-means clustering algorithm for power consumption prediction and anomaly detection. According to Benecki et al., RNN-based forecasting, together with a proper selected telemetry features used in prediction, can be effectively utilized on AGV telemetry data as a first step in anomaly detection schemes [10].

Long Short-Term Memory networks have emerged as powerful tools for time series forecasting, providing the ability to capture long-term dependencies and complex patterns in sequential data [9]. To improve prediction performance of LSTM, recent studies have explored various improvements to it architectures. For instance, Zhang et al. propose a hybrid LSTM model integrated with attention mechanisms to selectively focus on relevant temporal features, resulting in superior forecast accuracy in financial time series data [12].

Based on the study of Prakash et al., of all the state-of-the-art famous time series algorithms and combinations, including LSTM, Bi-Directional and Stacked LSTM, Prophet, GRU-LSTM, CNN-LSTM and LSTM with Attention, the simple algorithms have given the better result than hybrid and complex algorithms [13]. Song et al. employ Particle Swarm Optimization to optimize the essential configuration of the LSTM model and exhibit the outperformance of the proposed approach in comparing to traditional methods such as ANN, RNN and decline curve for predicting daily oil rate [14]. Livieris et al. propose a forecasting model of CNN-LSTM for the prediction of gold price and movement, which utilizes both LSTM layers and additional convolutional layers and exhibits a significant boost in increasing forecasting performance [15].

Besides theory and model development in using LSTM for time series analysis, open-source tool kits and libraries in the field of deep learning have also received much attention. For example, TensorFlow, an open-source library created by Google Brain, has gained popularity in recent years due to advances in machine learning. It is especially useful when combined with Long Short-Term Memory (LSTM) networks for time series analysis, because they can capture temporal dependencies and long-term memory [16].

Because of easy installation, relatively high speed, and easy customization, TensorFlow is used for different research aims based on LSTM by different researchers. Numerous domains, including finance, meteorology, air quality monitoring, and energy forecasting, have demonstrated encouraging outcomes with these models. Sang and Di Pierro emphasize the use of LSTM in modeling stock performance and forecasting market trends by utilizing TensorFlow's features [17]. Yazdan et al. investigate the use of LSTM to analyze the dynamics of energy consumption using renewable energy sources and emphasize TensorFlow's applicability as a neural network training and deployment framework for energy forecasting [18]. The use of LSTM models in TensorFlow for single-step and multi-step time series prediction of urban temperature is examined by Zhang et al. [19]. According to their research, longer-term dependencies and nonlinear correlations in temperature data can be captured by LSTM using TensorFlow and produce more accurate predictions.

Due to successful experience of TensorFlow for deep learning and especially for LSTM in the literature, it is also selected in this paper for the purpose.

3 PROBLEM STATEMENT OF THE CONCERNED AGV SYSTEM AND DATA PREPARATION

After introducing the concerned AGV system briefly, the data preparation for the LSTM model is explained, including the basic data set with irregular time intervals and the pre-processed data set with regular time intervals.

3.1 The Concerned AGV System and Research Aims

The automated guided vehicle system concerned in this paper is composed of five vehicles, which are responsible for moving semi-finished products between different processing stages of the whole highly automated production system. During operations of the AGV system, many different kinds of messages are recorded in a manner of irregular time intervals. Some of the messages are just records of events, which may not influence the AGV operation at all. Some of the messages are failures, which can be corrected by the system automatically. The rest of the 34 messages correspond to failures, which can only be corrected by the technician manually. The current situation in the company is firstly, these failures cannot be easily avoided and secondly, technician cannot prepare his/herself immediately for correcting the failures. If these failures cannot be corrected on time, the availability of the vehicles is then reduced. As a consequence, the semi-finished products cannot either be collected from some stages or be delivered to some stages of the production system. The productivity of the whole system is of course influenced.

A measurement could be to avoid or reduce failures, which are manually corrected. However, this is not the aim of the paper. The paper focuses mainly on developing predictive analytics based on LSTM model for failure forecasting. If the technician could be informed much earlier than the time when a failure happens, there could be more time for the technician to prepare the required materials and tools for correcting the failure and downtime of the AGV system could be reduced. If at the beginning of the shift, the technician receives predicted failure information for the next several hours, the technician can plan activities and schedules much better. For example, during periods of time, when An AGV does not run, the technician does not need to plan activities for other machines or systems. If the prediction results are relatively quite accurate, if an AGV failure occurs later, technicians can fix the problem almost immediately. The downtime of the AGV system can be reduced and the availability of the AGV system is of course higher. The main aim of the paper is to predict if there are failures or not in the next certain period by using a LSTM Model.

3.2 Preparation of Data Set as a Basis

To achieve the aim, a basic data set must be at first prepared. The first step is to collect event-based records in two months from the AGV controlling software. After analysing the original data set, which consists of approximately 50 columns, the data set is simplified to just seven columns as a basis for further analysis. Tab. 1 shows several rows of simplified data as examples.

Table 1 Prepared data of the AGV system

ID	Module	Message	Location	Vehicle	Time	Failure
0	32	1	502	4	23-10-12 02:23:40	23
1	32	1	502	4	23-10-12 02:25:41	26
2	2	10	2601	4	23-10-12 02:26:39	34
3	15	12	2601	0	23-10-12 02:27:37	34
4	15	6	2601	0	23-10-12 02:27:39	23
…						
9548	14	18	2617	0	23-12-12 08:50:38	20
9549	14	32	3407	0	23-12-12 08:56:41	20
9550	14	26	5	4	23-12-12 09:22:15	27
9551	15	13	5	0	23-12-12 09:22:41	16
9552	14	13	5	4	23-12-12 09:26:00	20

The first column "ID" serves just as the primary key for unique identification. The second column "Module" tells the number of the module in the system, which has a relationship to the failure. The third column "Message" tells the event number. A combination of both Module and Message results in a specific failure in the last column. The forth column "Location" corresponds to the block numbers in the layout, where the vehicles drive. That means, the locations where the failures happen can be obtained based on this column. The fifth column "Vehicle" is just the number of the five vehicles from 0 to 4. In the sixth column "Time" the exact time of the event to second is recorded. The last column "Failure" presents the number of the 34 manually corrected failures.

It is obvious to notice, that the time intervals are irregular, because the controlling software makes event-based records. In this table, only manually corrected failures as event are prepared. The rest events, which do not need manual interference, are just deleted from the original records dataset.

3.3 Pre-processed Data with Regular Time Intervals

Based on the basic dataset, several datasets with different regular time intervals for the LSTM model are created. These time intervals are 60 minutes or 1 hour, 30 minutes or half hour and 10 minutes.

The partial dataset with 10 minutes as time intervals is shown in Tab. 2. To create this dataset, irregular time intervals are firstly changed to regular time intervals of 10 minutes. Then a column of "Failure Label" is inserted. The values of this column are binary only. A value of 0 means there are no failures occurred in the next 10 minutes after the corresponding time in the same row and a value 1 means there is at least one failure occurred in the next 10 minutes after the corresponding time in the same row. For example, there are several failures after the time 12-10-23 02:20:00 in Tab. 1, hence the value of the column Failure Label corresponding to this timestamp is 1. Other datasets are similar to this dataset, but with other time intervals.

Table 2 Data samples with regular time intervals of 10 minutes

ID	Time	Failure Label
0	2023-10-12 02:20:00	1
1	2023-10-12 02:30:00	1
2	2023-10-12 02:40:00	0
3	2023-10-12 02:50:00	0
4	2023-10-12 03:00:00	1
…		
8825	2023-12-12 08:50:00	1
8826	2023-12-12 09:00:00	0
8827	2023-12-12 09:10:00	0
8828	2023-12-12 09:20:00	1
8829	2023-12-12 09:30:00	0

The reasons of creating different data sets with different time intervals are as follows. First, A 60-minute time interval is used, because it is a more appropriate length of time for planning and analysis. A time interval of two hours is also good. However, it is not proper for the case in this paper, because the occurring possibilities of failures in every 2 hours are almost guaranteed based on the preliminary analysis. In other words, there is almost always at least one failure in every 2 hours. Hence, it is not necessary to do forecasting.

The second time interval is set to be of 30 minutes. The shorter the time interval is, the greater the flexibility in planning and scheduling can be obtained. However, if the time interval is too short, the accuracy of the prediction will also decrease. This time interval must be practically tested to find out if the accuracy is high enough or at least acceptable.

The third time interval is set to be 10 minutes, which are in fact a little bit too short for planning. This time interval aims mainly at training the model and forecasting failure occurring in every 10 minutes. The obtained results are then used for generating prediction for every 60 minutes. If at least one 10-minute time interval in one hour has a failure, then there is at least one failure in this hour. That means the value of "Failure Label" corresponding to the timestamp of this hour is 1. Otherwise, if no 10-minute time interval in one hour has a failure, then this hour has the value of 0 for Failure Label. Of course, the data can also be used for predictions every 30 minutes.

4 LSTM MODEL AND RESULT ANALYSIS

As mentioned at the end of the second section, the tool kit of Keras in TensorFlow is used for building LSTM model. All data analysis and programming tasks are conducted within the environment of Jupyter Notebook. The LSTM model is composed of three layers. Each of first two layers has 50 neurons and the fully connected layer has one neuron. For the fitness function, a batch size of 32 is defined. The whole dataset is divided into a training set comprising 80% of the data and a test set comprising 20% of the data. As a suitable metric for evaluating models predicting values that are either 0 or 1, Mean Absolute Error (MAE) is selected for evaluating the accuracy of the train and test sets of our LSTM model.

Many experiments have been conducted and a selection of representative results is shown in Tab. 3. From the results, it is to notice, that the higher the epochs are, the lower the MAE values are and the more accurate the prediction can be achieved. This trend is adaptable to any time intervals. However, the difference between 300 epochs and 350 epochs is not very evident. The improvement of the prediction quality is limited after setting higher values for epochs than 350. Hence, only the results until 350 epochs are presented.

The best results for different time intervals are obtained when the value of epochs is set to 350. Hence, the following analysis focuses only on these results. The lower the time intervals for training the model are and the longer the time intervals for prediction are, the better results with lower MAE values can be achieved. Hence, the best result for predicting failure occurrences every hours among the experiments is obtained by using time intervals of 10 minutes for training the LSTM model. The MAE value of 0.030 is quite low, which means the prediction results are relatively reliable and promising.

Table 3 MAE values across different scenarios

Time intervals for model training: 10 Minutes				
Epochs	**50**	**150**	**300**	**350**
10 Minutes	0.312	0.184	0.086	0.085
30 Minutes	0.206	0.145	0.062	0.064
60 Minutes	0.164	0.088	0.036	0.030
Time intervals for model training: 30 Minutes				
Epochs	**50**	**150**	**300**	**350**
30 Minutes	0.180	0.155	0.060	0.064
60 Minutes	0.069	0.063	0.038	0.040
Time intervals for model training: 60 Minutes				
Epochs	**50**	**150**	**300**	**350**
60 Minutes	0.079	0.074	0.049	0.038

Corresponding to the best value of MAE, some samples of the actual and predicted values of "Failure Label", which shows the occurring possibilities, i.e. occurrences of AGV failures, are presented in Fig. 1. Three time periods of 500 hours are randomly selected. The red points correspond to predicted values of failure occurrences and the blue points correspond to actual values of failure occurrences. It is to notice, except for very less blue points, most blue points are covered by red points. This also fully demonstrates the prediction accuracy.

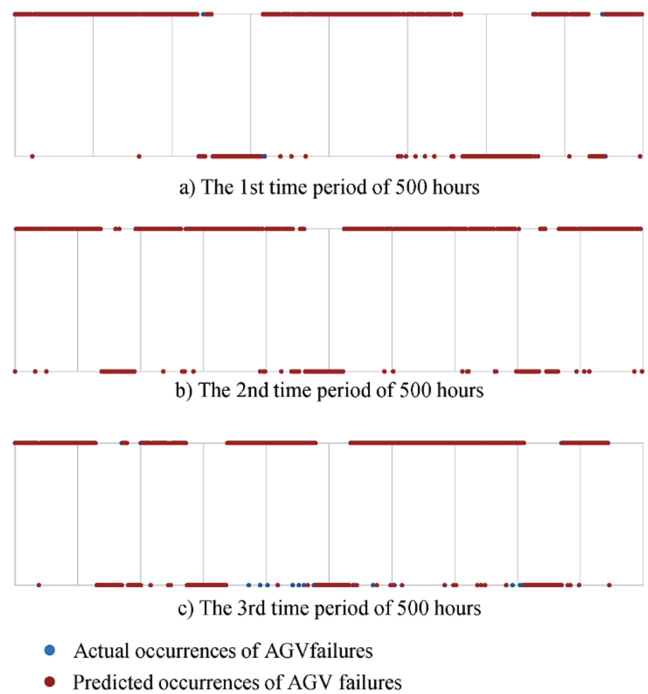

Figure 1 Data samples of actual predicted occurrences of failures

5 CONCLUSION AND OUTLOOK

Based on the evaluation of our LSTM Model, the key insight that the developed LSTM Model in TensorFlow demonstrates promising results in predicting failure events in terms of predictive performance, can be drawn. It exhibited low MAE values on the dataset, indicating a close fit between actual and predicted values showing failure occurrences. This method can be used for any AGV systems, if the required data can be available. However, the method is still very limited in its capability, which can only help the staff of doing his or her planning in a time interval of one hour.

Future research could focus on refining model architectures, exploring alternative algorithms, and incorporating domain-specific knowledge to enhance predictive accuracy for shorter time intervals. Additionally, the model performance and robustness could be improved by conducting further experiments with different datasets. Furthermore; multivariate LSTM model should be developed for predicting more information of AGV failures, including predictions of which failure, by which vehicle, at which location and at what time. If this aim is achieved, the technician can even better plan the activities, tools and materials for fixing failures.

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Authors' contacts:

Li Li, Prof. Dr.-Ing. PhD
(Corresponding author)
Technische Hochschule Ostwestfalen-Lippe,
Campusallee 12, 32657 Lemgo, Germany
Tel.: +49 5261 702-5280
E-mail: li.li@th-owl.de

Lothar Schulze, Prof. (i.R.) Dr.-Ing. habil.
Leibniz Universität Hannover,
Callin str. 36, 30167 Hannover, Germany
Tel.: +49 157 71456389
E-mail: schulze@pslt.uni-hannover.de