*Proceedings of the International Conference on Industrial Engineering and Operations Management*

Publisher: IEOM Society International, USA DOI: 10.46254/GC03.20260511
Published: February 2, 2026

# Deep Learning Driven Predictive Maintenance for Enhanced Monitoring of Pantograph Catenary System

**Driss EL Hor and Rachid Bannari**
Engineering Sciences Laboratory
National School of Applied Sciences
Ibn Tofail University
Kenitra, Morocco
driss.elhor@uit.ac.ma, rachid.bannari@uit.ac.ma

**Abdelfettah Bannari**
Faculty of Science and Technology
Sultan Moulay Slimane University
Beni Mellal 23000, Morocco
a.bannari@usms.ma

## Abstract

Pantograph-catenary conditions monitoring is a challenging issue in railway infrastructures. Thus, the failure of these critical systems causes considerable detriment with regard to availability and passenger safety and requires substantial human and financial resources for maintenance. However, rail operators still use traditional methods to control many equipment thorough visual inspections. In recent years, several research have suggested the use of Artificial Intelligence for conditions monitoring, the latest still incipient leading sometimes to unwarranted investments. In this context, the paper examines recent advancements in pantograph condition monitoring over the past five years, within the domain of predictive maintenance. It highlights the methods, algorithms, and monitored parameters through a comprehensive analysis of prior studies. The analysis revealed that the Convolutional Neural Networks (CNNs) and image processing techniques have been extensively employed. Furthermore, a comparative evaluation is provided, emphasizing performance across key metrics such as accuracy, precision and MRSE. Finally, we have proposed an unified Predictive Maintenance workflow of wear detection based on CNN and deep learning. In conclusion the study outlines the major challenges and limitations of current practices.

## Keywords
Predictive maintenance, Pantograph-catenary, Deep learning, contact strips, CNN.

## 1. Introduction
In the recent years, Predictive Maintenance has become a necessity to remain competitive for both railway manufacturers and rails operators, due to the large benefits provided on costs, availability and safety. Pantograph is the substantial train component that transfer power from the rail infrastructure called the catenary to the traction motors, it ensures the current collection for all electrical rolling stock vehicle. Several designations were found in the literature to describe the electric power source such as overhead contact (Na et al., 2020) and (Rodríguez-Arana et al., 2023), overhead current line (Lee et al., 2022) or pantograph- catenary system, the latest will be used for the rest of the paper. The Figure 1 shows the couple Pantograph-catenary for the Tram A in Bordeaux City on the right image, The left one present the main components that enable transferring energy from catenary to the train, there are described below:

- Catenary wire: high voltage 1500V DC or 25 000V AC, designed generally on cooper.
- Contact strips: carbon or graphite strips in continuous sliding with the catenary contact wire for the collection of the current required for locomotive movement.
- Lower arm: first part of articulated arm.
- Upper arm: second part of articulated arm.
- Pantograph Bow: the pantograph upper part that encompass contact strips, horns, crossbar.

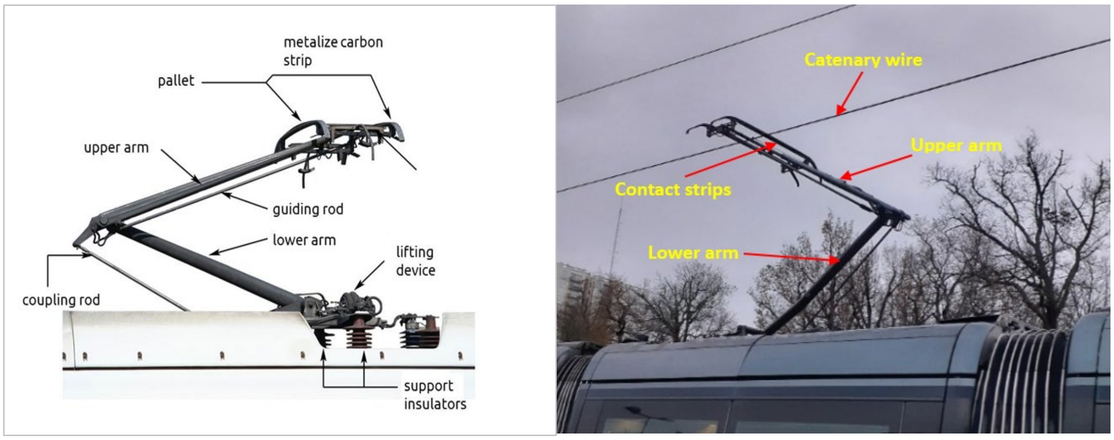


Figure 1. **A**-The main components of pantograph system. **B**- Pantograph-catenary system on Tram Line A, Bordeau city.

On Decembre 6 and 7, 2016 two severe incidents have greatly impacted one of the largest rail networks, in which the rail traffic has totally interrupted. The interruption was due to the catenary wire breakage, and consequently the loss of electric supply (SNCF 2016). The investigation performed has identified 2 potential causes, the first depends to the train faulty pantograph, the second issue was related to incorrectly assembly of the catenary's equipment caused by a missing pin. This accident raises concerns and highlights the critical importance of failure forecasting and predictive maintenance in preventing catastrophic incidents. In addition, pantograph catenary system presents one of the main systems of railway infrastructures (Brahimi et al., 2017), it plays a pivotal role in ensuring a high level of railway reliability and availability.

This paper aims to investigate the diverse failures of pantograph and to analyze their causes. The focus is given to recent contributions and proposed methodologies within the context of predictive maintenance. By conducting a comparative study of these approaches, the paper seeks to highlight both the strengths and limitations of current practices, as well as to identify potential avenues for improvement. The ultimate objective is to provide a comprehensive understanding of pantograph monitoring and to contribute to the advancement of predictive maintenance strategies. The rest of this paper is organized as follows: the next section presents a literature review and related work. Section 3 shed light on the main finding and discussed the results obtained with a proposed novel methodology. We have explored main limitations in section 4. Finaly further works and perspectives were presented in conclusion.

## 2. Literature review

Whatever the rolling stock types, pantograph-catenary system can be a subject for various nature of failures: mechanical, electrical or thermal defects. Thus, the major common causes of defects are: wear and tear of pantograph-catenary components, arcing, incorrect contact strip position, bad system dimensions (Richards et al., 2024). The work performed in (Brahimi et al., 2018) have showed that the pantograph-catenary breakdown is the first causes that contribute to the train delays with over 50% of global delays. Among the various types of equipment analyzed, corrective maintenance of the catenary wire accounts for approximately 25% of the total budget allocated to sustaining operational service. Furthermore, its adverse impact on train availability generates substantial economic costs and operational losses. Consequently, integrating predictive maintenance thorough condition monitoring techniques reduce failures cost and improve the lifespan of railway infrastructures (Karaduman & Akin, 2020).

Laffont, et al., (2008) have developed a pantograph monitoring system based on optical fiber sensors. The latest provide measurement of: 3D motion, contact force and image acquisition. The tests were realized in both laboratory and the railway tunnel in Suisse named “Lötschberg tunnel”, the results obtained have shown a correlation between the “train velocity, contact force” and the “infrastructure distortion, motion”. These measurements were designed to optimize several parameters, particularly the contact force, since inappropriate force values can lead to accelerated wear of the catenary wire, structural damage to the supports, and the occurrence of electric arc phenomena. Consequently, the monitoring center is able to initiate predictive maintenance actions to mitigate potential failures and prevent costly incidents.

The literature review we have conducted underscores that the majority of researches have been performed to monitor the wear of the railway electrical infrastructure. The authors have proposed numerous methodologies for conditions monitoring, such as the image processing, computer vision and deep learning. These methods use multiple signals: Image, current and voltage acquired by sensors as illustrated in the Table 1 below:

Table 1. Methods and signals used for pantograph detection systems

| **pantograph defects** | |
|---|---|
| | wear |
| | tear |
| | arcing |
| | incorrect contact strip position |
| | bad system dimensions |
| **Methodologies** | |
| | image processing |
| | computer vision |
| | deep learning |
| **Signals acquired by sensors** | |
| | Image |
| | current |
| | voltage |

Since 2016, the application of data-driven approaches in predictive maintenance has continued to evolve (El Hor & Bannari 2025). Table 2 presents the most recent articles addressing predictive maintenance and RUL of the pantograph system. These articles are thoroughly analyzed to extract the various methods, parameters, and metrics employed, which are presented in the following sections.

Table 2. Predictive maintenance of pantograph system in the last 5 years

| Ref | Paper Title | Year | Method | Algorithms |
|---|---|---|---|---|
| (Liu & Wu, 2025) | Predicting the Remaining Useful Life of Metro Pantograph Sliding Strips Using Gamma Processes and Its Implications for Maintenance Scheduling | 2025 | (RUL) prediction Model based method | Gamma process–based stochastic degradation model |
| (Tang et al., 2024) | High Precision Robust Real-Time Lightweight Approach for Railway Pantograph Slider Wear Monitoring | 2024 | Image processing Deep learning | WEPS Net (deep learning–based vision network optimized for real-time wear estimation) |
| (Guo et al., 2024). | Pantograph Slider Detection Architecture and Solution Based on Deep Learning | 2024 | Image processing Deep learning | CNN-based deep learning with enhanced feature extraction |
| (Na et al., 2023) | Condition Monitoring of Railway Pantograph Using R-CNN and Image Processing | 2023 | Image-based condition monitoring | R-CNN (Region-based Convolutional Neural Network) combined with image processing techniques |
| (Trilla et al., 2020) | Enhancing Railway Pantograph Carbon Strip Prognostics with Data Blending through a Time-Delay Neural Network Ensemble | 2020 | Prognostics using multi-source data blending | Ensemble of Time-Delay Neural Networks (TDNN) for temporal degradation prediction |

# 3. Results and discussion

## 3.1. Papers analysis and models evaluation

The article analysis has showed that the convolutional neural networks (CNNs) have become the dominant approach for monitoring of pantograph carbon strip, demonstrating notable advances in the last 5 years. The work performed by (Tang et al., 2024) emphasizes the importance of lightweight CNN architectures for embedded systems, achieving an accuracy of 95.3% and demonstrating suitability for real-time deployment in trains. Similarly, (Trilla et al., 2020) have integrates CNNs with time-delay neural networks, reporting a prognostic horizon of 0.82 and an α-λ metric of 0.79, highlighting the potential of multi-source data fusion for pantograph predictive maintenance. Complementing this, the Remaining Useful Life prediction of contact Strips is carried out by (Liu & Wu, 2025) using CNN feature extraction and Gamma processes, achieving a mean absolute error (MAE) of 0.087 and a C-index of 0.76, thereby offering a quantitative framework for estimating remaining useful life and supporting predictive scheduling. By contrast (Guo et al., 2024) have suggested the foundation for CNN-based pantograph monitoring but with comparatively lower performance, achieved an accuracy of 92.4% with an F1-score of 91.0%, while the study (Na et al., 2023) have reported a detection accuracy of 93.2%. These results, while significant, illustrate the incremental progress toward more robust and predictive models. In conclusion, the trend for the last 5 years shows a clear evolution from baseline CNN detection toward hybrid and high-resolution architectures for pantograph wear monitoring. Among these, the deep CNN approach reported by (Tang et al., 2024) stands out as the most performant, achieving the highest accuracy of 95.3% and precision.

Table 3 summarizes the key finding and provides a comprehensive overview of the principal performance metrics reported in the reviewed studies. It synthesizes these indicators in a structured manner and facilitates a comparative analysis across different research works that employed similar evaluation criteria for their predictive models. This comparative perspective not only underscores the relevance of these metrics in assessing deep learning robustness and reliability but also reveals how different approaches to predictive maintenance may yield distinct levels of effectiveness depending on the dataset characteristics and modeling techniques.

Table 3. Predictive maintenance metrics for pantograph system

| Reference | Accuracy | Precision | Recall | F1-score | mAP | IoU | RMSE | MAE | PH | α-λ | C-index |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (Liu & Wu, 2025) | – | – | – | – | – | – | 0.091 | 0.087 | – | – | 0.76 |
| (Tang et al., 2024) | 95.3% | 94.7% | 94.1% | 94.4% | – | – | 0.08 | – | – | – | – |
| (Guo et al., 2024). | 92.4% | 91.2% | 90.8% | 91.0% | – | – | 0.12 | – | – | – | – |
| (Na et al., 2023) | 93.2% | – | – | – | 92.7% | 0.84 | – | – | – | – | – |
| (Trilla et al., 2020) | – | – | – | – | – | – | 0.072 | – | 0.82 | 0.79 | – |

### 3.2. Performance metrics of predictive models

Deep learning techniques have been extensively applied to the prediction of pantograph failures. As highlighted in the preceding discussion, numerous parameters are monitored within the framework of predictive maintenance, among which the wear of pantograph contact strips emerges as a primary factor. Image processing methods, particularly those leveraging Convolutional Neural Networks (CNNs), have attracted significant attention due to their diverse architecture and modules. To evaluate the effectiveness of these predictive models, a wide range of performance metrics has been employed, including Accuracy, Precision, Recall, and the F1-score.

Here is a short explanation of each metric:

**Accuracy:** measures the proportion of correctly classified features (positive and negative) out of the total number of instances. It provides a general indication of the model's overall correctness.

**Precision**: evaluates the proportion of correctly predicted positive cases out of all cases predicted as positive. It reflects the model's ability to avoid false positives.

**Recall (Sensitivity):** measures the proportion of actual positive cases that were correctly identified by the model. It indicates the model's ability to detect true positives and avoid false negatives.

**F1 Score** is the harmonic mean of Precision and Recall. It balances the trade-off between the two, especially in cases of imbalanced datasets where accuracy alone may be misleading.

### 3.3. Input data of proposed methodologies

This section discusses the parameters considered for pantograph monitoring. As shown in Table 4, the majority have deployed the wear as a first indicator for pantograph degradation over time. The thickness rate was combined with images acquired by cameras in real-time to forecast defects during the train operations.

Table 4. The pantograph contacts strips monitored parameters

| Ref | Paper Title | Year | Monitored parameters |
|---|---|---|---|
| (Liu & Wu, 2025) | Predicting the Remaining Useful Life of Metro Pantograph Sliding Strips Using Gamma Processes and Its Implications for Maintenance Scheduling | 2025 | Residual thickness, wear rate, operating time, degradation history |
| (Tang et al., 2024) | High Precision Robust Real-Time Lightweight Approach for Railway Pantograph Slider Wear Monitoring | 2024 | Thickness profile, surface wear, real-time imaging |
| (Guo et al., 2024). | Pantograph Slider Detection Architecture and Solution Based on Deep Learning | 2024 | visual condition, dimensions |
| (Na et al., 2023) | Condition Monitoring of Railway Pantograph Using R-CNN and Image Processing | 2023 | Wear, cracks, material loss, defect location |
| (Trilla et al., 2020) | Enhancing Railway Pantograph Carbon Strip Prognostics with Data Blending through a Time-Delay Neural Network Ensemble | 2020 | Thickness evolution, sensor signals, historical maintenance data |

### 3.4. Wear detection workflow based on CNN and image processing

This section illustrates the main steps of wear detection process, The Figure 2 provides an overview about all phases since the image acquisition into its classification. The latest are compared to 4 level of wear and carbon strips degradation. The case study in Figure 3 describes experimental tools such as linear array camera, light source and CNN algorithms. The camera captures the original data set, then, these images will be pre-processed and cleaned using filters and Canny edge method (Guo et al., 2024). This data will be used as an input for CNN network, VGG16 in our case study. The deep learning was pr-trained on historical images captured during a long period. Then CNN classified the newly acquired images into 4 classes, that provide 4 levels of the wear of carbon contact strips. The models assessment use various metrics illustrated in previous sections. The full flow chart is provided in Figure 2 below.

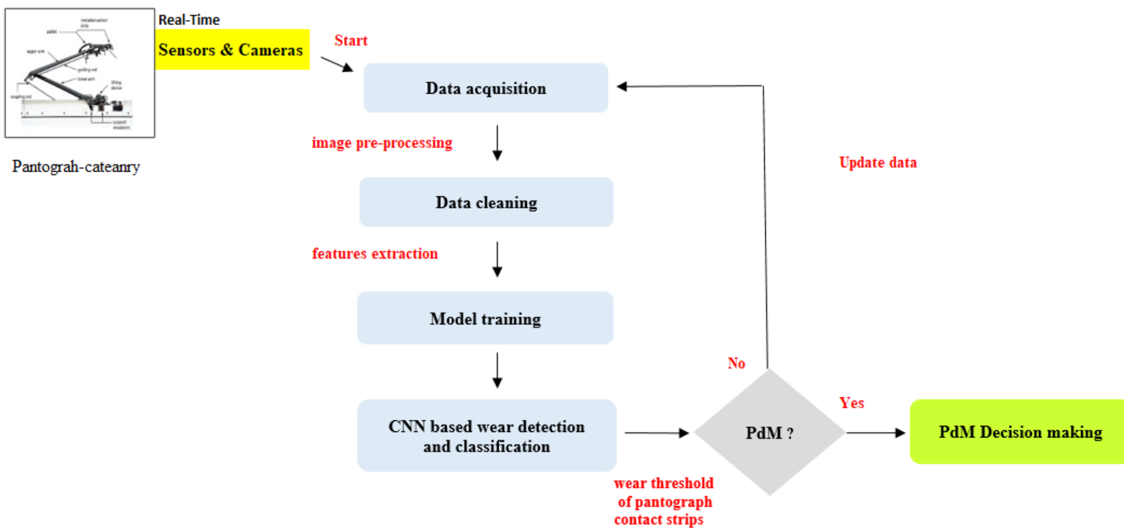


Figure 2. The process of pantograph predictive maintenance

Case study:

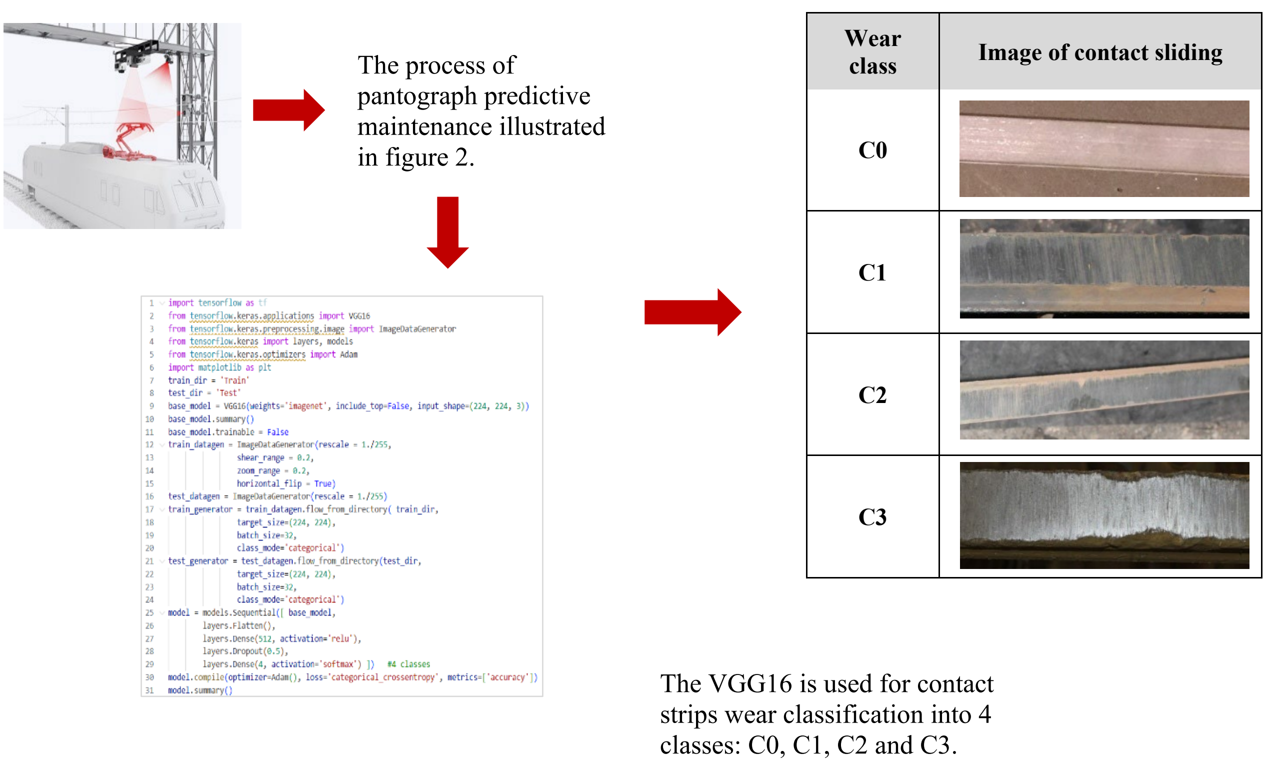


Figure 3. Experimental tools and sliding contact wear classification used VGG16 and cameras

### 3.5. Main challenges and limitations

Regarding the studies reviewed various challenges have been raised as a lack of historical data and the use of simple and less developed monitoring devices. In addition, the accuracy of deep learning algorithms is still challenging, the recent work suggests the combination of ensemble learning to reduce the error probability. The wear in current collector strip and catenary wire has been widely used as an indicator to prevent failures. However, to conduct an efficiency predictive maintenance solution, wear detection still insufficient and the risk of over-maintenance become frequent. To overcame this limitation, we suggest the combination of a risk assessment and wear prediction to optimize maintenance operations and decision making. The phase of pantograph risk evaluation could use FMECA or FTA method. Also, Data is a substantial element for predictive maintenance. Wrong or noisy data affects significantly the RUL values and the CNN performances, leading to an over-maintenance. These limitations continue to challenge researchers and industrial in rolling stock.

## 4. Conclusion

Maintenance has a crucial role in maintaining service and ensure reliable railway operations. Pantograph-catenary system presents one of the mainly rail infrastructure and the costly maintenance devices. Its defects are the first cause of train delays and line interruption. Therefore, this article explored the latest contribution in pantograph- catenary monitoring system underscoring the methods, algorithms and the monitored parameters. It suggests a synthetic flow chart for pantograph wear detection in the context of predictive maintenance. In conclusion the main limitations and challenges were presented. Future works improve the suggested methods and overcome the pinpointed challenges by adopting more accurate machine learning algorithms and high data quality.

## References

Akin, E., Karaduman, G., A deep learning-based method for detecting of wear on the current collector strips' surfaces of the pantograph in railways, IEEE Access, vol. 8, pp. 183799-183812, 2020.

Alvarado, U., Ciáurriz, P., Gil-Negrete, N., Rodríguez-Arana, B., A Non-Intrusive Monitoring System on Train Pantographs for the Maintenance of Overhead Contact Lines, Sensors, vol. 14;23(18):7890, 2023. doi: 10.3390/s23187890.

Brahimi, M., Développement d'une approche de 'Prognostics and Health Management' pour l'infrastructure ferroviaire, PhD thesis, Université de Franche-Comté, 2018.

Brahimi, M., Medjaher, K., Leouatni, M., Zerhouni, N., Development of a prognostics and health management system for the railway infrastructure – Review and methodology. 2016 Prognostics and System Health Management Conference (PHM-Chengdu), Chengdu, China, 2016, pp. 1-8, doi: 10.1109/PHM.2016.7819783.

Guo, Q., Tang, A., Yuan, J., Pantograph Slider Detection Architecture and Solution Based on Deep Learning, Sensors ,24(16), 5133; 2024. https://doi.org/10.3390/s24165133.

Laffont, G., Instrumentation de lignes caténaires par capteurs à réseaux de Bragg fibrés pour la surveillance du trafic ferroviaire - Du concept de l'instrumentation aux essais terrain, Mesures et Techniques Optiques pour l'Industrie, pp. –, 2008.

Lee, C. Y., et al., Modelling on the synergy of mechanical and electrical wear in a current line/catenary-pantograph system, Journal of Physics: Conference Series, 2345 (1) 12001 doi:10.1088/1742-6596/2345/1/012001.

Liu, J., Wu, C., Predicting the remaining useful life of metro pantograph sliding strips using gamma processes and its implications for maintenance scheduling, PLoS One 2025 20(7): e0327769. https://doi.org/10.1371/journal.pone.0327769.

Na, K.-M., Lee, K., Shin, S.-K., Kim, H., Detecting deformation on pantograph contact strip of railway vehicle on image processing and deep learning, Appl. Sci., vol. 10, no. 23, pp. 1-13, 2020.

Na, K.-M., Lee, K., Kim, H., Condition Monitoring of Railway Pantograph Using R-CNN and Image Processing, Journal of Electrical Engineering & Technology, vol. 18, pp. 2407–2416, 2024.

Richards, J., Golightly, D., Palacin, R., Cognitive Principles for Remote Condition Monitoring Applied to a Rail Pantograph System, Appl. Sci.2024, 14(13), 5801;https://doi.org/10.3390/app14135801.

Tang, Q., et al., High Precision Robust Real-Time Lightweight Approach for Railway Pantograph Slider Wear Estimation, IEEE Transactions on Intelligent Transportation Systems, vol. 25, no. 5, pp. 3973-3985, 2024.

Trilla, A., Fernández, V., Cabré, X., Enhancing Railway Pantograph Carbon Strip Prognostics with Data Blending through a Time-Delay Neural Network Ensemble, Proceedings of the PHM Society Conference. 12(1):9. 2020. DOI:10.36001/phmconf.2020.v12i1.1120.

## Biographies

**Driss EL HOR,** is a PhD student at National School of Applied Sciences Ibn Tofail University. He receives 2 degree the first in Electrical Engineering from ENSA Kenitra, the second in Industrial Risk Management from INSA CVL-Bourges, France in 2021. His research interests include reliability analysis, maintenance and electrical engineering.

**Pr. Rachid BANNARI,** is a full professor of applied mathematics and industrial engineering, recently director of the Engineering Sciences Laboratory at ENSA Kenitra. He receives a master degree in mathematics modeling from Bordeaux University in 2004. He had a PhD from Sherbrooke University Canada in 2009, in mathematic modeling and chemical engineering. He has more than 20 years of experience in academia and industry with various publications in different international journals, presentations at international conferences and research visits to international research centers.

**Pr. Abdelfettah BANNARI** is a full professor in engineering and applied sciences at Université Sultan Moulay Slimane in Beni Mellal, Morocco. He receives a PhD from Sherbrooke University Canada in 2008 in which he worked as an associate professor until 2018. His academic background is grounded in engineering, with a strong interest in mathematical modeling and decision-support systems. His research focuses mainly on multi-objective and bi-level optimization methods. He has a vast experience in academia and industry with various publications in international journals and conferences.