ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 1, 2025

Methods of Artificial Intelligence in Infrastructure System

*M.Harikumar [1]

[1]Assistant Professor, St. Martin's Engineering College, Secunderabad, Telangana – 500100

*Corresponding Author

Email: mharikumarit@smec.ac.in

Abstract : The artificial intelligence (AI) revolution offers significant opportunities to capitalise on the growth of digitalisation and has the potential to enable the 'system of systems' approach required in increasingly complex infrastructure systems. This paper reviews the extent to which research in economic infrastructure sectors has engaged with fields of AI, to investigate the specific AI methods chosen and the purposes to which they have been applied both within and across sectors. Machine learning is found to dominate the research in this field, with methods such as artificial neural networks, support vector machines, and random forests among the most popular. The automated reasoning technique of fuzzy logic has also seen widespread use, due to its ability to incorporate uncertainties in input variables. Across the infrastructure sectors of energy, water and wastewater, transport, and telecommunications, the main purposes to which AI has been applied are network provision, forecasting, routing, maintenance and security, and network quality management. The data-driven nature of AI offers significant flexibility, and work has been conducted across a range of network sizes and at different temporal and geographic scales. However, there remains a lack of integration of planning and policy concerns, such as stakeholder engagement and quantitative feasibility assessment, and the majority of research focuses on a specific type of infrastructure, with an absence of work beyond individual economic sectors. To enable solutions to be implemented into real-world infrastructure systems, research will need to move away from a siloed perspective and adopt a more interdisciplinary perspective that considers the increasing interconnectedness of these systems.

Keywords : Machine learning, Deep learning,AI method,Neuralnetwork, Knowledge representation, Infrastructure sectors

Introduction

Artificial intelligence (AI) methods enable machines to learn and infer from large volumes of data (Ertel, 2017). As infrastructure systems become increasingly interconnected, complex and digitalised, AI will be crucial in providing and maintaining services that ever-increasing numbers of people depend upon every day (Luckey et al., 2021). However, as interest in AI continues to grow, research into its application to infrastructure systems remains largely siloed. Most papers focus on a specific problem in isolation, and the handful of review papers cover either a specific subset of AI methods (Suganthi et al., 2015; Veres and Moussa, 2019), or a specific infrastructure sector (Abduljabbar et al., 2019). This review looks at the extent of research into the use of AI in infrastructure systems, focusing on the economic infrastructure sectors of energy, water and wastewater, transport, and telecommunications, and the intersections between sectors. As interdependent systems, there is a clear benefit to reviewing infrastructure networks as a whole,recognising areas of overlap such as the water–energy nexus, electric vehicles, and vehicular ad-hoc networks (VANETs), and common challenges, such as supply and demand forecasting, inspection, and maintenance. Not only does this review seek to ascertain which AI techniques are popularly used in infrastructure systems, but to compare the maturity and depth of research across systems, in the hope that potential research gaps can be discovered, and potential solutions informed by existing work in other fields.

Artificial intelligence fields

Alan Turing proposed his 'Turing test' to offer an operational definition of AI, stating that a truly intelligent system must be capable of matching human cognitive performance to an extent that a human interrogator cannot tell the

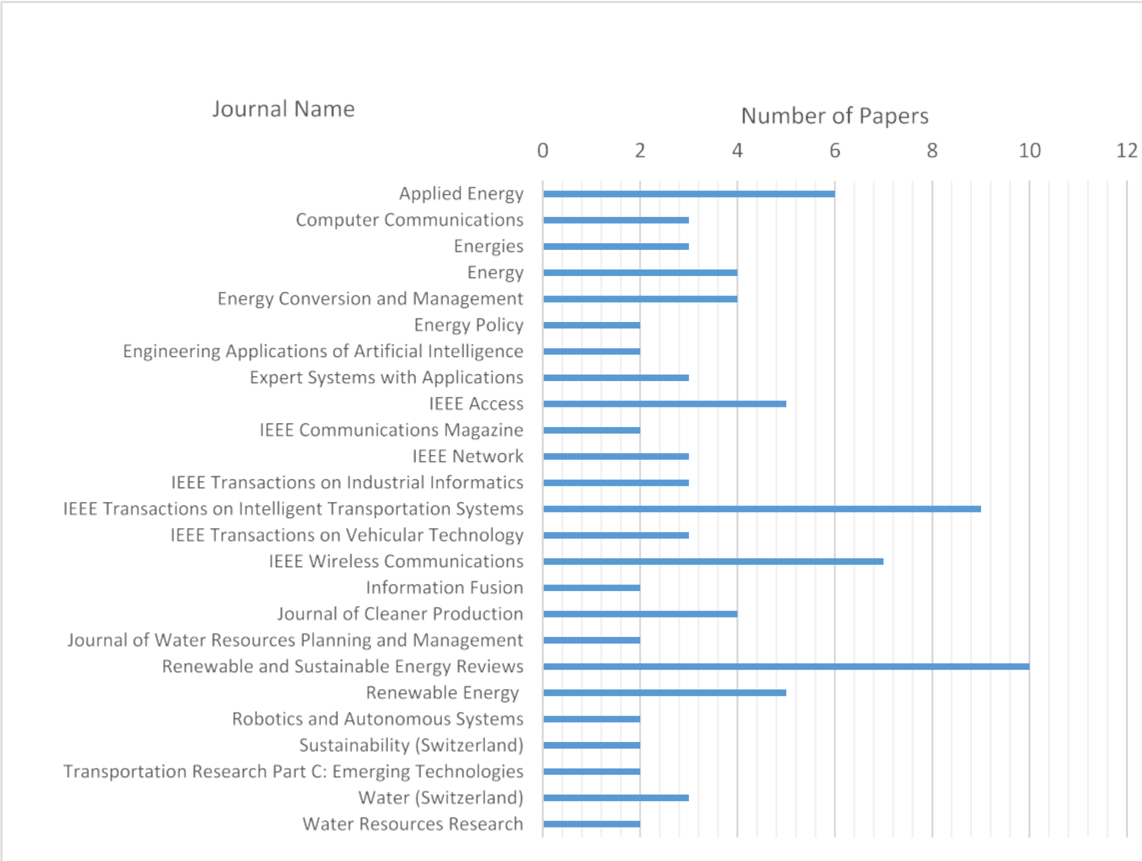
INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 1, 2025

different between human and machine when interacting via a teletype system In a 'total' Turing test, perception and physical abilities are tested alongside cognitive functioning. Each of the following components represents a field of AI that help to attain one or more of the Turing test's goals: • knowledge representation, to store data • automated reasoning, to infer and make use of conclusions from the stored data • machine learning, to identify patterns and modify behaviour • computer vision, to perceive the environment • robotics, to interact with the physical environment • natural language processing, to communicate in human language While these components can describe attributes of an ideal intelligent computer system, they can also be considered topics in the field of AI research, each concerned with techniques that contribute to an element of system intelligence. There is significant overlap between fields, with automated reasoning inherently dependent on the knowledge base it reasons from, machine learning techniques – particularly convolutional neural networks – increasingly utilised in computer vision systems, and such vision systems often integrated into intelligent robots. Models which include both a reasoning and machine learning element, such as adaptive neuro-fuzzy inference systems (ANFIS), are also growing in use. As the most widely adopted fields of AI in infrastructure research, machine learning and computer vision methods are reviewed below. The methods described in this section are not a comprehensive review of all techniques in machine learning and computer vision but rather the most common methods found in the body of work reviewed, as to provide context for further discussion.

Common machine learning models

Although the specific details of a model's architecture and algorithm vary for each individual case, there are a number of popular machine learning models that have established themselves as some of the best performing. Artificial Neural Networks (ANNs) Artificial neural networks (ANNs) are a popular type of machine learning model that simulates the mechanism of learning in the human brain, which contains networks of billions of nerve cells. In ANNs, a neuron is a computational unit consisting of 'dendrite' inputs scaled with 'synaptic' weights that affect the function computed at that unit, and an 'activation' internal state. Neurons exist in a network, forming a directed, weighted graph that is typically arranged in layers. The learning process occurs by modifying the weights and thresholds of the network to achieve accurate results. Although there are so many variations of ANNs in use today that it is impossible to cover all of them in detail, a few of the most popular model structures are outlined here. ANNs can be divided into two classes based on their general architecture: feed-forward and feed-back networks. Feed-forward networks are non-recurrent networks comprised of inputs, hidden layers, and outputs, where signals can only travel in one direction. Examples include multilayer perceptrons (MLPs) and radial basis function (RBF) networks. Use cases in infrastructure research have seen MLP models employed to predict energy consumption and for pollutant removal in water networks. RBF networks have also been applied to water treatment .Conversely, feed-back networks permit signals to travel in either direction, owing to the inclusion of feed-back loops. In feed-back networks, also called recurrent neural networks (RNNs), neurons can be connected in any possible format, which can account for dependencies between neurons. Popular RNNs are echo state networks (ESNs), and long short-term memory (LSTM) networks. Interesting examples in infrastructure have seen ESNs applied to demand forecasting in water networks, while LSTM networks can be found in a range of forecasting applications, where they have been used to predict energy use ,telecommunication traffic and accident risk in transport networks, to give just a few examples. Another type of ANN, convolutional neural networks (CNNs), have been widely used for image classification and object detection purposes. This particular application of AI can be described as computer vision and is covered separately.

ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 1, 2025



The structure of this analysis is based on a framework proposed by Sharifi, which consists of 11 qualities with associated evaluation criteria.This framework is concerned not only with innovative solutions, but effective implementation, which is often dependent on recognising the interconnections between systems and the interdisciplinary nature of work in cities and infrastructure additional criteria, comparison and vulnerability, have been added to the original framework in order to align the analysis with AI in infrastructure. Table 8 outlines how each criterion relates to infrastructure systems, as well as the extent to which each is satisfied by the overall body of research covered by this paper. Criteria with limited coverage would benefit from greater consideration in future research in this field; this is explored more in a later section on further work. Where possible, examples of a paper that meets the description of the criterion to a high degree are provided, as are examples which show a low level of sophistication in regard to a criterion, but do not neglect it entirely.

Vulnerability

The vulnerability of infrastructure systems concerns their susceptibility to both deliberate attacks and a variety of accidental causes of failure. As detailed earlier in this review, numerous papers have applied AI to the purpose of security. The field of telecommunications has been at the forefront of this research, utilising a range of machine learning tools in the detection of intrusion attacks, network anomalies, and denial-of-service attacks . While papers concerned with non-deliberate system failure are often less explicit in their discussion of vulnerability, it could be reasoned that there are far more variables contributing to accidental failure, making the breadth of this research much greater. There are specific instances of research focusing on non-deliberate failures, including the use of machine learning techniques for fault diagnosis in high-speed rail The fact that supervised machine learning techniques rely heavily on access to comprehensive training data is important in the discussion of vulnerability. The question of how to react to rare events, which occur so infrequently that their presence in existing data is sparse, is

ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 1, 2025

one that is crucial to the prevention of potential system failure. Several papers have approached this by teaching a model the normal state of a network and setting a threshold beyond which behaviour is considered abnormal and flagged Other techniques have begun to be developed, although more work in this area would be beneficial, particularly outside of the field of telecommunications.

Future Enhancement

This work was limited in scope to economic infrastructures. Further work could broaden this definition of infrastructure to explore the use of AI in, for example, solid waste, finance, agriculture and food networks, or in social infrastructures such as healthcare, education, arts and culture. This work also identified limited research at the intersections of different infrastructure sectors, something which could be further explored in future work. The criteria identified as having limited coverage in Table 8 would benefit from further consideration in future research. For example, having identified a gap in literature that takes an action-orientated approach, future work could seek to bring together the findings of research covered in this paper to suggest areas where it can inform action plans and guide policy. This could look to bridge the gap between research in this field and the governance of infrastructure systems. Similarly, this research recognises that, while technical developments in AI have led to significant improvements in the accuracy of solutions, there remains a lack of focus on the feasibility of potential interventions. Future work may wish to explore the possibilities and limitations of AI in infrastructure systems through this lens, perhaps by exploring the financial, technical, and regulatory requirements of implementing AI-based techniques in different geographies and economies.

Conclusion

This paper reviews the applications of AI across the economic infrastructure sectors of energy, water and wastewater, transport, and telecommunications. The main purposes to which AI has been applied are system provision, forecasting, routing, monitoring and security, and quality assessment and improvement. AI methods are increasing in popularity and capacity, with deep learning and CNNs examples of recent developments in this field. The application of AI to infrastructure is also likely to continue to grow as infrastructure systems becoming increasingly instrumented and digitalised, providing data for AI tools.recent works, and the new field of deep learning has proven effective in instances concerned with large volumes of data. Sensor networks are beginning to be recognised as a potential architecture for intelligent infrastructure systems through the ‘Internet of Things’. However, if they are to see widespread use, further research in knowledge representation will be needed. Ontologies and semantic approaches have been proposed, but rarely incorporated into larger artificially intelligent systems. Robotics is another branch of AI that is yet to be fully exploited in infrastructure. While the potential of fully autonomous robots in several infrastructure environments has been identified, existing robots in reported infrastructure research are largely short of autonomous. Some of the most exciting examples of intelligent robots in infrastructure to date incorporate computer vision or machine learning techniques, and other sectors could benefit from research into inspection of water and electrical infrastructure by AUVs and UAVs respectively.