Towards Detection of Anomalies in Automated Guided Vehicles Based on Telemetry Data

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Abstract. The rapid evolution of smart manufacturing and the pivotal role of Automated Guided Vehicles (AGVs) in enhancing operational efficiency, underscore the necessity for robust anomaly detection mechanisms. This paper presents a comprehensive approach to detecting anomalies based on AGV telemetry data, leveraging the potential of machine learning (ML) algorithms to analyze complex data streams and time series signals. By focusing on the unique challenges posed by real-world AGV environments, we propose a methodology that integrates data collection, preprocessing, and the application of specific AI/ML models to accurately identify deviations from normal operations. Our approach is validated through extensive experiments on datasets featuring anomalies caused by mechanical wear or excessive friction and issues related to tire and wheel damage, employing LSTM and GRU networks, alongside traditional classifiers like K-nearest neighbors and SVM. The results demonstrate the efficacy of our method in forecasting momentary power consumption as an indicator of mechanical anomalies, and in classifying wheel-related issues with high accuracy. This work not only contributes to the enhancement of predictive maintenance strategies but also provides valuable insights for the development of more resilient and efficient AGV systems in smart manufacturing environments.

Keywords: automated guided vehicles · anomaly detection · telemetry anomaly detection · machine learning

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1 Introduction

The smart manufacturing industry frequently relies on automated component or manufactured products delivery performed by Automated Guided Vehicles (AGVs) [9]. These vehicles autonomously transport goods to or between assembly stations on production lines, await unloading after successful docking, and then return to begin another operational cycle. The uninterrupted production in manufacturing that relies on a fleet of AGVs necessitates continuous monitoring of the vehicles and their characteristics through telemetry, detecting anomalies and, thus, predicting upcoming failures [23]. These tasks would not be possible without observing various signals captured by onboard gauges and sensors. Small IoT devices installed on AGVs may collect data, communicate with other devices and central servers to exchange the data, and perform more sophisticated analyses supporting predictive maintenance tasks [8, 25]. They can gather signal values and sensor readings directly from the PLC controllers onboard the AGV, transmitting them to analytical systems for further analysis.

Deviations from the normal operation of an AGV are typical indicators of wear of its components, adverse environmental impact, or human error or influence [24]. For example, the progressive change in the wheel diameter resulting from its wear has a negative impact on the accuracy of the planned route in the odometry system. The slippery ground may result in inaccurate turns and route errors or incorrect docking. Excessive vehicle load causes increased energy consumption, reduces the use time of AGVs, and increases the risk of wear of their parts. Frequent stops caused by people entering the vehicle's route not only disrupt the entire delivery schedule but also cause parts to wear out faster. All these deviations can be captured by prior observation of various internal signals of the vehicle and their subsequent analysis.

Recent works in anomaly detection predominantly rely on employing Artificial Intelligence (AI) algorithms and analyzing data streams with various Machine Learning (ML) models [11]. However, despite the general inference capabilities of the existing AI/ML algorithms, each detection task requires a separate reasoning model that should be deployed specifically for the problem and particular data preparation. Detecting anomalies in real AGV environments that produce industrial data streams and expose time series signals poses unique challenges beyond simple training and testing various ML models [22].

The paper advances smart manufacturing by introducing ML-based methods for detecting anomalies in AGVs, focusing on mechanical wear and tire or wheel damage. It fills a gap in predictive maintenance, enhancing AGV operational efficiency and reliability. By providing accurate forecasts of power consumption and classifying wheel-related issues, this research not only improves current AGV management but also sets a foundation for future advancements in the field.

The remainder of this paper is organized as follows: Section 2 reviews the current literature on anomaly detection in AGVs, highlighting the key methodologies and gaps that this study aims to address. Section 3 delves into the proposed methodology for anomaly detection, including data collection, pre-processing and specific AI/ML models used. Section 4 describes the experimental datasets

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in detail, covering their collection, characterization and justification for their use. Section 5 presents the results of our anomaly detection experiments, offering insights into the performance and effectiveness of the models. Section 6 reflects the results, discussing their implications for smart manufacturing and AGV operations, and outlines future research directions.

2 Related Works

The growing adoption of AGVs across diverse sectors, particularly in logistics and manufacturing, has sparked substantial research endeavors aimed at improving their operational efficiency and dependability. A key focus of these endeavors is the advancement of sophisticated techniques for anomaly detection based on AGV telemetry data, optimization of energy consumption, and the utilization of ML for predictive analytics on time series data. This section delves into the state-of-the-art methodologies and their implications for AGV technology.

The capability to detect anomalies based on AGV telemetry data is critical for predictive maintenance (PdM) and operational efficiency. The study by Malhotra et al. stands out for its pioneering use of LSTM networks, offering a robust framework for identifying anomalies in time-series data [14]. Complementing this, Hundman et al. explored the use of LSTMs and nonparametric dynamic thresholding for detecting spacecraft anomalies, illustrating the potential of these methods in complex operational contexts akin to AGV environments [12]. The versatility of LSTM models in capturing temporal dependencies makes them particularly suited for AGV telemetry, where anomalies must be detected in real-time to prevent operational disruptions.

Efficient energy management is crucial for sustainable AGV operations. The work by Khan et al. in modeling AGV energy consumption laid the groundwork for integrating predictive analytics into energy management strategies [17]. The application of ML for time series anomaly detection transcends the specific use case of AGVs, offering a wealth of methodologies that can be tailored to this context. Lai et al. presented a comprehensive approach using Recurrent Neural Networks (RNNs) for modeling both long- and short-term temporal patterns while analyzing AGV telemetry data [13]. Additionally, the review by Zhang et al. on deep learning for financial time series provides a solid foundation for adopting similar techniques in the operational analysis of AGVs [1].

Integration of edge computing and IoT is crucial for enhancing real-time data processing capabilities. The study by Shi et al. emphasizes the role of edge computing in facilitating the real-time analysis of AGV data, thereby enabling more immediate and localized decision-making processes [20]. This approach significantly reduces latency in anomaly detection and energy consumption optimization, essential for maintaining continuous and efficient AGV operations. In addition to ML and edge computing, the application of Federated Learning (FL) techniques in monitoring AGV is gaining interest. FL allows for the decentralized processing of data, enabling AGVs to learn from distributed data sources without the need to centralize sensitive information. Our previous studies [21]

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were focused on the effectiveness of using FL for AGV to improve the forecast of signals in time and the effectiveness of this approach in terms of energy consumption. We also used LSTM networks to forecast momentary energy consumption (MEC), the signal identified as the one reflecting possible anomalies in the AGV operation. However, none of these works were focused on specific anomalies of the AGVs working within their operational environment. This paper extends these efforts toward real anomaly detection.

3 Anomaly Detection based on AGV Telemetry Data

Anomaly detection in AGVs requires telemetry and exchanging data between various IT systems within a factory. The topology of the system composition is usually complex, and anomalies usually occur rarely. These factors hinder the development of accurate anomaly detection models but can be mitigated by extracting appropriate data, integrating them, and performing appropriate experimental scenarios engaging AGV vehicles.

3.1 Data in Intralogistics Systems

Modern intralogistic systems are composed not only of the hardware layer, which consists of AGVs and other types of transportation robots. IT systems which enable various operability functions are equally important. One of the most crucial is the Transportation Management System class (TMS), which evolved from the fleet management system. Among solving traffic problems, its tasks are related to formulating transportation orders, selecting and dispatching AGVs for specific tasks, managing the logic of transportation flow, scheduling and reporting tasks as well as providing detailed diagnostics of the state and behavior of the fleet. In parallel, the fleet of AGVs needs to communicate and cooperate with industrial environments and infrastructure. Therefore, integration with existing industrial third-party systems, such as Warehouse Management Systems (WMS), Manufacturing Execution Systems (MES), Business Intelligence (BI), or Computerized Maintenance Management Systems (CMMS), is required.

Intralogistics systems operate on many communication layers, like data exchange with field devices, acquisition of traceability, process data, or generating asset management information. Due to this fact, a vast amount and diversity of data can be used for multiple cases, from general process control tasks through optimization of transportation orders based on current utilization and energy consumption of the fleet to support the maintenance, e.g., via the calculation of Overall Equipment Effectiveness (OEE) or utilization in predictive maintenance approaches based on data mining.

3.2 Overview of the Methodology

Anomaly detection in the AGV operation follows the general methodology illustrated in Fig. 1. The approach begins with the stage of data generation from

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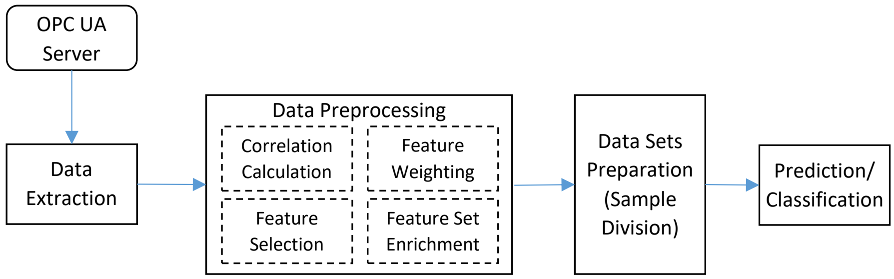

Fig. 1. Overview of the general methodology applied for predicting anomalies in the AGV operation.

AGV onboard devices and systems as well as from the fleet supervisory layer. Signals are acquired either directly from measurement devices such as battery management systems providing momentary currents, voltages, and temperatures of the power system or from process controllers, which generate statuses, diagnostic information, or states of work of AGVs. An important factor is that data generation and collection from multiple endpoints are synchronized in time. This guarantees that, e.g., calculations of MPC are reliable and refer to corresponding statuses and states of work of AGV and its devices. The methodology covers capturing data from intralogistics systems and exposing them through the OPC UA Server, from which they are extracted in the form of a collection of time series signals (a wide time-dependent data stream). Then, we perform a data preprocessing step that may include finding correlations between signals in the data stream, feature selection, and weighting based on the calculated correlation coefficients, and feature set enrichment by deriving other features based on existing ones or based on a wider view of feature's values (e.g., within a time window). This phase is followed by the preparation of data sets, which covers more or less sophisticated strategies for data/sample division. Finally, depending on the anomaly, forecast or classification is performed, which employs dedicated AI/ML algorithms. Data preprocessing steps and data set preparation strategies depend on the specific use case for anomaly detection and the requirements of the forecasting/classification algorithms applied.

3.3 Anomalies caused by mechanical problems

The operability of AGVs leads to the degradation of their components. This can be caused by many factors, but in most cases, they result from the mechanical wear of onboard components. Exposure to negative phenomena like vibrations, strokes, overloading, or working in hazardous conditions shortens the lifetime of traction systems or onboard electronics. As a result, AGVs can require more frequent maintenance, which is costly and excludes them from production. Mechanical wear, particularly in bearings and components experiencing larger friction in vehicles, involves several mechanisms, among them the following [10]:

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1. Adhesive wear, occurs when surfaces weld together and tear apart, which is common in bearings.
2. Abrasive wear caused by particles or uneven sliding across a surface.
3. Corrosive wear, chemical or electrochemical reaction with the environment.
4. Fatigue wear due to cyclic loading.

Modeling or examining real worn systems is either hard or ineffective due to the time necessary to observe the actual wear [10, 15, 16]. One of the possibilities to observe similar effects is overloading a vehicle. This can indeed be used to emulate the situation where the wear has already occurred, simulating the reduced performance and altered operational characteristics that worn components would exhibit [6]. This method does not accelerate wear but instead aims to mimic the effects of wear on the vehicle's performance.

3.3.1 Modelling: We assume that a vehicle operating with payloads up until a chosen threshold is in normal operation, and payloads above the threshold are emulating more mechanical wear and friction. Therefore, we trained the forecasting models on a subset of normal data and evaluated on other non-overlapping sequences from normal data and data considered anomalous. The description of the data used in this experiment is provided in section 4.1.

Models used here forecast short-term (a 10-second ahead forecast horizon Δt) MPC using features from the whole acquired telemetry. This is a common approach in such telemetry-related tasks, which allows taking measures when the expected energy consumption differs significantly from the observed values, which often indicate an anomalous event [5, 12, 19]. A concise overview of how the forecasting operates is illustrated in Fig. 2.

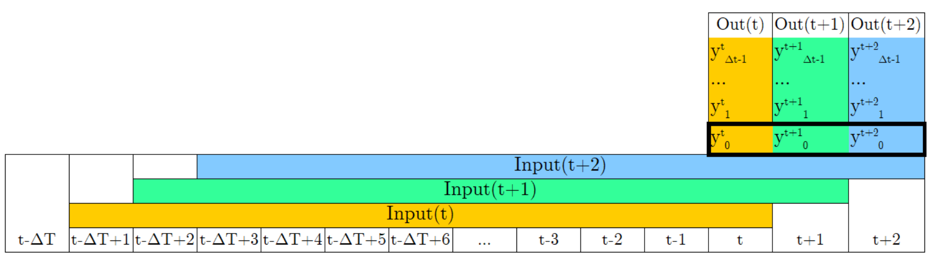

Fig. 2. Forecasting of MPC in time windows of a size ΔT moving over an input time series X. Δt elements ahead are forecasted (forecast horizon). Only the first elements y_0 of forecasts are taken to form an output sequence (elements in a bold frame).

With such an approach, it is possible to evaluate if the model forecasts values correctly during normal operations and if its performance deteriorates with more unusual patterns, which is an expected behavior here. In the context of mechanical wear and vehicles, this method allows for predictive maintenance strategies.

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By detecting anomalies early, maintenance can be scheduled proactively to address wear and tear before it leads to failure [7].

3.4 Anomalies caused by tire and wheel damage

One of the mechanical wears that lead to the lowered performance of AGVs is the uncontrolled and unintended change of diameter of traction wheels. In all types of kinematic models, AGVs use odometry for maneuvering. The odometry is calculated from pulses or the frequency measured by encoders installed on traction axes. This requires prior knowledge of wheel diameter, as the odometry transforms the number of pulses or the frequency into the traveled distance. Then, the distance can be used for closed-loop control when providing drive commands to motors. However, if the diameter changes due to its wear or uncontrolled change, e.g., during abrasion or sticking of dust, the odometry is calculated incorrectly. This increases the error of calculated traveled distance in time. As a result, the navigation system generates an increased number of corrections and, through this, increased consumption of energy as well as faster wear of mechanical components. To keep a good quality of navigation, it is important to control the condition of the traction wheels.

4 Datasets

The experiments were conducted using data obtained from an actual industrial CoBotAGV known as Formica. This AGV is a product developed by AIUT Ltd. and smarticized with AI by the Silesian University of Technology [22].

4.1 Test drives with changing payload weight

Our investigations rely on data acquired in October 2022 based on test drives with changing payload weight (Fig. 3). These tests produced ca. 50,000 time steps acquired with a frequency of 1 Hz. Table 1 presents how many data points are available for different weight values. The data contains 56 features (numeric and boolean) covering energy signals, left/right motor drive statuses, vehicle PLC signals, LED statuses, natural navigation signals, odometry, and safety statuses.

Table 1. Payload weight (Wt) and corresponding sample counts (# Smpl.) during test drives in October 2022

Wt [kg]	# Smpl.	Wt [kg]	# Smpl.	Wt [kg]	# Smpl.	Wt [kg]	# Smpl.	Wt [kg]	# Smpl.
0	276	100	812	200	6336	300	1943	400	756
20	860	120	915	220	888	320	1722	420	1070
40	804	140	739	240	722	340	1727	440	2190
60	807	160	893	260	676	360	1599	480	943
80	860	180	825	280	2071	380	1644	498	17564

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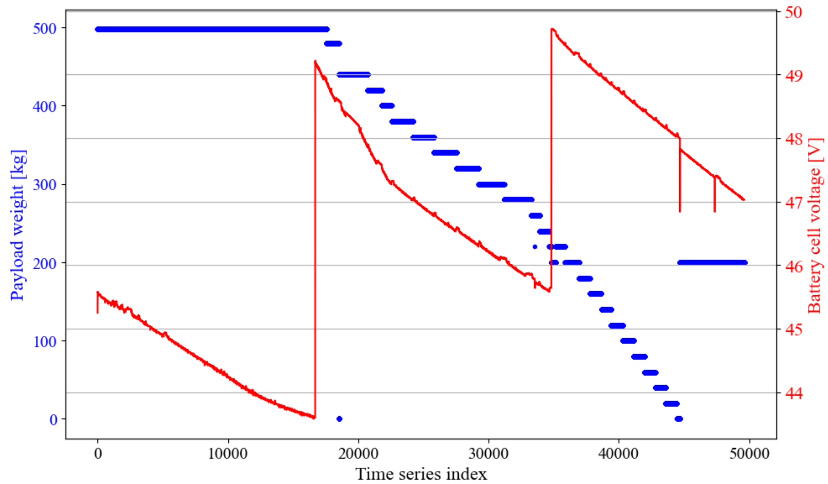

Fig. 3. Payload weight (blue) changes during test drives in October 2022. The test drives also included different levels of battery voltage (red), with two charges in between.

4.2 Distorted natural navigation data

This data comes from test runs executed in July and August 2023, which included changes in the diameter of one of the wheels passed to the natural navigation subsystem. The value was not changed physically but by software means, however, it resulted in natural navigation corrections anyway through mechanisms described in section 3.4. The data consists of ca. 121,000 time steps acquired with a frequency of 1 Hz. Table 2 presents how many data points are available for different wheel diameters, and Fig. 4 presents a short outline of how natural navigation is distorted with false gradually changed wheel diameter.

Table 2. Wheel diameters (Ø) used during test drives in July and August 2023 with sample counts (# Smpl.) for each diameter.

Ø [mm]	# Smpl.	Ø [mm]	# Smpl.	Ø [mm]	# Smpl.	Ø [mm]	# Smpl.	Ø [mm]	# Smpl.
52.90	54494	54.75	2162	56.55	262	59.51	2449	61.51	2431
53.16	1299	54.97	1797	57.93	5031	59.77	2858	61.83	2385
53.42	1939	55.23	5340	58.19	3019	60.04	1795	62.09	2158
53.69	2195	55.49	1929	58.46	577	60.31	2053		
53.95	2065	55.76	2308	58.72	999	60.57	2035		
54.22	2516	56.03	2319	58.99	2714	60.99	2009		
54.48	2161	56.29	2321	59.23	1505	61.26	2485		

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Table 3. Spearman's correlations highlight the 10 features most closely related (either positively or negatively) to the wheel diameter value. Among these, only the signals marked in bold are pertinent; the remaining ones are considered either artifacts (such as inclinations) or the result of spurious correlations, which arise as the battery discharges concurrently with a gradual change in wheel diameter.

Signal	Spear. CC	Signal	Spear. CC
Distance average corr.	**0.6475**	*Momentary current consumption*	*0.3336*
Y inclination	*0.6360*	*Momentary power consumption*	*0.2481*
Difference heading average corr.	**0.5268**	*Odometry: cumulative distance right*	*0.2253*
Battery cell voltage	*0.4103*	*Cumulative energy consumption*	*0.1674*
State Of Charge	*0.3887*	*X inclination*	*0.1593*

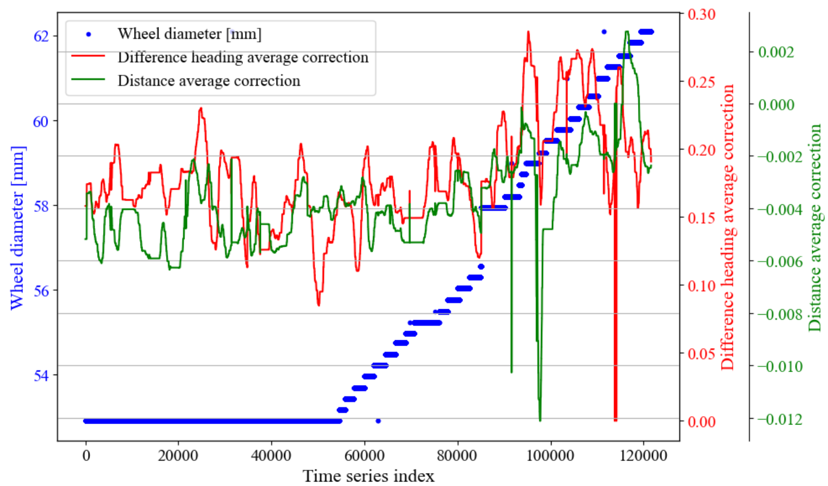

Fig. 4. Wheel diameter (blue) changes and resulting natural navigation correction values (red and green) during test drives in July and August 2023

5 Experimental validation

This section details the methodology and experimental validation results aimed at detecting anomalies in mechanical systems and components due to wear or excessive friction and wheel degradation. Through a series of experiments utilizing recurrent neural network (RNN) models, this research investigates the efficacy of forecasting models on datasets emulating mechanical anomalies by varying payload thresholds. The experiments extend previous work by exploring the impact of model training and validation under conditions of normal and overload test drives, employing momentary power consumption (MPC) as a predictive metric. Additionally, we include the detection of wheel-related anomalies, such as excessive tire wear. Utilizing traditional two-class classifiers, we aim to thoroughly assess and enhance the system's diagnostic capabilities concerning wheel integrity.

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5.1 Detecting potential mechanical wear or excessive friction

The first series of experiments was focused on finding anomalies caused by mechanical wear or excessive friction. As mentioned in section 3.3 those were emulated by changing payload over the chosen threshold. The input dataset described in section 4.1 was used to train a 2-hidden layers (with 80 units per layer) LSTM (Long Short-Term Memory) and 2-hidden layers (with 80 units per layer) GRU (Gated Recurrent Unit) models forecasting MPC, which proved to be effective in our previous works [2–4]. Similarly, the input window size was set to $\Delta T = 50$ elements and the forecast horizon to $\Delta t = 10$.

The objective of this fragment of experimental validation was to check if it is possible to train and validate a model that gives good forecasting quality on normal data (without excessive load) and the quality of its results deteriorates on data resulting from overload test drives. To achieve that, the dataset described in section 4.1 was split into fragments based on payload weight, each fragment ranging 40 kg of payload. The structure of the resulting division is shown in Table 4. A fixed boundary in payload weight was set first to 200 kg and in a second part to 320 kg. Data below the thresholds was treated as *normal* and above – as *anomalous*.

The models were trained on part of data from *normal* ranges: 0–40, 80–120, 160–200 for the first and 0–40, 80–120, 160–200, and 240-280 for the second part. The rest of data from *normal* was treated as *normal test* set and all data above the threshold was used as *anomalous test* set. The training was executed for 200 epochs with early stopping after 20 epochs without improvement of the loss function.

The forecasting quality was evaluated using the Mean Square Error (MSE) metric computed over the resulting output sequence as shown in Fig. 2. Additionally, input data was preprocessed to 1) contain or not the MPC feature [4] and 2) use or not feature weighting [3]. That, together with two models (LSTM/-GRU), gave eight experiments for the two previously mentioned dataset splits. Additionally, to assess whether the resulting forecasting errors were statistically significantly different from forecasts on *normal test* fragments, the Student's t-test was conducted.

The results are presented in Table 5. It can be observed that errors between expected (forecasted) and actual values of MPC are significantly larger than in *normal test* set in most of the ranges in *anomalous test* sets, especially for the experiment with a threshold set to 320 kg. That would allow to employ an error-thresholded anomaly detection [12]. Also, for most of *normal test* payload ranges, error values do not differ significantly from the expected values. However, for cases where this does not stand (e.g., range 280–320 in Table 6), the errors still can be thresholded not to report false positive anomalies. Also, it was confirmed that the weighting of features contributes to better forecasting [4]. Additional processing (e.g., error thresholding [12]) is required after forecasting to achieve the final anomaly detection result. Also, this method allows for near real-time processing, since similarly as in [4], the processing time for the whole test set is

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ca. 0.1–0.2 s (the machine used is equipped with an AMD Ryzen 5 processor, NVIDIA GeForce GTX 1080 Ti GPU, and 16 GB of installed RAM).

Table 4. Payload weight (Wt) distribution in the dataset in terms of sample counts (# Smpl.).

Wt [kg]	**# Smpl.**	**Wt [kg]**	**# Smpl.**	**Wt [kg]**	**# Smpl.**	**Wt [kg]**	**# Smpl.**
0–40	1940	160–200	7161	320–360	3326	480–500	17564
40–80	1667	200–240	1610	360–400	2400		
80–120	1727	240–280	2747	400–440	3260		
120–160	1632	280–320	3665	440–480	943		

Table 5. Results of forecasting for models trained on data assuming payloads $<$ 200 kg to be normal. Numbers stand for MSE computed on values inferred on test sequences. Greater $>$ /less than $<$ marks denote values statistically significantly different from the *normal test* set and the direction of inequality. Ranges 40–80 and 120–160 constitute a *normal test* set, thus, they are presented separately.

			MSE - *normal test*			**MSE - *anomalous test***							
MPC present	**Weighted**	**Model**	**Whole**	**40-80**	**120-160**	**200-240**	**240-280**	**280-320**	**320-360**	**360-400**	**400-440**	**440-480**	**480-500**
−	−	GRU	0.095	0.091	0.099	0.117	0.113	0.173 >	0.186 >	0.243 >	0.371 >	0.424 >	0.542 >
−	−	LSTM	0.124	0.152	0.096 <	0.156 >	0.171 >	0.218 >	0.212 >	0.302 >	0.498 >	0.418 >	0.511 >
−	+	GRU	0.104	0.100	0.108	0.091	0.093	0.138 >	0.169 >	0.223 >	0.343 >	0.381 >	0.506 >
−	+	LSTM	0.121	0.106	0.136	0.114	0.121	0.153 >	0.195 >	0.245 >	0.373 >	0.372 >	0.522 >
+	−	GRU	0.088	0.089	0.087	0.120 >	0.103	0.140 >	0.203 >	0.229 >	0.379 >	0.509 >	0.518 >
+	−	LSTM	0.139	0.163	0.113	0.167	0.142	0.148	0.211 >	0.250 >	0.458 >	0.509 >	0.536 >
+	+	GRU	0.093	0.083	0.104	0.088	0.175 >	0.156 >	0.202 >	0.175 >	0.335 >	0.317 >	0.439 >
+	+	LSTM	**0.082**	0.079	0.086	0.091	0.089	0.137 >	0.189 >	0.213 >	0.342 >	0.427 >	0.551 >

5.2 Detecting problems with wheels

This experimental section fragment focuses on finding anomalies that are caused by excessive tire wear or objects that are accidentally attached to the wheel surface. The test data is described in section 4.2 and relies on distortions in the natural navigation subsystem (NN). As it was described previously, the problems are visible through larger amounts of corrections reported by the NN.

We employed traditional two-class classifiers such as K-nearest neighbors, Naive Bayes, Decision Tree, Random Forest, and Support Vector Machines (SVM). Hyperparameters of the models were not tuned – defaults from SciKit-Learn [18] were used. The key component of classification is to properly select features that

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Table 6. Results of forecasting for models trained on data assuming payloads < 320 kg to be normal. Numbers stand for MSE computed on values inferred on test sequences. Greater > / less than < marks denote values statistically significantly different from the *normal test* set and the direction of inequality. Ranges 40–80, 120–160, 200–240, and 280–320 constitute the *normal test* set, thus, they are presented separately.

			MSE - *normal test*					**MSE - *anomalous test***				
MPC present	**Weighted**	**Model**	**Whole**	**40-80**	**120-160**	**200-240**	**280-320**	**320-360**	**360-400**	**400-440**	**440-480**	**480-500**
−	−	GRU	0.119	0.096 <	0.112	0.112	0.135 >	0.199 >	0.299 >	0.531 >	0.413 >	0.537 >
−	−	LSTM	0.122	0.117	0.102	0.123	0.134	0.213 >	0.264 >	0.463 >	0.413 >	0.497 >
−	+	GRU	0.112	0.110	0.089 <	0.101	0.127 >	0.168 >	0.238 >	0.384 >	0.410 >	0.541 >
−	+	LSTM	0.145	0.161	0.139	0.126	0.149	0.200 >	0.245 >	0.533 >	0.723 >	0.516 >
+	−	GRU	0.114	0.094 <	0.098	0.095 <	0.139 >	0.167 >	0.213 >	0.312 >	0.348 >	0.468 >
+	−	LSTM	0.104	0.084 <	0.109	0.092	0.117	0.192 >	0.220 >	0.329 >	0.332 >	0.459 >
+	+	GRU	0.095	0.076 <	0.096	0.080 <	0.110 >	0.154 >	0.183 >	0.309 >	0.330 >	0.484 >
+	+	LSTM	**0.094**	0.062 <	0.082	0.088	0.115 >	0.158 >	0.200 >	0.337 >	0.357 >	0.468 >

are fed to the classifier [26,27]. Since we have the prior knowledge that anomalies in the dataset are arising with more modified wheel diameter, it was expedient to use the features that are most correlated with the diameter. As shown in Table 3, the most correlated features are corrections from NN together with some other falsely correlated signals. Thus, we decided to use NN correction signals as input for the classifiers, namely *distance average correction* and *difference heading average correction*.

During experiments, it was also planned to check whether feature engineering improves the classification. Thus, two additional moving mean [27] of size 300 were added for both features, and different feature set configurations were passed to the classifiers. The data was labeled as a "normal" class where the diameter of the wheel was not changed and "abnormal" in other cases (ca. 45% / 55% of data points respectively). 20% of all data was taken as a training set, and the remaining 80% was used as a test set. Such a setting was enough to train a well-working model and evaluate it on a broader test set. Different combinations of features mentioned above were examined. Results for classifiers are reported in Table 7.

It can be noted that classification works very well using basic classifiers, such as K-nearest neighbors. More sophisticated methods like SVM were not performing well here. Even using single correction features results in 91–94% accuracy, combining them gives almost 99%, and adding the moving average increases the classification result to nearly 1.0. The limitation of such an approach is related to the possibility of real-time operation. Although the classification requires no history (sequence) of samples, implicitly using the moving average of length L involves a delay of $L/2$ time steps to process the classification. However, if it

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Table 7. Results of classification to normal/abnormal wheel diameter based on natural navigation data. The first four columns denote whether a feature is present in the input data. DHAC – difference heading average correction, DAC – distance average correction, MA stands for moving average. The best results in each column are in bold.

				K-nn		Gauss. NB		Dec. tree		Rand. forest		SVM	
DHAC	**DHAC(MA)**	**DAC**	**DAC(MA)**	accuracy	AUC-ROC	accuracy	AUC-ROC	accuracy	AUC-ROC	accuracy	AUC-ROC	accuracy	AUC-ROC
+	-	-	-	0.915	0.964	0.592	0.685	0.936	0.935	0.936	0.968	0.672	0.732
-	+	-	-	0.732	0.821	0.590	0.684	0.698	0.694	0.698	0.805	0.669	0.732
-	-	+	-	0.926	0.970	0.712	0.770	0.943	0.946	0.943	0.973	0.713	0.818
-	-	-	+	0.807	0.885	0.711	0.770	0.767	0.764	0.767	0.872	0.712	0.818
+	+	-	-	0.927	0.978	0.632	0.686	0.956	0.956	0.963	0.992	0.661	0.739
+	-	+	-	0.986	0.996	**0.723**	0.770	0.987	0.987	0.989	0.999	0.770	0.863
+	-	-	+	0.980	0.996	0.722	0.771	0.987	0.987	0.990	0.999	0.768	0.864
-	+	+	-	0.976	0.996	0.718	0.770	0.986	0.985	0.990	0.999	0.762	0.866
-	+	-	+	0.981	0.997	0.720	0.771	0.976	0.976	0.982	0.998	0.772	0.867
-	-	+	+	0.944	0.984	0.711	0.771	0.964	0.964	0.972	0.994	0.717	0.819
+	+	+	-	0.997	0.999	0.717	0.756	0.994	0.994	0.998	1.000	0.773	0.862
+	+	-	+	0.998	**0.999**	0.719	0.756	0.994	0.994	0.998	1.000	0.766	0.866
+	-	+	+	0.998	0.999	0.713	**0.784**	0.994	0.994	0.998	1.000	0.774	0.867
-	+	+	+	0.997	0.999	0.714	0.784	0.994	0.994	0.998	1.000	0.772	0.874
+	+	+	+	**0.999**	**0.999**	0.716	0.772	**0.996**	**0.996**	**0.999**	**1.000**	**0.775**	**0.880**

is possible to stay with ca. 1 percentage point lower accuracy, then real-time processing is feasible (i.e., for the combination $+-+-$ in Table 7).

6 Discussion and Conclusions

This study demonstrated the application of machine learning techniques for the detection of anomalies based on Automated Guided Vehicle (AGV) telemetry data, a critical aspect of maintaining operational efficiency in smart manufacturing environments. Through the application of LSTM and GRU models, along with traditional machine learning classifiers, we have addressed two significant types of anomalies that can affect AGVs: mechanical wear or excessive friction and tire or wheel damage.

The experiments conducted here showed that the proposed approach can forecast momentary power consumption and thus be used to find potential mechanical issues. Similarly, the classification of wheel-related anomalies achieved very good accuracy, highlighting the effectiveness of our feature selection and engineering approach. These results underscore the potential of machine learning in enhancing predictive maintenance strategies, thereby reducing downtime and improving the reliability of AGVs in industrial settings.

However, the implementation of such systems does not come without challenges. The collection and preprocessing of telemetry data require careful consideration to ensure the quality and relevance of the information being analyzed.

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Additionally, the dynamic nature of manufacturing environments means that models must be continually updated and refined to adapt to new conditions and anomalies. The limitation of our research is that changes in power consumption can be due to other reasons than mechanical issues. Addressing that topic would need additional thorough research.

In conclusion, this research contributes valuable insights into detecting anomalies in AGV operations, offering an approach to improving the resilience and efficiency of smart manufacturing systems. Future work could focus on expanding the types of anomalies detectable by our models, improving the automation of data preprocessing, and exploring the integration of these models into real-time AGV management systems for immediate anomaly detection and response.

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