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The Impact of Climate Conditions on the Geometry of Railway Tracks in Iran: A Deep Learning Approach

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Climate is one of the most important factors in railway infrastructure, and future changes in climate and extreme weather conditions will increase the risks concerning its stability and performance. Understanding and mitigating these risks is vital for ensuring the longevity and safety of railway networks. The research work presented here examines the association of climatic conditions with the geometric degradation of railway lines in Iran using Deep Learning models.

The research is based on the geometric data obtained from track measurement machines over 14 years, encompassing track gauge, profile, and twist. These data were matched with meteorological records such as temperature, humidity, rainfall, and wind speed for different regions of Iran. By combining these datasets, deep learning models are developed to analyze and predict the pattern of track degradation resulting from various climatic conditions.

The added value of using meteorological data in training predictive models is assessed by comparing the performance of models trained with and without meteorological data. More precisely, one model predicts track degradation without considering meteorological data, while the other includes climatic information. This comparison allows for an evaluation of the effectiveness of weather data in improving the accuracy of track degradation predictions.

This research is, therefore, likely to contribute to critical knowledge of how climatic variables influence railway infrastructure, allowing for more realistic forecasts of track life and better planning for maintenance schedules.

Given the challenges associated with climate change, the present study addresses the call to develop more resilient railway infrastructure for operational safety across varied climatic conditions.

1. Introduction

Rail systems truly stand as some of the most analytically important transit structures, greatly serving a deeply key function in nations' economies and overall progress. These networks are always influenced by many factors that are able to affect their performance as well as safety. Of these factors, weather patterns are particularly important. Climate change and the measurably increasing frequency of seriously extreme weather events have introduced new risks to railway tracks. These risks effect both the stability and the overall performance of railway tracks [1, 2, 3].

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Changes to temperature, humidity, precipitation, and wind speed can lead to geometric deterioration of railway tracks. For instance, several temperature fluctuations can cause rail expansion as well as contraction. This subsequently leads to several instances of unevenness in addition to changes in track geometry [4, 5]. Alternatively, important precipitation may induce subgrade breakdown as well as diminish its strength [6].

Therefore, completely understanding and precisely predicting the effect of severely harsh climatic conditions on railway tracks is exceptionally important for guaranteeing the complete overall safety and greatly long-term longevity of this important infrastructure [2].

In this context, past research has shown that machine learning prediction models are helpful for forecasting infrastructure failure [7, 8, 9].

This particular study thoroughly investigates the definitive connection between certain weather conditions and the measurable geometric wear of railroad tracks in Iran. The main purpose of this study is to develop deep learning models to examine and forecast track degradation patterns using geometric and weather data. Geometric data obtained from track measurement machines across 14 years are used for this purpose. The data includes track gauge, profile, as well as twist. These data are carefully matched with thorough meteorological records such as temperature, humidity, precipitation, as well as wind speed for different regions of Iran.

To determine the importance of meteorological data in the development of predictive models, a comparison is conducted regarding the effectiveness of models developed using meteorological data versus those developed without it. We can use this assessment to determine the extent to which weather data improves the accuracy of track degradation forecasts [10].

This detailed research's results can add to especially important knowledge regarding how climatic variables directly affect railway infrastructure, allowing for more accurate predictions of track life as well as considerably better planning for maintenance schedules. This analysis examines how to develop more resilient railroad infrastructures for secure operations during variable weather conditions, considering the problems associated with climate change.

2. Literature Review

Impacts of climate change on transportation infrastructure, particularly railway infrastructure, have become a significant matter for the whole world. Rising temperatures, changing precipitation patterns, and increased frequency of extreme weather events pose new challenges to railway system performance and stability [1, 2]. This literature review aims to research previous studies into the effects of climate change on railway geometry and the application of deep learning algorithms for estimating those effects. In addition, the review highlights prior gaps in knowledge and sets the context for this study, where the focus lies on the application of meteorological observations in integrating deep learning with railway track wear estimation in Iran.

Climate change affects railway geometry in various mechanisms. Expansion and contraction of the rails can be induced by changes in temperature, leading to geometric irregularities in the long term [2, 4, 5]. For instance, Zhang et al. (2019) pointed out that thermal expansion and contraction of the rails due to changes in temperature may result in misalignment of tracks, which requires increased maintenance. Similarly, heavy rain events-induced subgrade erosion threaten the structural integrity of the tracks [5, 6, 10, 11]. The above research emphasizes that climatic conditions and their relation to the degradation of railway tracks is an essentiality in imparting railway infrastructure with safety and resilience.

More recent studies have established the application of machine learning-based models to effectively predict infrastructure degradation [7, 9, 11]. Deep learning techniques, particularly, offer high-end capability of scrutinizing detailed data and defining patterns that might be difficult to identify using common techniques. As an example, Wang et al. (2023) used Long Short-Term Memory (LSTM) networks for estimating track geometry deterioration and found the models performed in a better manner relative to the traditional means concerning accuracy. By incorporating historical climatic data into meteorological records of railway lines, deep models of learning have the potential to increase the accuracy of degradation forecasting [12]. Further, Davies et al. (2021) established that incorporation of meteorological information in the models used for predictive purposes significantly boosts their performance, particularly in places where the climatic conditions are extreme [4].

Integration of the meteorological information into the model of prediction has been the major area of inquiry. Climate conditions such as temperature, humidity, rain, and wind speed have been identified to affect railway track deterioration gravely. For instance, Kostianaia et al. (2021) showed that temperature and humidity were unavoidable parameters for the prediction of rail expansion and contraction [1]. In addition, IPCC (2022) emphasized the importance of considering climate change in planning infrastructure and undertaking maintenance. Such findings highlight the need to integrate meteorological data into forecast models for purposes of addressing the effect of climate change on rail tracks [3].

While present research recognizes the potential in deep learning in infrastructure management, more studies specifically for applying such models to estimate climate-induced deterioration in rail networks are necessary. Furthermore, the integration of several climate factors and their influence on different railway geometry components must be investigated. For example, temperature and rainfall have been the main areas of interest for most studies, but wind speed, humidity, and solar radiation can also play a significant role in track degradation [10]. Furthermore, there is limited evidence of the application of deep learning models in regions with certain climatic conditions, such as northern Iran with high humidity and heavy rainfall.

The literature review identifies the necessity for reducing the impact of climate change on rail infrastructure and the potential of utilizing deep learning approaches for predictive maintenance. The current study aims at bridging the gap by conceptualizing and testing deep learning models that incorporate climatic information for predicting railway geometry degradation. Through this, it facilitates the development of more durable railway infrastructure capable of withstanding varied climatic conditions. The integration of meteorological data into predictive models offers a workable way to improve the precision of degradation prediction and ensure railway network safety and longevity.

3. Methodology

In this chapter, the methodology of this study is described to predict the geometrical degradation of railway tracks in the north of Iran using deep learning methods with Long Short-Term Memory (LSTM) networks [12]. The LSTM network was implemented using the Keras library [13], and data preprocessing and evaluation were carried out using the scikit-learn library [14]. The approach integrates geometric data from train tracks with meteorological data in order to increase the accuracy of degradation predictions. The process is divided into several key steps: data collection, preprocessing, model construction, training, and testing. The method aims at addressing the research gaps as indicated in the literature review, specifically failure to include weather data in prediction models of track degradation of the railroad [15, 16].

3.1. Data Collection

The research is based on two main datasets: geometric data of the tracks from railway and meteorological data from weather stations in northern Iran.

3.1.1. Geometric Data

Geometric measurements were made by the EM120 track measurement vehicle during 14 years (from 1388 to 1401 in the Persian calendar, corresponding to 2009–2023). Measurements cover track gauge parameters (GAU), longitudinal level (LLL and LLR), cross-level (XLV), alignment (ALL and ALR), twist (TWS32, TWS50, TWS100), and accelerations (ACCV, ACCH, ACCL, ACCT). These parameters, measured by the sensors of the track measurement vehicle, are listed in Table 1. Additionally, a schematic of the placement of sensors for measuring each geometric parameter of the railway track is provided in Fig. 1. The measurements were conducted twice yearly, once during the first half and once during the second half of every year, and spanned the northern half of Iran from kilometer 115 to 442. The volume of geometric data that was captured was some 150 gigabytes, which conveys the extent and magnitude of the measurements.

3.1.2. Meteorological Data

The meteorological data were collected from the Iranian Meteorological Organization for the same time. The data comprise synoptic daily observations like temperature (t), relative humidity (u), minimum and maximum temperature (tmin, tmax), rainfall (rrr24), wind speed (ff-max), wind direction (dd-max), solar radiation (radglo24), and snow depth (ess). A summary of the meteorological parameters obtained from the Iranian Meteorological Organization is provided in Table 2.

The north area was subdivided into four areas according to closeness to weather stations:

- Section 1 (Kilometer 115 to 248): Meteorological data from Firouzkooh weather station (Station ID: 40756).
- Section 2 (Kilometer 248 to 315): Meteorological data from Pol Sefid weather station (Station ID: 99360).
- Section 3 (Kilometer 315 to 380): Meteorological data from Sari weather station (Station ID: 40759).
- Section 4 (Kilometer 380 to 442): Meteorological data from Galugah weather station (Station ID: 99299).

This subdivision and the selected weather stations are illustrated in Fig. 2.

Table 1. The parameters measured by the EM120 track measurement vehicle. [17]

Signal Name	Description	Measuring Position
SPD	Running Speed	-
LLL1	Longitiudinal Level Left 1	Left side of A2
LLL2	Longitiudinal Level Left 2	Left side of A4
LLL3	Longitiudinal Level Left 3	Left side of A5
LLL4	Longitiudinal Level Left 4	Left side of A6
LLR1	Longitiudinal Level Right 1	Right side of A2
LLR2	Longitiudinal Level Right 2	Right side of A4
LLR3	Longitiudinal Level Right 3	Right side of A5
LLR4	Longitiudinal Level Right 4	Right side of A6
ALL1	Alignment Left 1	Left side of MAF
ALL2	Alignment Left 2	Left side of MAC
ALL3	Alignment Left 3	Left side of MAR
GAU1	Gauge 1	Center of MAF
GAU2	Gauge 2	Center of MAC
GAU3	Gauge 3	Center of MAR
ALC	Alignment Compensation Center	Center of MAC
LVM	Superelevation Device	-
ACCH	Horizontal Acceleration	-
ACCV	Vertical Acceleration	-
ACCL	Longitiudinal Acceleration	-
TEMP	Ambient Temperature	-

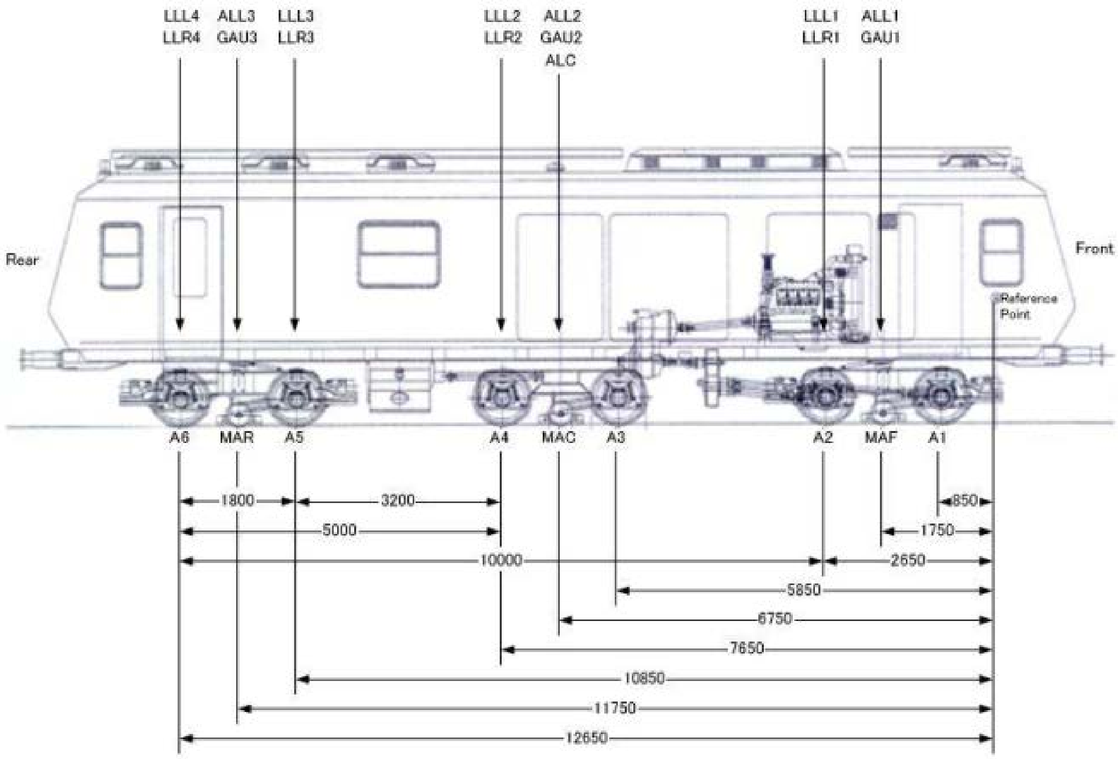

Figure 1. Location of sensors for measuring geometric parameters on the EM120 track measurement vehicle [17].

Table 2. Daily synoptic meteorological data.

Parameter Name	Description
ess	Snow depth
u	Relative humidity
tmin	Minimum temperature
tmax	Maximum temperature
radglo24	Solar radiation in the past 24 hours
sshn	Sunshine hours
rrr24	Total rainfall in the past 24 hours
ff-max	Maximum wind speed
dd-max	Maximum wind direction
ew	Vapor pressure
t	Temperature
p0	Station pressure
nhl1	First layer cloud cover
ss	Snowfall

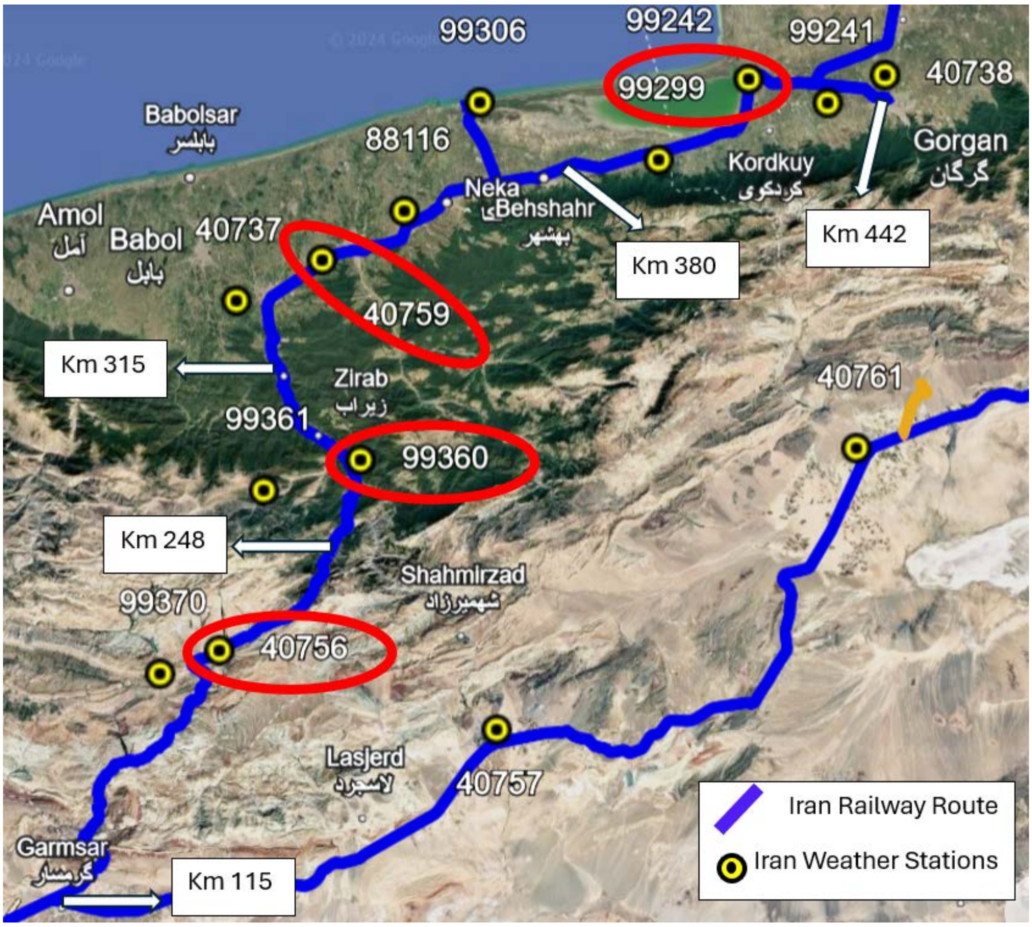

Figure 2. Subdivision of the northern Iran railway region and selection of weather stations.

3.2. Data Preprocessing

Data preprocessing is a necessary step in order to provide quality and usable data for training the model. The following preprocessing operations were utilized:

3.2.1. Data Cleaning

- Deleting duplicate rows and unnecessary columns.
- The kilometer-based errors were corrected based on superelevation changes for data uniformity.
- Incomplete records were deleted to ensure data integrity because the dataset was large and strong enough to tolerate the elimination of incomplete records without affecting the overall analysis substantially.

3.2.2. Data Aggregation

- Geometric data was averaged over every 200 meters of the rail track to remove noise along with computational complexity.
- For meteorological features, the time gap between two adjacent track measures was taken into account, and aggregation techniques were used to summarize the weather conditions in between this time. In other words, for each weather feature (temperature, humidity, precipitation, wind speed), the average, variance, minimum, and maximum were calculated. The summary statistics were fed into the model in order to take into account the uncertainty and extremes of weather conditions in between measurements.

3.2.3. Data Integration

Geometric and meteorological data were blended in accordance with the corresponding time and location. Using this blending, the model could consider both track geometry and weather simultaneously.

3.2.4. Data Splitting

Data was divided into training (80%) and validation and testing (20%) sets with the train_test_split function of scikit-learn to avoid biased evaluation [14].

3.2.5. Feature Scaling

Meteorological and geometric features were scaled with scikit-learn's StandardScaler for improved model convergence [14].

3.3. Model Development

The research utilizes LSTM networks, a variant of RNN, in track degradation forecasting. LSTM networks are well adapted to time-series data as they can learn long-term dependencies [18]. The LSTM architecture was realized utilizing Keras's Sequential API [13].

3.3.1. Model Architecture

- The LSTM model consists of multiple layers such as input, LSTM, dropout, and dense layers.
- It takes preprocessed data with meteorological and geometric features as input.
- This LSTM layer is utilized to learn temporal dependencies in the input data.
- Dropout layers are included to avert overfitting through the random dropout of neurons while training.
- The dense layer provides the ultimate output, which is the estimated track degradation.

3.3.2. Hyperparameter Tuning

The model was optimized with a grid search method using scikit-learn's GridSearchCV to find the best hyperparameters from among the values listed in Table 3.

Table 3. Considered values for hyperparameters.

Hyperparameter Name	Value
Number of neurons	100, 200, 400
Batch size	32, 64, 128
Number of epochs	50, 100, 200
Dropout rate	0.2, 0.3
Window size	2, 3, 4, 5, 6
Optimizer	Adam, RMSProp

3.4. Model Training and Evaluation

The data was divided into training (80%) and validation and testing (20%) sets. The model was trained using the training set, and its performance was tested using the validation and testing sets. The validation and testing sets combined represent 20% of the data.

3.4.1. Evaluation Metrics

- Root Mean Squared Error (RMSE): The average size of the prediction errors [19]. Computed through scikit-learn's mean_squared_error [14]. The formula for RMSE is given in Eq. (1).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

Variables:

y_i: Observed value for the i-th data point,

$\hat{y}_i$: Predicted value for the i-th data point,

n: Total number of data points.

- Mean Absolute Error (MAE): Mean of the absolute difference between forecasted and observed values [19]. Calculated through scikit-learn's mean-absolute-error [14]. The formula for MAE is given in Eq. (2).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{2}$$

Variables:

y_i: Observed value for the i-th data point,

$\hat{y}_i$: Predicted value for the i-th data point,

n: Total number of data points.

- R-squared (R^2): Explains the proportion of variance in the dependent variable that can be explained by the independent variables [20]. Derived from scikit-learn's r2_score [14]. The formula for R^2 is given in Eq. (3).

Variables:

y_i: Observed value for the i-th data point,

$\hat{y}_i$: Predicted value for the i-th data point,

$\bar{y}$: Mean of the observed values,

n: Total number of data points.

3.4.2. Prediction of Individual Geometric Parameters

Model performance metrics (RMSE, MAE, R^2) were used to predict all the geometrical parameters such as track gauge (GAU), longitudinal level (LLL and LLR), cross-level (XLV), alignment (ALL and ALR), twist (TWS32, TWS50, TWS100), and accelerations (ACCV, ACCH, ACCL, ACCT). Each parameter's results were noted and compared to assess the model's performance on various elements of track geometry.

3.4.3. Forecasting a Combined Railway Index (TGI)

A composite railway index, the Track Geometry Index (TGI), was also forecast. TGI is a composite index that combines several geometric parameters into one value and gives a general indication of track condition [21]. The performance of the model in forecasting the TGI was computed on the same measures (RMSE, MAE, R^2), and comparisons were made with individual parameters. The formula for TGI is given in Eq. (4).

$$TGI = \frac{2UI + TI + GI + 6AI}{10} \tag{4}$$

Variables:

UI: Index for unevenness,

TI: Index for twist,

GI: Index for gauge,

AI: Index for alignment.

3.4.4. Ablation Study

In order to determine the contribution of meteorological data to forecast accuracy, two models were constructed:

- Model 1: Trained on purely geometric data.
- Model 2: Trained on meteorological and geometric data.

The performance of both models was compared based on the above evaluation metrics.

4. Results

Ablation study was performed to establish the contribution of various input features towards the performance of the model. Two models were compared:

Model 1: Trained on purely geometric data (e.g., track gauge, alignment, twist).

Model 2: Trained on both meteorological and geometric data (i.e., temperature, rainfall, humidity).

To determine the optimal window size for the LSTM model, we evaluated the Root Mean Squared Error (RMSE) for TGI at Sari station across varying window sizes. As illustrated in Fig. 3 , the RMSE initially decreases with increasing window size, reaching a minimum at a window size of 4.0, before slightly increasing. This suggests that a window size of 4.0 provides the best performance for our LSTM model for this case.

Fig. 4 illustrates the training loss (RMSE) of the LSTM model for TGI prediction at Sari station over 500 epochs. The graph demonstrates a rapid decrease in loss during the initial epochs, indicating effective learning and convergence of the model. Specifically, the loss plummets from approximately 0.00010 to below 0.00003 within the first 200 epochs. After this initial rapid decline, the loss continues to decrease, albeit at a slower rate, eventually stabilizing around 0.00002. This stabilization suggests that the model has reached a point of minimal error and further training is unlikely to yield significant improvements in performance. The consistent low loss values in the later epochs confirm the model's ability to accurately predict TGI at Sari station after sufficient training.

The results of the ablation study for the LSTM model across all four sections of the northern Iran railway are presented in Tables 4-7.

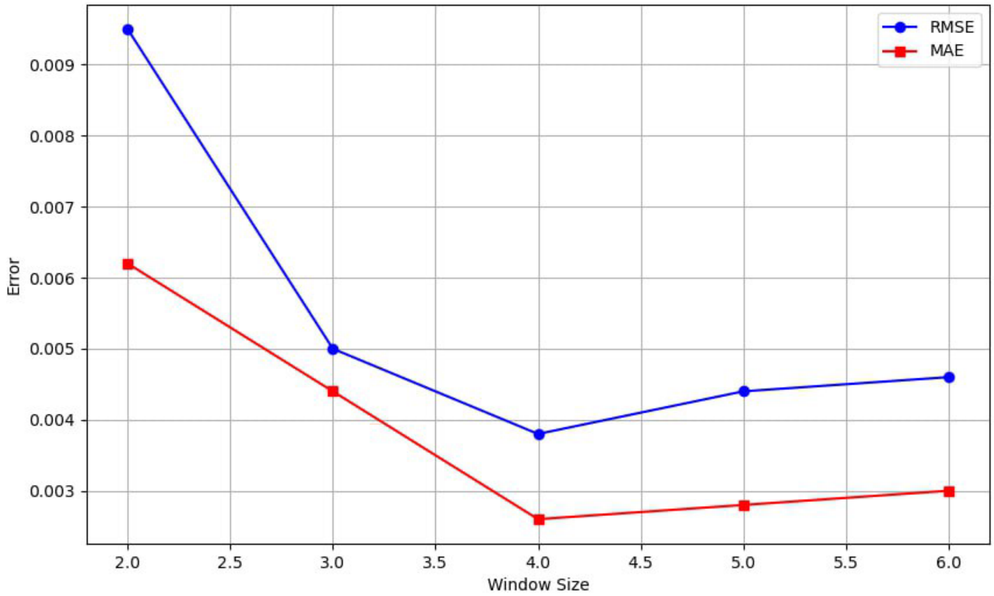

Figure 3. Error graph by window size.

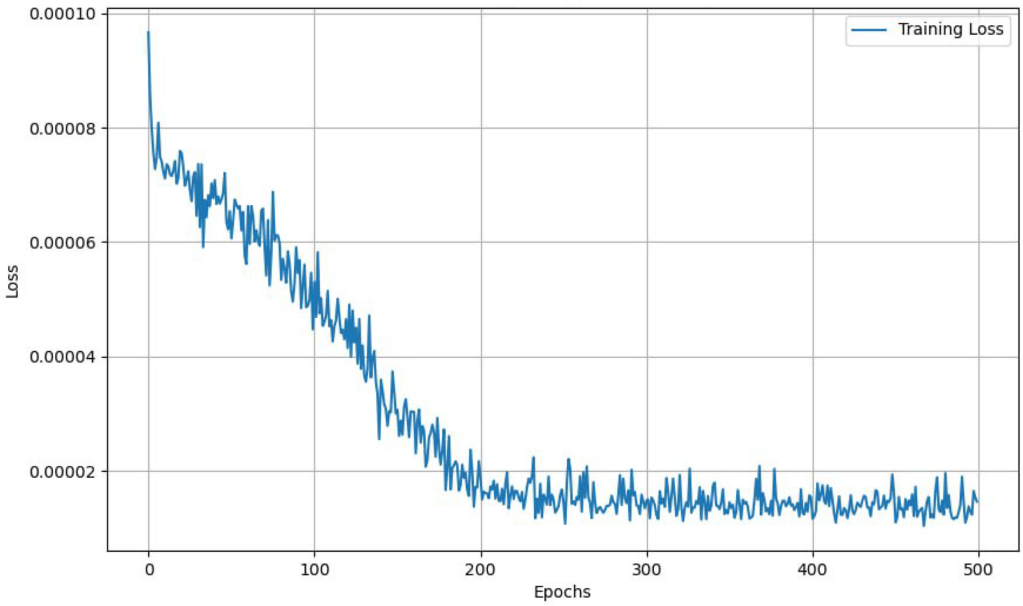

Figure 4. Loss graph by epochs.

Model 2 performed better than Model 1 with a 15.2% decrease in RMSE and a 10% increase in R^2.

For a single geometric parameter (e.g., GAU, LLL, XLV), the inclusion of meteorological data enhanced predictability, with RMSE reductions of between 8% and 18%.

The Track Geometry Index, TGI, which is the overall railway index, was also better predicted by Model 2 with RMSE of 1.92 and R^2 of 0.88.

5. Discussion

5.1. Impact of Meteorological Data

Table 4. Model results for the Firouzkooh station.

Without weather data				With weather data			
Index	RMSE	MAE	R^2	Index	RMSE	MAE	R^2
ALL	0.0080	0.0060	0.743	ALL	0.0058	0.0043	0.766
ALR	0.0078	0.0055	0.770	ALR	0.0053	0.0040	0.809
GAU	0.0074	0.0054	0.758	GAU	0.0052	0.0038	0.785
LLL	0.0093	0.0070	0.721	LLL	0.0066	0.0049	0.767
LLR	0.0094	0.0072	0.703	LLR	0.0093	0.0070	0.721
TWS32	0.0095	0.0068	0.691	TWS32	0.0068	0.0048	0.720
XLV	0.0080	0.0060	0.753	XLV	0.0056	0.0042	0.773
TGI	0.0081	0.0061	0.751	TGI	0.0054	0.0041	0.786

Table 5. Model results for the Pol Sefid station.

Without weather data				With weather data			
Index	RMSE	MAE	R^2	Index	RMSE	MAE	R^2
ALL	0.0039	0.0026	0.826	ALL	0.0035	0.0023	0.854
ALR	0.0045	0.0032	0.714	ALR	0.0042	0.0029	0.744
GAU	0.0044	0.0031	0.724	GAU	0.0042	0.0029	0.749
LLL	0.0070	0.0061	0.566	LLL	0.0072	0.0063	0.560
LLR	0.0080	0.0066	0.414	LLR	0.0073	0.0061	0.445
TWS32	0.0043	0.0036	0.565	TWS32	0.0044	0.0036	0.668
XLV	0.0059	0.0042	0.775	XLV	0.0040	0.0025	0.813
TGI	0.0037	0.0025	0.835	TGI	0.0030	0.0021	0.865

Table 6. Model results for the Sari station

Without weather data				With weather data			
Index	RMSE	MAE	R^2	Index	RMSE	MAE	R^2
ALL	0.0049	0.0029	0.830	ALL	0.0031	0.0021	0.875
ALR	0.0046	0.0026	0.840	ALR	0.0033	0.0022	0.860
GAU	0.0035	0.0023	0.723	GAU	0.0026	0.0018	0.743
LLL	0.0070	0.0060	0.510	LLL	0.0073	0.0063	0.507
LLR	0.0084	0.0069	0.383	LLR	0.0058	0.0050	0.403
TWS32	0.0090	0.0063	0.546	TWS32	0.0071	0.0050	0.564
XLV	0.0065	0.0039	0.755	XLV	0.0044	0.0025	0.801
TGI	0.0034	0.0025	0.872	TGI	0.0032	0.0021	0.881

Table 7. Model results for the Galugah station.

Without weather data				With weather data			
Index	RMSE	MAE	R^2	Index	RMSE	MAE	R^2
ALL	0.0046	0.0031	0.800	ALL	0.0046	0.0030	0.805
ALR	0.0051	0.0038	0.740	ALR	0.0053	0.0037	0.731
GAU	0.0064	0.0046	0.672	GAU	0.0059	0.0042	0.695
LLL	0.0077	0.0065	0.571	LLL	0.0073	0.0063	0.582
LLR	0.0064	0.0059	0.647	LLR	0.0063	0.0052	0.656
TWS32	0.0058	0.0043	0.692	TWS32	0.0039	0.0028	0.785
XLV	0.0053	0.0033	0.726	XLV	0.0049	0.0028	0.766
TGI	0.0045	0.0029	0.837	TGI	0.0042	0.0027	0.850

The results of the ablation study confirm that meteorological data significantly enhances the model's predictive capability. This also agrees with findings by Zhang et al. (2019), who emphasized the role of environmental factors in railway track degradation [6].

These variables of temperature, rain, and humidity were strongly correlated to geometric deterioration, especially for variables like track gauge (GAU) and longitudinal level (LLL).

5.2. Model Performance

The better performance of Model 2 validates the necessity of fusing multi-source data (geometric and meteorological) for precise degradation prediction. This agrees with research by Wang et al. (2023), who emphasized the advantages of incorporating heterogeneous datasets into predictive maintenance models [22].

The TGI index as a composite was used efficiently, allowing the track condition to be determined more easily in general without loss of accuracy.

5.3. Limitations

The study has a limitation that it is based on historical data from one region (northern Iran). It may need supplementary data and re-calibration to apply the model to other areas with varying climatic conditions.

Further model performance improvement could be done based on the incorporation of other contributing factors such as train traffic intensity and material track properties.

6. Conclusions

The ablation study revealed that combining meteorological data with geometric information significantly enhances the precision of predictions regarding railway track degradation.

The TGI index surfaced as a dependable combined metric for evaluating track conditions, with Model 2 yielding a root mean square error (RMSE) of 1.92 and an R^2 value of 0.88.

These results can assist railway operators in implementing more efficient predictive maintenance techniques, thereby decreasing costs and elevating safety standards.

Utilizing the TGI index streamlines decision-making processes by offering a single, all-encompassing assessment of track condition.

Subsequent research should investigate the incorporation of further data sources, such as train traffic volumes and attributes related to track materials, to enhance model accuracy.

It will be crucial to validate the model across various geographical locations and under diverse climatic circumstances to improve its applicability

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