

AI-Enabled Rail Electrification and Sustainability: Optimizing Energy Usage with Deep Learning Models

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Abstract

This work focuses on the optimization of metric parameters for rail electrification systems to minimize energy usage and CO2 emissions. A novel approach based on deep learning models is proposed for accurately predicting the need for new plants or for aligning existing systems. The whole workflow for dataset collection, model generation, and model usage is developed, explaining the key points of the process by testing the models on real sections. In this application, the use of deep learning techniques raised unexpected links between variables and allowed for a reduction in the number of inputs to the minimum requirements in real product usage. The data input and their technical meaning are listed to allow the right use for the specific plant geometry and for the specific cost function to be addressed (e.g., minimizing CO2 emissions instead of power usage). A detailed sensitivity analysis on the impact of input parameters is also provided to further investigate the key internal variables on the power requirement. According to the results, the models endorse a manageable approximation of the step impedance at different operating conditions, leading to a simplified representation of the pantograph interaction with the rail traction line. By reducing the input parameters—which are entirely real-time achievable—the proposed model can be utilized for feasibility studies of non-electrified railway lines or as a tool for prediction and comfort applications for other trains passing under energized catenaries, provided the proper training is addressed.

Keywords: Rail Electrification, Energy Optimization, CO2 Emissions, Deep Learning, Sensitivity Analysis, Model Prediction, Pantograph Interaction, Input Parameters, Feasibility Studies, Real-time Data.

1. Introduction

The electric railways not only consume less energy than others but also have no noise and air pollution compared with diesel railways. Nowadays, many countries and regions in the world are making great efforts to promote the advanced electrification of their railways. In recent years, thanks to the advantages of globalization, low cost, and regularity, high-speed rail has gained more and more shares and become the most important transport type in some traffic corridors. However, during the electrification of the high-speed rail, problems caused by the lack of clear development stage guidance, such as conflicts between high-speed rail and traditional railways, serious labor consumption, etc., still exist and need to be resolved effectively. The occurrence of these problems will not only cause delays and overruns in the high-speed rail's construction periods and investments but also affect the normal operation of the high-speed rail and produce huge negative social and economic impacts. In addition, these problems also significantly reduce the quality of the high-speed rail and undermine operational safety.

To alleviate the above phenomena, it is suggested that China, which has become one of the leading countries in high-speed rail construction and has installed the most length of high-speed rail in the world, can accomplish the advanced electrification of traditional railways first, and then transform these traditional railways into the high-speed rail in a staged manner. Through this method, the conflicts between the high-speed rail and the traditional railways can be resolved from the root. The successful experiences of other foreign countries indicate that the advanced electrification of traditional railways is highly necessary and of great significance to convert into a successful high-speed rail. The paper will analyze the demand distribution of traditional railways first in the initial stage, and then share the successful global experiences of high-speed rail operations, which will provide a preliminary decision basis for the advanced electrification of traditional railways. In the proposition and implementation of advanced electrification of traditional railways, the obtained fund-saving and effective recommendations will also contribute to the smooth realization of a successful high-speed railway business model.

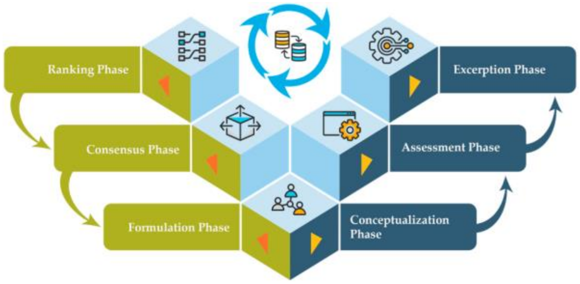

Fig 1 : AI-Enabled Energy Policy for a Sustainable

1.1. Background and Significance

Railways are an essential component of modern urban life, enabling the transportation of people and goods across short and long distances. While incremental advances have been made in improving rail vehicles, tracks, and signaling systems, electrification remains a lynchpin of increased efficiency and sustainability in railway transportation. Electric trains directly leverage the greater energy density, improved spectral availability, and, in many jurisdictions, reduced environmental externalization of electrical power to and from the railway. Globally, some 60% of the route length of the world's railroads and 90% of the world's passenger rail traffic use electricity for propulsion. With global rail ridership continuing to increase and nations steadily moving away from the combustion of fossil fuels, rail electrification is seeing a prolonged period of growth as an environmentally friendly mode of travel. Even in less environmentally driven scenarios, partially electrified railway operators are being constructed or are planned in many world regions, where the barriers to capital investment can be more easily realized.

Railway electrification is capital-intensive, with substantial investments required in catenary systems, substation outfits, power lines, and electrified tracks. Building on a railway system without considering electrification barriers, with the hope of introducing it later, can freeze the development of such a system in a suboptimal cycle. If operational conditions require more power than purely diesel traction allows (e.g., due to steep inclines, heat problems, auxiliary generators versus separate power cars, or the capital costs of the locomotives), thermal riders, electric locomotives, or multiple system locomotives could be procured. Goods locomotives exist both for electrical and diesel traction; freight trains can switch locomotives at the borders, or diesel locomotives can transport cargo trains along the non-electrified part.

1.2. Research Objectives

Traditionally, the electric traction energy optimization problem focused on train-level energy optimization, or sometimes sub-problems like optimal regulation of regenerative power and supply of power in the feeder system. However, these solutions do not provide optimization of available overhead line power across all tracks in the network, which is critical for the electrification of multiple future paths and the overall reliability of the electrification system. This necessitates the move from traditional engineering-based perspectives toward deep analysis of complex electromagnetic interactions of the components of the traction power supply system. It could thus be very beneficial to leverage recent advances in artificial intelligence and machine learning, especially within the domain of deep learning models, to develop unique traction power supply system characterization indicative of a wide range of network operating conditions. The development and utilization of shape-changing deep learning models for AI-enabled energy time-series data complexity assessment of the traction power supply system area of interest are presented.

The primary purpose of this ongoing research is to show that despite a relatively high complexity, the periods of high traction power supply system voltage diversity could be discreetly categorized within a time series and used downstream to ensure the accuracy of complex planning decisions required for efficient traction power system capital investments. The secondary purpose is to prove that the concept of deep decision-making is valid and scalable for practical utilization in very diverse real-world settings, such as long-term asset investment planning, after-equipment-failure replacement, or spare parts purchasing decisions. The main novelty of the proposed approach is the utilization of state-of-the-art deep learning models for characterizing energy time-series data to support traction power supply system investments.

Equation 1 : Energy Demand Prediction

Using historical energy consumption data and influencing factors to forecast future energy demand:

$$E(t) = \beta_0 + \beta_1 T(t-1) + \beta_2 P(t) + \beta_3 R(t) + \epsilon$$

Where: $E(t)$ = predicted energy demand at time t

$T(t-1)$ = historical energy consumption at time $t-1$

$P(t)$ = passenger load at time t

$R(t)$ = route characteristics (e.g., gradients, distance)

$\beta 0, \beta 1, \beta 2, \beta 3$ = model coefficients

ϵ = error term

2. Rail Electrification and Sustainability

Compared to other vehicle electrification efforts, we have seen much slower advancement in electric rail transportation, particularly in the United States. Building a railroad seems to come with fewer obstacles when compared to the large political opposition and several freedom-motivated lawsuits against high-speed railway projects. Proponents raised numerous concerns regarding both short-term and long-term emissions. In the short term, construction led to air pollution. Once operational, proponents predicted a large reduction in carbon dioxide emissions, as one of the greatest benefits of high-speed rail came from direct emissions savings in the transportation sector. Although opening a high-speed railway resulted in an increase in CO2 emissions due to the lengthy construction and substantial indirect emissions, if the railway ever reached 50% ridership, it accrued a significant monetary and environmental benefit.

On the other hand, by transitioning to electric power, operations of the railway created zero greenhouse gas emissions. Subsequently, the railway could further optimize its carbon footprint by maximizing the efficiency of electric trains. Further minimizing the emission of greenhouse gasses, railways could integrate renewable sources of energy into train transportation networks, ensuring that they are a vital element of future climate-friendly cities.

2.1. Current Challenges in Rail Electrification

Accurate train-load-based estimations are essential to compute the required energy consumption to plan airtight operations or to forecast the state of charge of the onboard storage system in a railway system. An accurate estimation is challenging; however, due to significant train-to-train variations in speed profiles and due to the lossy transformation of electric power from kWh to kW, when mass in motion and speed are the main contributors to energy consumption. Since train load data acquisition lies ahead on the railway lines, the train load for each train circulation has to be estimated in an airtight and low-intrusive manner. Additionally, the border effect and harmonics are known to significantly decrease the quality of alternating current measurements, which can be translated into less accurate estimations.

2.2. Benefits of AI in Rail Electrification

The application of AI deep learning models in the optimization of train operations has quickly become a popular entry point for AI technologies in the railway industry. Recent works have mainly focused on the use of AI models for improving train dispatching problems, energy cost efficiency, prediction of real-time railway traffic occupancy, and forecasting of train delays. The significant benefits of applying AI to the electric system can be summarized in the following aspects.

Significant growth in efficiency. The electric power system feeding the railway overhead power lines is normally connected to the public electric power network at specific locations, which are fed by substations. The substations control the voltage, provide the train energy, and guarantee that the voltage is not lower than a predefined threshold, thereby ensuring passenger comfort. In certain transportation agencies, the electric system is connected to the high-voltage side of the voltage regulator, while in others it might be connected to the medium voltage side. Given the increase in concern over the obstacles that higher-frequency voltage variations can have on many other consumer types, especially random short-term energy demands, the voltage control has to be well-designed to avoid high current flow in the public electric power network, which might lead to sag or flicker issues in the voltage profile. AI prediction models can help train dispatchers cope with issues such as power interruptions and extreme peak loads while optimizing the performance of the system and the costs associated with power purchase. Additionally, the intelligent management of energy supplied to trains can avoid peaks in voltage and ampere loading of the transmission, thereby increasing the total amount of energy that can be extracted along the total feeding system. The reactive power requirements of the train are also governed by the inlet and return feeding conditions of the substation. Proposing a different train trajectory or speed can therefore reduce the necessity for the electrical power system to supply reactive power to the railway, in turn improving the efficiency of the total electric power subsystem.

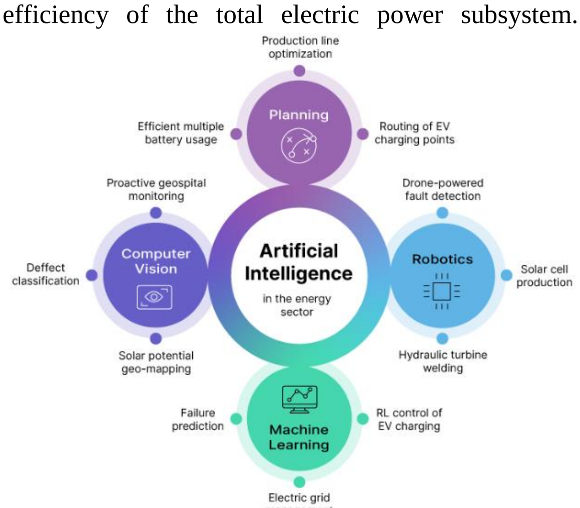

Fig 2 : Artificial Intelligence in the Energy Sector: Benefits and Use Cases

Effective minimization of the cost of train operations. A representative way of understanding the AI application context is the design of efficient train operation models that consider the driving dynamics and anticipation technology in the train ATP system. The application of AI models—such as deep-neural-network-based models—can have a real application to the electric power system used in the railway network. These models are trained under different load conditions to take the place of state-of-the-art train ATP technology and deliver a better variable for the energy storage system. In doing so, the designed platform dynamically captures the driving conditions of local passenger train services and remotely secures the efficiency of scheduled railway operations. Such systems can then guide the decision-making of the railway operator.

Data-driven operational decision support. The data-driven decision support tools focus on the interaction between the railway infrastructure manager and the passenger service operator and can address different aspects of railway performance. About the electric power system, data-driven approaches make it possible to detect the load condition of a train and the charging profile of the operation; optimize the implementation strategy; improve the productivity of railway operations; cope with the auxiliary power needs of the train; or identify the speed of the train before it enters a tunnel or anywhere with symmetry limitations in the feeding system.

3. Deep Learning Models in Energy Optimization

In this section, we first provide a brief overview of deep learning. We then describe deep learning models with a focus on novel recurrent neural network model development for the class of decision-making problems addressed. We discuss techniques to generate high-fidelity training data to characterize the system physics needed to train the deep learning models. Finally, we describe techniques to utilize the trained deep learning models to design and optimize actions for energy savings.

3.1. Recurrent Neural Network Models We briefly review deep learning and describe a deep learning model that is designed to capture longer-range system dynamics and is particularly well-suited for the high-dimensional decision-making problems involving sequential operations addressed in this study. In the last decades, artificial intelligence technologies have played an increasingly important role in industrial systems. With a large volume of data generated by various sensing devices and digital representations contributed by a myriad of operational systems, it is possible to learn complex relationships between operational variables and aim to explore improvements in system performance. All existing operational states at the data center are collected and categorized. In doing so, a large volume of labeled data can be utilized to develop learning models that could accurately mimic the operational system exhibiting a change in performance as a function of input.

3.1. Overview of Deep Learning

Deep learning has a rising popularity in various research applications, thanks to its outstanding task performance with raw sensory input data. Over the past few years, researchers have identified a wide spectrum of learning models suitable for numerous prediction and modeling tasks in energy systems and other domains. Widely acknowledged deep learning models used in different research fields include convolutional neural networks, recurrent neural networks, and graph-based neural networks. Many of the most successful deep learning models stem originally from fundamental concepts, implemented together with relatively simple tools, and used building blocks as elementary components. Previously developed models that have demonstrated high performance and versatility often use basic building blocks, preconfigured tasks, and standard data sources during their training processes. However, there is not a single model that outperforms all others for all possible tasks, and therefore there is also a need for task-specific model developments, some form of hyperparameter optimization, or custom training pipeline augmentations that favor a particular model type.

Deep learning techniques constitute a fast-growing ecosystem of powerful and complementary methods to model, understand, and simulate complex energy systems. Parallel increases in available computing power, a wealth of data, and accessible libraries have rendered many types of deep learning models increasingly mainstream in power systems. Researchers have used deep learning to aid the convolutional inversion of electromechanical dynamic state estimation with incomplete information, to forecast short-term renewable energy generation, or to detect scenarios most critical for cascading failure simulations. Neural networks have been found efficient for accelerating detailed simulation models or for battery health indicators and pack-level state estimation. They have also proven to assist network component identification or expand and integrate sensor placement, fault classification, and learning-based control.

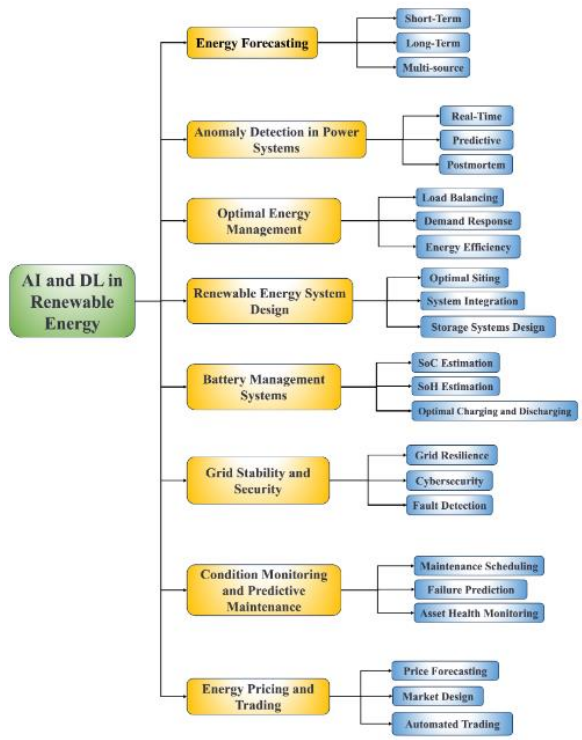

Fig 3 : The application of AI and DL in the field of renewable energy; orange represents the different application scenarios

3.2. Applications of Deep Learning in Energy Optimization

Among the early applications of deep learning in electrical engineering, the most well-known include the data-driven enhanced wind energy model in which deep belief networks are used to better capture physical phenomena and increase feature extraction ability, and the application to wind turbine power curves to improve accuracy, as well as the application of deep belief networks in demand forecasting in a smart grid environment, where an adjustable robust chance-constrained probability model for optimal operation among microgrids is proposed. Similarly, deep belief networks and deep convolutional neural networks are proposed specifically for room occupancy as a response to increasing energy consumption in office buildings. Regarding system parameters and operating conditions, a committee of random forests based on two deep learning models is proposed to determine relay parameters in electrotechnical equipment. A traffic prediction model is developed based on a threshold-based convolutional network, which is also used for pattern recognition via lidar data regression. This can be stretched to energy consumption reduction in industry, as an effective way to reduce energy usage and improve environmental impacts. In an industry, where significant energy requirements exist, one way to address this is to utilize energy optimization procedures to improve the quality of the environment. Recently, deep learning has been applied to the optimization of refrigeration energy consumption by predicting the energy consumption of buildings. A deep learning-based data-driven approach to predict building energy consumption is suggested, outperforming an existing prediction method that uses conventional machine learning data processing algorithms. Moreover, to deal with power allocation, machine learning-based algorithms are used. Recently, it has been proposed that the machine learning model can achieve the optimal power allocation at the needed time, providing energy efficiency benefits with reliable green cells.

Equation 2 : Deep Learning Model for Energy Optimization

To optimize energy usage using a neural network model: $H^l = \sigma(W^l H^{l-1} + b^l)$

Where: *Hl* = output of layer *l*

Wl = *w*eight matrix for layer *l*

bl = bias vector for layer *l*

σ = activation function (e.g., ReLU, sigmoid)

4. Case Studies and Applications

This section presents case studies and applications of DL models solving electrification problems for various infrastructures and trains. The case studies present examples of the following outputs: real-time power consumption and their forecast for different nodes of the electrification system; flow of air coming back from the auxiliaries; impacts of previous to failure contact resistances from collector to pantograph; estimation of catenary wear. All the outputs are very useful to the infrastructure manager to reduce the cost of the infrastructure, maintain the infrastructure, reduce energy consumption, lower the cost of energy, and derive strategies to improve the quality of the transportation service for the passenger. We aim to provide a tool that estimates the power consumption, detects failures even in real-time, and supports the decision-making process about the optimal moment for replacing or performing maintenance on the railway overhead contact system, which is a central and important component of the railway electrified infrastructure. We consider a case study and apply several deep learning models to implement this framework.

4.1. Real-World Implementations of AI in Rail Electrification

The key values that AI enables in a rail electrification system are as follows: (i) Data-driven decision making – with accurate predictions and timely warnings, AI allows operations and maintenance decisions to be much more data-driven compared with traditional techniques. (ii) Accurate and flexible models – In general, accurate decision-making is key for the efficient operation of infrastructure. Compared with traditional data-driven models, non-linear deep learning models are shown to provide more accurate modeling of complex data, thereby accommodating the more complex infrastructure operational demands – such as rapid train acceleration, slow down, and stop thermodynamic behavior. (iii) AI-guided infrastructure investments – with the assurance provided by AI models, infrastructure investments can be made more confidently and with higher ROI. For example, delay predictions in level crossings could guide data-driven plausibility studies to convert level crossings into under/overpasses, with the assurance that adequate traffic economics increase post-infrastructure investments.

Some key considerations that come into play while implementing AI in railways are a) Integration to real-world processes – with high utility models, i.e., what AI designs must work in practice and derive benefits in the field, b) Consistency of model predictions – define trust and design constraints that ensure consistent model predictions through time and space, c) Integrating into decision-making processes – what decisions are enabled by AI model predictions and how these decision support systems can be integrated into railway system authority processes and d) Regulations and fairness – ensure that the use of AI models and the decision-making processes developed are following set standards and are fair to all stakeholders. To provide detailed and quantifiable insights, this paper deep dives into a carefully selected use case from the rail electrification system – in the context of traction power optimization of the Indian Railway network. As well as being a perfect fit for this test case, this study is also of high importance given that the Indian Railway network is the fourth largest railway network in the world in terms of geographical presence, with a total of 68,155 route kilometers.

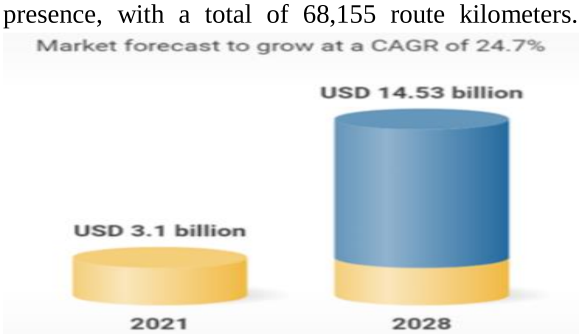

Fig 4 : Artificial Intelligence (AI) in Energy and Power Market

5. Future Directions and Conclusion

Within the energy industry, there is a growing focus on making system architecture and human operations 'data-driven.' However, the key barrier here is not the fundamental theory of how to perform this optimization, but rather the cost and effort of getting access to the high-quality and high-resolution data needed to implement these methods. All stakeholders in both the private and public sectors must work together to revisit how data is reported and stored across the energy industry to break down these silos and drive innovation across the board. For the specific case of electrification and the energy consumption optimization of electrified transport networks, large amounts of data can drive not only operation costs down but also maintenance and investment, as in many cases rail infrastructure can be considered an asset more than a liability. The impact of the types of studies outlined in this review takes all its value when put within the global context of the transition towards a greener, post-carbon, and more sustainable society. Efforts should be made to accelerate access to an infrastructure shared between academic centers and private industry, with proprietary safeguards active, to allow further research in this area. As the amount of energy consumed by electrification is also bound to grow in absolute terms globally in the future, incorporating effective sustainability protocols at the design and implementation level will be pivotal in a protracted, even if not self-propelled, shift towards decarbonization.

5.1. Emerging Trends and Technologies in AI for Rail Electrification

Several recent studies have shown the benefits of using artificial intelligence (AI)-)-enabled methods for transformative changes in the railway industry. These technological advancements have been made possible due to the vast improvement in AI algorithms and the increased availability and maturity of computing and communication technologies, enabling access to and use of vast and more comprehensive railway data. Depending on the specificity of the problem, the data can come from various sources within and outside the operating economics of railways. For specific problems such as finding the most efficient use of railways' physical structures, data are collected from the railway infrastructure to create predictive models. This branch of AI research considers leveraging collected data from a specific railway environment to build solutions that solve problems within that environment.

A recent AI research trend includes building local-based systems that replace remote, static, and heuristic models with real-time, dynamic deep learning models trained and executed locally in edge IoT devices for safety and operational improvements. To improve the safety and reliability of railway networks around the world, the railway industry collaborates with AI researchers by providing valuable insights about railway operations and safety-critical applications for integrating deep learning into railway systems. Unlike recent studies on guiding energy management or onboard intelligent diagnostics focusing on minimizing the carbon footprint of a moving train, this research focuses on the carbon footprint of electrified trains when they are static. Additionally, it presents how different architectures of deep learning can leverage the measurement data for calculations and predictions that facilitate energy generation specifically in rail electrification settings.

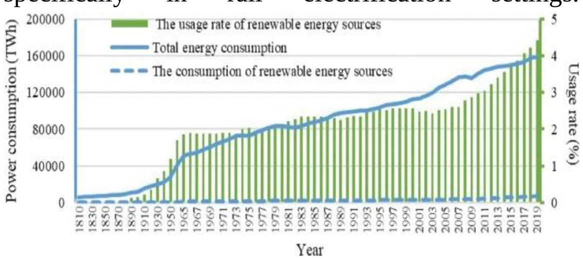

Fig 5 : Global power consumption and renewable energy usage

5.2. Summary of Key Findings

This section offers concluding remarks providing a comprehensive summary of various sections of this study. To address the energy consumption issue, AI applications in rail electrification engineering have been studied from several perspectives. The application of AI-enabled models can be classified into localization, segmentation, and anthropogenic event detection for asset condition monitoring, and two subcategories including dynamic routing adaptation and predictive tools for demand-side management. Due to the dependency on the amount of energy required to enable operations, it is essential to be able to set up and operate OLE systems. Given the rising cost-price ratio for electricity consumption and the fact that the electricity bill is often one of the highest expenses on the operational balance sheet, the design and operation should address this issue.

The first key finding of this study reveals that there are also many application scenarios for using AI-enabled models to digitize rail electrification site operations. The performance of LC-based algorithms achieved an average precision score of 67.39% by the weighted label and imbalance detection technique. The real-time position of the OLE monitoring system has been proposed as a priority for future methodologies, especially for high-speed applications. In brief, more progress and further studies are likely to offer priceless pieces of knowledge concerning designing and operating rail electrification systems that could establish a successful initiation for sustainable rail transportation projects. The real-world deployment of AI technologies in the rail electrification engineering process will be inevitable, and due to this main fact, both current and future digitalization strategies in this sector should address the role of AI technologies to significantly change the future of rail transportation for sustainable purposes.

Equation 3 : Energy Recovery from Regenerative Braking

To calculate energy recovery during braking:

$$E_{recovered} = \eta \cdot \sum_{j=1}^{M} F(j) \cdot d(j)$$

Where:

Erecovered = total energy recovered from braking

η = efficiency of the regenerative braking system

F(j) = force applied during braking for segment *j*

d(j) = distance of segment *j*

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