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Original Article

Artificial Intelligence Predictive Models for Infrastructure Wear and Maintenance Need

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Abstract: *Growing demand for strong and efficient infrastructure has led artificial intelligence (AI) to be implemented into predictive maintenance models. Artificial intelligence-driven predictive analytics allow to identify wear and possible flaws in infrastructure systems, therefore improving maintenance schedule and reducing costs. Predictive maintenance using artificial intelligence approaches including sensor-based Internet of Things (IoT) integrations, deep learning (DL), and machine learning (ML) generates quite accurate prediction models. These models find trends, anomalies, and forecast breakdowns before they develop by means of real-time and historical data analysis, therefore supporting proactive maintenance programs.*

This paper investigates the function of artificial intelligence in predictive maintenance by means of several AI-driven approaches—including supervised and unsupervised learning, neural networks, and reinforcement learning—underlines the need of data collecting, processing, and integration as well as the challenges applying artificial intelligence-based predictive maintenance in actual infrastructure systems.

Case studies from several disciplines, including transportation, energy, and smart city management, also show how effectively artificial intelligence based predictive maintenance performs. Among these are wind farms using AI-based analytics to optimise turbine performance, train systems using AI-powered sensors to monitor track conditions, and bridges employing deep learning algorithms for structural health monitoring. These pragmatic applications demonstrate how artificial intelligence may increase operational costs, enhance safety, and extend the lifetime of infrastructure components.

Although artificial intelligence-based predictive maintenance has advantages, data security and privacy issues, computational resource constraints, and data quality issues challenge it. This paper also addresses future prospects including improvements in artificial intelligence explainability, federated learning, and quantum computing which are expected to increase predictive accuracy and strengthen infrastructure resilience.

Ultimately, artificial intelligence-driven predictive maintenance signals a paradigm revolution in infrastructure management, therefore facilitating proactive, data-driven decision-making. As artificial intelligence technologies grow so as to ensure the lifetime and sustainability of vital infrastructure systems, their inclusion into infrastructure maintenance will become more vital.

Keywords: *Artificial Intelligence; Predictive Maintenance; Machine Learning; Deep Learning; Infrastructure Wear; Smart Cities; Iot; Data Analytics; Structural Health Monitoring; Predictive Modelling.*

I. INTRODUCTION

Infrastructure is mostly responsible for society's advancement and economic development. Roads, bridges, trains, and energy networks define modern civilization's backbone; these require continuous maintenance to ensure lifetime, efficiency, and safety. Conventional maintenance methods, however, usually reactive or scheduled-based, neglect real-time wear and random failures. From this follows unplanned downtime, safety hazards, and additional maintenance costs. Driven by artificial intelligence (AI), predictive maintenance offers a transformational solution by tracking infrastructure conditions and forecasts of problems before they occur using data analytics, machine learning, and the Internet of Things (IoT).

Artificial intelligence-based predictive maintenance rely on the compiling of enormous volumes of data from sensors integrated into infrastructure systems. Among the various sensors these ones track are structural integrity, temperature, pressure, humidity, and vibration. After that, artificial intelligence algorithms examine the acquired data in order to identify trends, point up anomalies, and project possible problems. Unlike more conventional maintenance programs, predictive maintenance reduces operating costs, increases the lifetime of key infrastructure components, and minimises unnecessary inspections.

Machine learning (ML) and deep learning (DL) approaches significantly help applications of predictive maintenance. Originally trained on past failure data, supervised learning models include random forests, decision trees, and support vector machines (SVMs) forecast future maintenance requirements. Among other unsupervised learning methods, clustering and anomaly detection systems help to identify possible dangers and outliers in real-time. Additionally looking at complex infrastructure data like image-based evaluations of bridge or train track deformations, deep learning architectures including convolutional neural networks (CNNs) and recurrent neural networks (RNNs)

Still another vital component of AI-driven predictive maintenance is integration of IoT devices and cloud computing. IoT-enabled devices continuously communicate real-time data to centralised databases from which artificial intelligence algorithms evaluate and analyse the data. This real-time monitoring helps to assure infrastructure safety and consequently reduces downtime by allowing maintenance teams to react pro-active. Moreover, advances in edge computing enable distributed data processing, hence reducing latency and improving decision-making efficiency.

Artificial intelligence applications of predictive maintenance have gained favour in smart city management, transportation, and energy among other fields. By finding track deviations and predicting rail breakdowns, AI-powered sensors in railway systems help to lower derailment risks and increase passenger safety. Artificial intelligence techniques also look at stress and corrosion rates in bridge maintenance to determine structural component remaining useful life (RUL). In the energy sector, predictive maintenance driven by artificial intelligence helps wind farms maximise turbine performance and reduce unscheduled breakdowns, hence improving energy efficiency.

Artificial intelligence-driven predictive maintenance has disadvantages even if there are many advantages. The dependability of predictive models depends on high-quality data; but, data variations might jeopardise model accuracy. Moreover required for implementation are big computational resources and artificial intelligence-based technological understanding. Ensuring data security and privacy is another problem since cloud storage and large data collection define infrastructure monitoring.

Predictive maintenance coming forward will be driven by developments in artificial intelligence explainability, federated learning, and quantum computing. AI explainability will increase confidence in predictive models by means of open insights into decision-making procedures. Safe data exchange between different infrastructure systems enabled by federated learning will not compromise privacy. Concurrently, quantum computing will significantly increase processing capability, allowing artificial intelligence models to more closely investigate vast amounts of data.

Eventually, artificial intelligence-powered predictive maintenance is changing infrastructure management by letting proactive, data-driven decision-making possible. IoT, ML, and artificial intelligence predictive models enable to raise operational efficiency, reduce maintenance costs, and extend lifetime and safety of significant infrastructure assets. As artificial intelligence technologies grow to provide strong and sustainable infrastructure for next generations, their inclusion into infrastructure management will become ever more important.

II. ARTIFICIAL INTELLIGENCE BASED PREDICTIVE MAINTENANCE

Artificial intelligence (AI) has evolved into a transformational tool in predictive maintenance by using advanced computer tools to analyse data, spot trends, and project possible faults before they start. Artificial intelligence is used in predictive maintenance since it can process vast amounts of real-time and historical data, therefore guaranteeing that infrastructure systems work efficiently with minimum downtime. Using machine learning (ML), deep learning (DL), the Internet of Things (IoT), and computer vision among other technologies, AI-driven predictive maintenance systems help to enhance accuracy and dependability in recognising wear and possible defects.

Machine learning techniques become indispensable in predictive maintenance by means of lessons learnt from past infrastructure failures and performance metrics. Supported vector machines (SVMs) and regression analysis categorise wear conditions and project failure rates in trained on labelled datasets supervised learning models. Unsupervised learning approaches including principal component analysis (PCA) and clustering techniques which find hidden trends in maintenance data make early warning systems and anomaly detection viable. Reinforcement learning especially increases artificial intelligence's capacity for decision-making by always refining maintenance plans relying on real-time feedback.

Deep learning models have revolutionised infrastructure monitoring particularly with respect to convolutional neural networks (CNNs) and recurrent neural networks (RNNs). CNNs in high-resolution photos from visual inspections amazingly precisely identify surface flaws, corrosion, and fractures. RNNs, long short-term memory (LSTM), and sequential time-series data from sensors all project degradation trends and maintenance needs over time. These models highly improve forecast accuracy by capturing complex temporal correlations and non-linear trends in infrastructure wear.

Artificial intelligence coupled with IoT sensors enhances predictive maintenance real-time monitoring capability. IoT-enabled sensors by constantly gathering data on temperature, pressure, vibration, and structural integrity discover issues and project when maintenance should be done using artificial intelligence systems processing this sensor data. Wireless sensor networks positioned in pipelines, bridges, and tunnels enable real-time condition monitoring that helps to reduce dependancy on hand inspections and maintenance expenses.

Predictive maintenance today mostly relies on computer vision driven by artificial intelligence. Automated drone inspections suited with AI-driven picture processing reveal surface defects, corrosion, and material fatigue of large-scale infrastructure. Edge artificial intelligence reduces data transmission latency by letting real-time visual data processing direct at the inspection point, so increasing efficiency. By combining computer vision with machine learning models, artificial intelligence increases the accuracy of structural health assessments, therefore allowing rapid maintenance interventions.

Natural language processing (NLP) facilitates predictive maintenance by means of study of maintenance logs, technician reports, and historical data. From unstructured textual data, AI-driven NLP models identify reoccurring issues, failure trends, and optimal restoration methods. Combining NLP with other artificial intelligence techniques helps predictive maintenance solutions to become more flexible and responsive to infrastructure wear conditions.

Big data analytics supports predictive maintenance driven by artificial intelligence by managing and analysing vast volumes of data. Artificial intelligence models trained in big data frameworks can improve decision-making processes, allocate resources most wisely, and spot growing failure trends. Edge computing and cloud computing technologies enable to manage real-time data, thereby ensuring that predictive maintenance systems remain scalable and efficient.

Artificial intelligence applied in predictive maintenance crosses several spheres of infrastructure. To optimise maintenance plans in transportation, artificial intelligence models study traffic patterns, road surface conditions, and vehicle effect on highways. Predictive analytics help to reduce interruptions by evaluating track quality, wheel-rail interactions, and signalling systems in railroads. Artificial intelligence-driven predictive maintenance guarantees the dependability of pipelines, wind farms, and power grids in energy infrastructure by recognising stress areas and prospective failures before they become more severe.

Despite recent advances, artificial intelligence in predictive maintenance still suffers with cybersecurity, data quality, and model interpretability. Strong data validation and preparation techniques are definitely required since inconsistent or insufficient data could compromise artificial intelligence predictions. Black-box artificial intelligence models could lack openness, which would make maintenance team decision-making process comprehension difficult. Explainable artificial intelligence (XAI) approaches are developed to increase model interpretability and trustworthiness. Moreover, IoT sensor network cybersecurity problems have to be addressed to ensure integrity of predictive maintenance systems and stop data breaches.

Artificial intelligence in predictive maintenance is expected to provide notable changes in self-learning AI models, quantum computing applications, and AI-driven automation. Self-learning artificial intelligence systems will continuously change to fit evolving wear patterns and maintenance requirements, hence improving predictive accuracy over time. Faster and more complex infrastructure simulations will be enabled by quantum computing raising AI's processing capability. Artificial intelligence-driven automation including robotic maintenance and autonomous inspection devices can considerably change predictive maintenance by lowering human involvement and optimising infrastructure lifetime.

Ultimately artificial intelligence has transformed predictive maintenance by combining ML, DL, IoT, computer vision, and big data analytics into infrastructure monitoring. Artificial intelligence driven models enhance maintenance efficacy, reduce downtime, and improve resource use. Constant artificial intelligence technical advancement will help to increase predictive maintenance capacity even if security, interpretability, and data quality still provide challenges. A big first towards more reasonably priced, intelligent, and robust maintenance techniques is the acceptance of artificial intelligence in infrastructure wear evaluation.

III. INFORMATION COLLECTING AND PROCESSING

Artificial intelligence-driven predictive maintenance for infrastructure systems largely depends on the quality and volume of the obtained data. Precise prediction of data collecting and processing is necessary to create trustworthy predictive models capable of fairly foreseeing wear and possible failures. Infrastructure maintenance calls for numerous data sources: historical records, real-time sensor data, ambient conditions, visual inspection data. These datasets must be preprocessed, arranged, and investigated if artificial intelligence models are to acquire important insights for predictive maintenance.

Built on past maintenance records, AI models provide required knowledge about past infrastructure failures, repair strategies, and performance patterns. These data enable machine learning systems to detect trends in repeated failure and establish correlations between certain factors and wear conditions. By means of analysis of years of maintenance data, artificial intelligence models can foresee when such issues may arise and propose preventative maintenance actions.

Sensor-based data collecting is another basic component of predictive maintenance driven by artificial intelligence. Infrastructure systems abound in IoT-enabled sensors that constantly monitor operating performance, environmental impacts, and structural concerns. Common sensor data include load-bearing capability, temperature variations, vibration intensity, pressure levels, humidity changes. Artificial intelligence models can detect anomalies implying possible wear or failure before they become critical using this real-time data. For example, strain gauges and accelerometers placed in bridges and roadways identify micro-movements and stress areas, therefore helping authorities to schedule suitable repair.

Predictive maintenance also rely significantly on environmental data like traffic load, seismic activity, and weather elements. All of which can exacerbate infrastructure deterioration—extreme heat, plenty of rain, or frigid temperatures—can also damage structures. AI models look at sensor data in line with weather trends to identify how outside factors affect wear and tear. Traffic density and load data can allow one to project how increased use will effect roads, bridges, and railroads, therefore influencing maintenance plans.

Drawn from drones, high-resolution cameras, and automated imaging systems, visual inspection records provide perceptive structural data. AI-powered computer vision models process these images to identify surface deformations, corrosion in infrastructure components, and cracks and rust in LiDAR-equipped drones scan large-scale buildings including tunnels, bridges, and power plants, collecting high-precision images AI systems examine for early-stage degradation. These advanced imaging technologies help to reduce reliance on hand inspections by increasing accuracy in identifying any defects.

Once data arrives from numerous sources, preprocessing and feature engineering become critical to guarantee its usability in artificial intelligence models. The core of data preparation is cleaning, normalising, and arranging unprocessed data to find duplication, errors, and missing information. Preprocessing is critically crucial since consistent predictions generated by artificial intelligence models depend on consistent input forms. Feature engineering helps artificial intelligence performance even more by selecting the most relevant characteristics from the dataset—such as stress levels, temperature variations, or corrosion rates—and turning them into meaningful indicators of infrastructure health.

Data fusion techniques help to merge several data sources thereby enhancing predicting accuracy. Artificial intelligence models usually mix environmental variables, sensor inputs, and historical data to offer a holistic picture of infrastructure wear. Combining data from many disciplines enables artificial intelligence-driven predictive maintenance systems to have a more thorough awareness of structural behaviour and failure risks. Using a multidimensional analysis instead of depending just on one data source allows infrastructure managers to make sensible decisions.

Big data analytics also greatly support artificial intelligence-driven predictive maintenance by means of organisation and analysis of massive volumes of acquired data. Large-scale databases created by infrastructure systems require high-performance computing techniques for real-time processing. Cloud-based artificial intelligence technologies let businesses efficiently store, assess, and display maintenance data, therefore enabling faster decision-making. By means of predictive trend analysis, anomaly identification, and pattern recognition—big data machine learning approaches guide infrastructure maintenance towards data-driven, proactive solutions.

Dependable artificial intelligence predictions rely on addressing problems with data collecting and processing. One of the primary challenges is guaranteeing accuracy and quality of data. Inconsistent or inadequate datasets could generate biassed or erroneous AI models, therefore reducing their predictive potential with respect to failures. Companies must use rigorous data validation techniques, sensor calibration methods, and regular audits if they are to maintain high-quality datasets. Moreover, IoT sensor network cybersecurity problems need to be under control to prevent data breaches or manipulation, therefore ensuring the dependability and safety of predictive maintenance systems.

Managing computer needs and data storage adds still more challenge. Artificial intelligence based predictive maintenance depends on continuous data collecting from many sources, which creates massive storage requirements. If infrastructure managers want to efficiently manage data, scalable cloud-based solutions and edge computing techniques have to be embraced. Edge computing helps to reduce latency and boost response times for uses including real-time predictive maintenance by letting artificial intelligence models look straight at the sensor level.

Advancement in sensing technology and artificial intelligence-driven automation should drive data collecting and processing in predictive maintenance ahead. Artificial intelligence powered self-learning systems will always improve in prediction ability by tuning maintenance recommendations and reacting to new data patterns. Moreover, advances in quantum computing could raise the processing capability of artificial intelligence models, hence enabling more precise and fast failure predictions.

Data collecting and processing are ultimately absolutely vital for predictive maintenance guided by artificial intelligence to be successful. By combining prior maintenance records, real-time sensor data, ambient variables, and visual inspections, artificial intelligence models can forecast infrastructure degradation and maximise repair timetables. Big data analytics, fusion, and data preparation increase predictive accuracy, thereby guaranteeing infrastructure systems work efficiently with little downtime. Still, problems with data quality, cybersecurity, and storage have to be addressed if we are to fully use artificial intelligence-driven predictive maintenance. As artificial intelligence technologies evolve, data collection and processing methods will become increasingly sophisticated, so improving the dependability and efficiency of predictive maintenance models.

IV. PREDICTIVE MAINTENANCE AI MODELS

Artificial intelligence systems are very vital in predictive maintenance by means of data trend analysis, anomaly detection, and prediction of possible breakdowns before they happen. Among other artificial intelligence techniques, machine learning (ML), deep learning (DL), and reinforcement learning (RL) help to maximise maintenance schedule and increase prediction accuracy.

Support vector machines (SVMs), decision trees, and regression models are several times used in wear evaluation and failure prediction under machine learning. Among other regression models, linear and logistic regression can project the remaining usable life (RUL) of infrastructure components. Random forest algorithms and decision trees help to enhance classification by assessing different failure scenarios depending on historical and real-time data. SVMs effectively classify both normal and deviant wear patterns; they also produce early warning signals for possible breakdowns.

Deep learning techniques have improved still more predictive maintenance capability. Convolutional neural networks (CNNs) evaluate high-resolution images from infrastructure inspections before highly precisely pointing up structural defects including cracks, rust, and corrosion. Sequential sensor data analysis combined with long short-term memory (LSTM) models and recurrent neural networks (RNNs) forecasts degradation patterns and optimises maintenance strategies. These models significantly help time-series forecasting since they let infrastructure managers schedule preventative repair before big incidents.

Reinforcement learning (RL) has also gained popularity in predictive maintenance by allowing AI models maximise maintenance decision-making using trial-and-error learning. Two examples of RL techniques that constantly modify maintenance plans depending on environmental feedback are deep Q-networks (DQNs) and Q-learning, hence improving system reliability and cost economy. Including RL with IoT-enabled sensors allows artificial intelligence models to dynamically change maintenance schedules in real-time based on changing wear conditions.

Combining many approaches, hybrid artificial intelligence aims to raise predicting accuracy. Combining many machine learning models in bagging and boosting ensemble learning approaches helps to improve failure prediction robustness Federated learning guarantees total failure analysis without compromising data privacy by letting artificial intelligence models be trained on distributed datasets from several infrastructure sites.

Applications of artificial intelligence methods in predictive maintenance have demonstrated somewhat remarkable performance in several fields. Structural stress levels and vibration pattern analysis help artificial intelligence-driven predictive algorithms maximise railway track maintenance in transportation. Artificial intelligence projects possible pipeline and power grid breakdowns in energy infrastructure by measuring temperature changes, pressure levels, and corrosion rates. In civil engineering, artificial intelligence-based structural health monitoring (SHM) systems enabled by deep learning and computer vision enable evaluation of bridge, tunnel, and road integrity, therefore reducing the danger of catastrophic collapses.

Predictive maintenance artificial intelligence systems suffer with computing complexity, interpretability, and data quality even with their advantages. Strong data preparation techniques are therefore crucial since inconsistent or insufficient data could lead to incorrect projections. Especially deep learning systems, black-box artificial intelligence models lack openness, which makes it difficult for engineers to grasp decision-making procedures. Developed to increase model interpretability are explainable artificial intelligence (XAI) methods include SHAPley Additive Explanations and attention procedures. Moreover, the great computational requirements of deep learning models necessitate scalable cloud-based and edge computing solutions to ensure real-time processing efficiency.

Predicted to shape artificial intelligence algorithms in predictive maintenance include future advancements in self-learning AI models, quantum computing applications, and automated maintenance systems. Self-learning artificial intelligence will enable predictive maintenance systems to continuously adapt to changing infrastructure conditions and enhance failure forecasts throughout time. Quantum computing has the power to change artificial intelligence models by significantly accelerating processing rates and addressing difficult optimisation problems in infrastructure maintenance. Among other AI-driven automaton tools, robotic inspections and predictive maintenance drones will help to lower human involvement and improve maintenance accuracy.

Artificial intelligence technologies have revolutionised predictive maintenance generally by offering exact failure forecasts, effective resource allocation, and long infrastructure lifetime. In civil engineering, energy, and transportation, ML, DL, RL, and hybrid AI techniques combined together have improved predictive capacity. Continuous artificial intelligence improvements will help to improve predictive maintenance models, therefore guaranteeing more intelligent and resilient infrastructure management even if data quality, interpretability, and processing efficiency still provide challenges.

V. CASE EXAMPLES

Many real-world case studies demonstrate how effectively artificial intelligence-driven predictive maintenance works for infrastructure management. One well-known example of this is railroads using artificial intelligence. Track conditions were tracked and pre-failure predictions produced by United Kingdom's Network Rail using IoT sensors and machine learning techniques. By monitoring vibrations, temperature changes, and train-induced stresses, artificial intelligence models efficiently reduced derailment risks and streamlined maintenance schedules, so saving huge expenses and enhancing operating efficiency.

Another case study examines how artificial intelligence might be applied for bridge maintenance. Built inside the Golden Gate Bridge in San Francisco, AI-powered sensors detect minute changes in material stress and corrosion rates, so tracking structural integrity. By means of deep learning approaches, engineers can predict the remaining useful life (RUL) of bridge components, therefore ensuring timely repairs and preventing structural collapses.

Artificial intelligence-driven predictive maintenance has started to be somewhat popular in energy-producing wind farms. Leading wind turbine company Siemens Gamesa tracks turbine performance and projects possible defects using artificial intelligence-based analytics. Artificial intelligence models search data from vibration sensors, temperature monitors, and meteorological variables in order to maximise maintenance schedules and increase energy output. The company has so recorded a notable decline in turbine downtime and maintenance costs.

Artificial intelligence is also quite crucial for maintaining the infrastructure of smart cities. The Land Transport Authority of Singapore has introduced artificial intelligence-driven predictive analytics into road maintenance projects. LiDAR data, high-resolution cameras, and machine learning algorithms enable the system to detect road surface degradation, cracks, and potholes before they turn dangerous. By this proactive approach, road safety has been substantially improved and repair expenses have been reduced.

These case studies highlight the practical benefits of predictive maintenance driven by artificial intelligence in many different areas. Artificial intelligence combined with IoT, deep learning, and big data analytics has helped to minimise infrastructure failures, maximise resource allocation, and extend the lifetime of significant assets. As artificial intelligence technologies advance, more sectors are probably going to rely on predictive maintenance solutions to ensure wiser, more solid infrastructure management.

VI. CONCLUSION

Including artificial intelligence into predictive maintenance has completely altered the management of infrastructure systems. By use of IoT-driven data collecting, deep learning models, and advanced machine learning algorithms, artificial intelligence has enabled exact failure forecasts, reduced downtime, and optimal maintenance schedules. From transportation, energy, and urban infrastructure to other industries, real-world uses demonstrate how effectively predictive maintenance driven by artificial intelligence increases cost-effectiveness, safety, and efficiency.

Notwithstanding its successes, data quality concerns, computational resource requirements, and the need of better interpretability in AI-driven decision-making, still offer challenges. Solving these challenges requires constant edge computing development to enable real-time analytics, federated learning for safe data sharing, and artificial intelligence explainability.

Predictive maintenance going forward will most certainly be shaped by developments in self-learning artificial intelligence models, quantum computing applications, and autonomous maintenance systems. These advances will ensure proactive maintenance strategies, raise infrastructure resilience, and enable further enhancement of forecast accuracy. Artificial intelligence will become ever more important in predictive maintenance as it advances, providing a foundation for more clever and ecologically friendly infrastructure management all around.

VII. REFERENCES

[1] brown, K. and Smith, J.- [2021] Predictive maintenance application of machine learning IEEE Proceeds on Industrial Informatics, 17(4), 2245–2257.
[2] Chen, X.- and Lee, Y.- Development of AI-driven infrastructure wear diagnosis tool Journal of Infrastructure Engineering, 12 (2), 145–160.
[3] Chen, R., & Zhao, W. (2019) IoT sensors and system of maintenance artificial intelligence. Sensors, Journal of 19 (5), 2321–2334.
[4] Li, P.; Wong, M.). (20211) Deep learning predictive maintenance applications. Intelligent cities and artificial intelligence, 15(3), 98–115.
[5] Tango, J.; Rogers, C. Review on Computational Engineering, 20(4), 335–350 2020 neural networks for maintenance of infrastructure.
[6] H.; Davis; Patel, N. 2020]). Predictive maintenance applications of big data analytics. Big data science: Journal, 18(1), 50–75.
[7] R. Singh, see Jones, L. (20211) Predictive maintenance reinforcement learning application. Developments in Machine Learning, 13(4), 201–220.
[8] Wilson, D.. 2019 Structural health monitoring integrated with artificial intelligence Review in Structural Engineering, 16(2), 100–118.
[9] Korea, H. Park, M.; () 202. Edge computing in connection to artificial intelligence-driven maintenance Journal of Intelligent Technologies, 14(3), 125–140.
[10] Zhao, X.? & Lin, J. 2020). Artificial intelligence enhanced models of railway forecasts. Review of Railway Technology, 22 (1), 89–105.