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Review

Artificial Neural Networks for Sustainable Development of the Construction Industry

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Abstract: Artificial Neural Networks (ANNs), the most popular and widely used Artificial Intelligence (AI) technology due to their proven accuracy and efficiency in control, estimation, optimization, decision making, forecasting, and many other applications, can be employed to achieve faster sustainable development of construction industry. The study presents state-of-the-art applications of ANNs to promote sustainability in the construction industry under three aspects of sustainable development, namely, environmental, economic, and social. The environmental aspect surveys ANNs' applications in sustainable construction materials, energy management, material testing and control, infrastructure analysis and design, sustainable construction management, infrastructure functional performance, and sustainable maintenance management. The economic aspect covers financial management and construction productivity through ANN applications. The social aspect reviews society and human values and health and safety issues in the construction industry. The study demonstrates the wide range of interdisciplinary applications of ANN methods to support the sustainable development of the construction industry. It can be concluded that a holistic research approach with comprehensive input data from various phases of construction and segments of the construction industry is needed for the sustainable development of the construction industry. Further research is certainly needed to reduce the dependency of ANN applications on the input dataset. Research is also needed to apply ANNs in construction management, life cycle assessment of construction projects, and social aspects in relation to sustainability concerns of the construction industry.

Keywords: artificial neural networks; construction industry; energy management; sustainable construction management; sustainability; environmental aspects; socio-economic aspects

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1. Introduction

The construction sector is a high-energy and natural-resource-demanding field with high greenhouse gas emissions and waste generation [1]. To reduce the environmental impact of concrete used in industries, dedicated research to improve the sustainability of concrete construction is required [2]. There are opportunities in the construction industry for energy forecasting and material optimization analysis for lower carbon emissions and lower costs using machine learning and Artificial Neural Network (ANN) methods [3]. Bilal et al. [4] studied the opportunities and future trends of big data in the construction industry. The role of Artificial Intelligence in construction engineering for sustainable development is reviewed by Manzoor et al. [5] and Yusel et al. [6]. The application of machine learning for sustainable and resilient buildings was surveyed by Kaswan and Dhatterwal [7]. Artificial Neural Networks constitute the most popular and potential technology used for optimization, decision making, and forecasting to achieve sustainability

in construction engineering. D'Amico et al. [8] collected a large database of civil and structural engineering for application in neural networks to develop a more sustainable built environment. Maya et al. [9] proposed the ANN approach to predict construction project performance in Syria's construction industry. The primary advantages of ANNs include their ability to learn from existing applications (historical construction projects) and generalize solutions for forthcoming applications (future construction projects). Other advantages include the ability to extract information from incomplete and noisy data and their suitability for problems in which algorithmic solutions are difficult to develop or do not exist [10].

Sustainable development of the industrial sector is essential for minimizing the exploitation of Earth's natural resources and preventing the destruction of its ecosystem. The application of digital technology such as Artificial Intelligence (AI) and machine learning can be utilized for the sustainable development of the construction industry due to their proven accuracy and efficiency in control, estimation, optimization, decision making, and forecasting. The study presents state-of-the-art applications of ANNs, the most popular and widely used Artificial Intelligence (AI) technology, to promote construction industry sustainability, including sustainable construction materials, energy management, cost-effective control, and sustainable construction characteristics, i.e., environmental and socio-economic aspects of sustainability.

1.1. Sustainability

Sustainable development in the construction sector is the development that reduces the impact on the environment and the resources used during and after construction. In sustainable development, the emphasis is primarily on sustainable management, energy reduction, socio-economic uplift, and the environment by adopting solutions to unsustainable challenges [11]. The term sustainability is used to describe the functionality, systems, and stages involved in efficiently utilizing resources. Sustainability consists of three main stakes, namely, environmental, financial, and communal, also referred to as earth, gain, and human [3]. Sustainable development of the construction industry aims for the adaptation of environmental and energy policies to support economic development and not threaten natural life [12]. Sustainable construction is a new approach to construction that improves the way people construct and live. Economic sustainability is a provision of the steady public and private investment flow with efficient usage and management of resources and the assessment of economic efficiency with social criteria instead of return concerns [13]. Hong et al. [14] discussed the necessity to develop local environmental sustainability in the construction industry. Oyedele [15] evaluated how sustainability has affected the design and development of civil engineering infrastructure. He concluded that the design and construction of infrastructure can have an impact on structures' sustainability, minimize global warming, and improve user health.

1.2. Artificial Neural Networks (ANN)

The ANN technique was initially presented in 1943. It is an information-processing method that simulates the human brain and the nervous system regarding features such as learning ability, creativity, intelligence, generalization, and flexibility. The ANN trains the network through a learning process. After training, the validation of the network is necessary to confirm the trustworthiness of the ANN model in dealing with the difficulties before setting the model into action. Three layers make up an ANN network: The input layer, any hidden layers, and the output layer, each with its own set of neurons. Specific datasets serve as the sources of signals for input layers. The leading phases of ANN include hidden layers, which give the system its crucial computing capability. The final decisions and output results are made by the output layers. The input layer broadcasts a pattern to all hidden nodes during training. The output value must then be calculated by the system, which broadcasts the result to the output nodes. The resulting actual outcome is then calculated by each output node using a weighted sum. The system then has to determine

whether, if any, further learning is necessary, which is achieved by comparing the overall difference it has calculated with an acceptable error that the system developer has defined. In the event that the objective is not achieved, the output nodes compute the derivatives of the error with respect to the weights, and the result is transmitted back through the system to all of the hidden nodes. Following that, each hidden-layer and output-layer node will adjust its weights to reflect the corrections. The computation restarts when the weights have been modified. The cycle is repeated until the desired result is obtained. Finally, the successful ANN system can be used to forecast the outcome of an input that it had not previously observed. Neural networks may use useful tools for decision making, prediction, identification, and optimization [16]. The artificial neural network's pathways are presented in Figure 1.

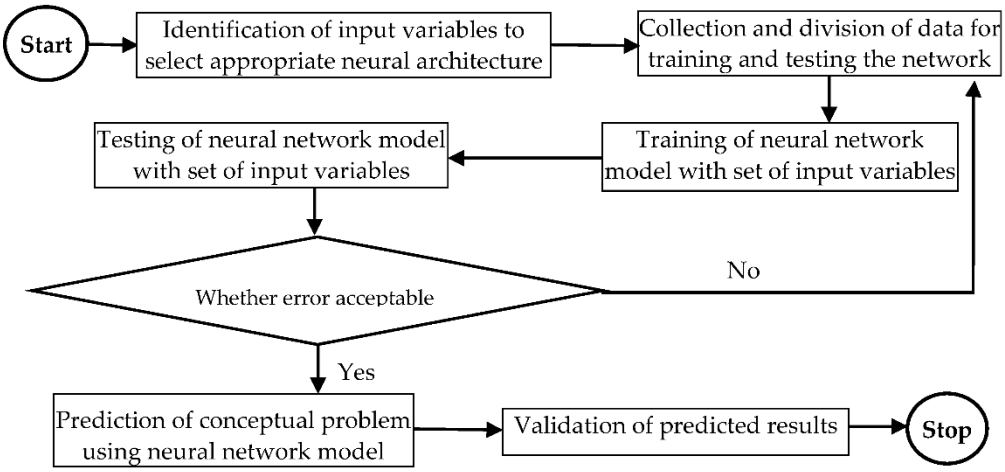

Figure 1. Artificial neural network model development pathways [17].

2. Research Methodology

The main objective of this study is to review the application of Artificial Neural Network (ANN) methods for sustainable development of the construction industry, i.e., the industry satisfying environmental (high functional performance and environmentally friendly usage) and socio-economic (communal and financial) aspects of sustainability. The environmental aspect surveys the ANN application in sustainable construction material, energy management, material testing and control, infrastructure analysis and design, sustainable construction management, infrastructure functional performance, and sustainable maintenance management. The economic aspect covers financial management and construction productivity using the ANN application. The social aspect reviews society and human values and health and safety issues in the construction industry. The research methodology is established on the analysis of secondary data, i.e., published research and books. The secondary data are taken from the databases of scientific articles, including Scopus, ScienceDirect, and Google Scholar. It focused on the main keywords artificial neural networks and sustainability and was supported by other keywords, for example, construction materials, material and structure testing, construction industry, energy management, construction management, productivity, social, etc.

3. ANNs Application in Environmental Aspect of Sustainable Development of Construction Industry

3.1. Sustainable Construction Materials

Due to environmental challenges and socio-economic requirements, traditional construction materials are being transformed into new-generation high-performance and sustainable materials. The utilization of sustainable materials is a global demand in the construction industry. Adel et al. [18] surveyed the application of machine learning, such as ANNs, evolutionary algorithms, and support vector machines, to develop construction materials with sustainability considerations. The properties of sustainable mortar with

different mixtures of ingredients were estimated using the ANN technique by Naderpour and Mirrashid [19]. The ANN was applied by Kuppusamy et al. [20] to predict the material mixture design of eco-friendly geo-polymer composites. An ANN–Python-based methodology was presented by Mater et al. [21] to predict the mechanical properties of green concrete materials. Kurpinska and Kułak [22] evaluated the performance of lightweight concrete manufactured from the waste material aggregate by means of an ANN. ANN-based thermally dependent material models were developed by Abbas et al. [23] and Naser [24] to determine the residual strength of concrete materials after exposure to an extreme heat environment. Elemam et al. [25] carried out optimization of green and hardened properties of self-consolidating concrete, containing waste and recycled materials, by applying the ANN technique. An analytical model based on an ANN was used by Ghafari et al. [26] to determine the relationship between the input and output parameters of ultra-high-performance concrete (UHPC) for achieving the required material performance. The genetic algorithm combined with a neural network (GANN) technique was implemented by Rao et al. [27] to demonstrate the potential of the artificial neural network model to predict the durability level of high-performance concrete through chloride ion permeability. The durability conditions of self-consolidating concrete containing glass powder and micro-silica with the same packing density were predicted by Hendi et al. [28] using an ANN model considering residual compressive strengths, volume loss, and mass loss in an H_2SO_4 environment (sewage water). They concluded that concrete with higher compressive strength will not be a cost-effective remedy for application in a high-sulphate medium. The application of ANN models to predict the durability properties of cement-based materials was performed by Chen et al. [29] where materials were exposed to sulphate attack. A surface chloride concentration prediction in waste-containing concrete for marine structures employing the ANN approach was carried out by Ahmed et al. [30]. Jahanbakhsh et al. [31] recommended the development of a sustainable concrete mixture using the ANN technique containing highly reclaimed asphalt pavements and recycling agents for resistance to chloride ions and carbonated water. Al-Mansour et al. [32] elaborately discussed the application of materials, along with the constraints that exist, in the production of sustainable concrete. Bondar [33] developed an ANN model to predict the compositions of natural alumina-silica-based geopolymer concrete. Açikgenç et al. [34] developed an ANN simulation to predict the mix compositions of steel-fiber-reinforced concrete.

3.2. Energy Management

Building construction and operations in the construction industry are responsible for 36% of global energy use and 39% of energy-related carbon dioxide (CO2) emissions [35]. The continuous increase in infrastructure construction activities put tremendous pressure on the construction sector to achieve the aim of saving energy and reducing carbon emissions. Rodrigues et al. [36] surveyed ANN-based research initiatives for forecasting renewable energy to promote a sustainable future in the construction industry. Policies are needed to increase the awareness of the necessity for stakeholders of the construction industry to reduce energy consumption [37]. Verma et al. [38] discussed the reduction in energy consumption by using geo-polymer concrete for the sustainable development of construction industries. ANNs have showcased successful applications in energy forecasting [39]. Kumar et al. [40] and Georgiou et al. [41] presented surveys of the application of artificial neural networks in building energy consumption analysis. ANN-based load-forecasting models' good performance in energy management systems was outlined by [42]. Basic architectural features such as the building shape, orientation, and the window-to-wall ratio, other building factors such as users' behavior, building type, building location, the climate, and the external environment such as solar radiation and the speed, direction, strength, and duration of wind have a huge impact on energy consumption [43]. Researchers have paid attention to the use of ANNs for modelling and prediction in the field of energy systems of buildings, including the prediction of solar radiation and wind and solar energy systems [44]. Zhai and McNeill [45] discussed the importance of building simulation tools

in developing sustainable building designs. Building performance is significantly affected by early design, and over 40% of the energy-saving potential comes from the early design stage [35]. Echenagucia et al. [46] observed that at the early stage of a construction project, the energy-saving design of buildings can help designers to achieve significant energy savings. Due to the rapid and accurate prediction of a building's energy consumption at the early design stage, ANNs can be used for the energy-saving design system [47]. Li et al. [48] developed an ANN simulation for energy prediction with little building energy data using the learning transfer technique. Attoue et al. [49] applied an ANN model for indoor temperature forecasting of a smart building to optimize energy devices and ensure occupant comfort as well as energy optimization. Orosa et al. [50] trained and used the constructed neural network model for indoor environments with internal covering materials in various buildings to predict the indoor temperature and relative humidity as a function of weather conditions and estimated the local thermal comfort conditions and energy consumption. An environment prediction model for occupant comfort management of residential buildings using the recurrent neural network technique was proposed by Jin et al. [51]. A neural-network-based approach to forecast the microclimatic behavior of greenhouse gases was developed by Nicolosi et al. [52]. They showed that it is possible to maintain improved indoor climatic conditions by using controlled parameters.

3.3. Material Testing and Control

In the construction industry, in order to design a durable, cost-effective, and optimal structure, the structural designer must have a deep understanding of the properties of materials, and for this, the designer should rely on the results of experimental tests. Moreover, performance evaluations of infrastructure within the construction industry are dependent on the results of experimental tests of structure prototypes, which are not only expensive to undertake but also take a significant amount of time. The unconventional method of deriving information through learning to model non-linear material behavior has created immense interest in the field of neural networks for material testing and control. Neural network digital computing techniques are advantageous because they can learn from examples and generalize solutions to new renderings of a problem, adapt to fine changes in the nature of a problem, are tolerant to errors in the input data, can process information rapidly, and are readily transportable between computing systems [53]. Messner et al. [54] proposed an ANN technique for optimally choosing structural member materials within the bounds of the building design and the construction project's requirements. A state-of-the-art review of the application of ANNs for the determination of mechanical properties of basic concrete material was presented by Chandwani et al. [55]. There are a number of research studies devoted to ANN applications for the development of various-quality concrete and their properties, for example, modelling of self-compacting concrete by Belalia et al. [56]; rubberized concrete by El-Khoja et al. [57]; ferro-cement concrete by Khan et al. [58]; concrete containing fly ash, silica fume, metakaolin, and bottom ash mineral admixtures by Vidivelli and Jayaranjin [59]; concrete containing nano-silica by Gupta [60]; concrete containing nano-silica and copper slag by Chithra et al. [61]; recycled aggregate concrete by Xu et al. [62]; concrete containing construction and demolition waste by Dantas [63]; high-strength concrete by Yue et al. [64]; lightweight concrete mortar by Tanyildizi [65]; environmentally friendly ultra-high-performance concrete by García et al. [66]; and polymer-modified concrete by Al-Janab et al. [67] to save time, effort, and costs of material testing and contribute to the sustainable development of the construction industry. The back-propagation neural network formulation is developed by Ghaboussi et al. [68] to investigate the performance of concrete in a state of plane stress under monotonic biaxial loading and compressive uniaxial cyclic loading. The prediction of FRP–concrete interfacial bond strength using an explicit neural network with a large database was performed by Zhou et al. [69]

ANN-based carbonation modelling is presented by Kwon and Song [70] to investigate carbonation behavior in concrete. The ANN approach is used to design the green concrete mixture by Wu et al. [71]. The ANN technique was used by Zavrtanik et al. [72] to

model the air void content in an aggregate mixture. Saridemir et al. [73] employed ANN and fuzzy logic to forecast the long-term strength of ground granulated blast-furnace slag (GGBFS) mixed concrete. Chandwani [74] developed a slump prediction model of ready-mix concrete using genetically evolved artificial neural networks. The chloride penetration in self-consolidating concrete (SCC) mixes containing various types of minerals was predicted by Mohamed et al. [75] using the ANN technique in which training was conducted using published data and validation was carried out using chloride penetration experimental data. ANN-based prediction of the concrete's interfacial transition-zone fracture properties was performed by Xi et al. [76] to understand the cracking behavior to develop quality concrete. The ANN model was used by Nazari [77] to predict the percentage of water absorption of waste-ash-based geopolymer concrete. The thermal performance of a composite material using the back-propagation-based ANN was studied by Brown et al. [78] considering the environment, constituent materials, and component ratios used in the composite production. ANN-based forecasting of concrete properties through non-destructive test data was performed by Tahwia et al. [79]. The properties of concrete material were predicted by Lande and Gadewar [80] by employing the ANN method and ultrasonic pulse velocities.

Artificial neural networks (ANNs) are well suited to modeling complex and variable materials such as soil and concrete. ANNs have been applied to geotechnical engineering applications with great success [81]. Anysz and Narloch [82] proposed the proportional design of materials (water, soil, and cement) for soil stabilization with a cost-saving and sustainable solution using an ANN. Salahudeen et al. [83] used the ANN for the prediction of compaction characteristics in the soil stabilization process. The pile-bearing capacity of a single driven pile in sandy soil was determined by Maizir et al. [84] using finite element and ANN formulations and dynamic load test data. A multilayer perceptron (MLP) was utilized by Alavi et al. [85] to construct comprehensive and accurate models relating the MDD and OMC of stabilized soil to the properties of natural soil such as particle-size distribution, plasticity, linear shrinkage, and the type and quantity of stabilizing additives. The application of ANN to predict the constitutive relations of granular soil was performed by Ellis et al. [86]. The multi-layer perceptron and B-spline neurofuzzy network-based ANNs were implemented by Shahin and Jaksa [87] to predict the pull-out capacity of tent anchors. The application of an ANN for the prediction of the specific gravity and compaction properties of highly heterogeneous material and fly ash was performed by Das and Sabat [88]. The shear strength parameters of granulated waste rubber were determined by Eidgahee et al. [89] using an ANN and the group method of data handling. An ANN model using sieve analysis, Atterberg limits, optimum moisture content, and maximum dry density data was applied by Bhatt and Jain [90] to predict the California bearing ratio of soils. Mahamat et al. [91] predicted the mechanical characteristics of the soil in termite mound soil activated by alkali. Nazemi et al. [92] predicted the absorption and volume of water in porous construction materials by applying the ANN approach. Efficient and economic soil characterization using the ANN technique was carried out by Sharmik et al. [93]. Shi et al. [94] presented a study of ANNs for forecasting settlements of soil during the construction of tunnels. Sivakugan et al. [95] explored the possibility of using neural networks to predict the settlement of shallow foundations on granular soils.

3.4. Infrastructure Analysis and Design

The application of Artificial Neural Networks (ANNs) has been shown to be highly competent as fast and accurate solutions to a wide variety of challenging engineering problems that are computationally beyond the capability of conventional methods of analysis and design, particularly at the early design stage. Improved sustainability can be achieved in the concrete industry by making the life cycle of concrete structures more resilient through quality materials and integrated structural design with risk-based durability modelling. The ANN technique can be used to analyze various civil engineering problems [96]. The success of implementing neural networks in structure analysis is de-

pendent on the quality of the data used for training, the type and structure of the network, the method of training, and the way in which both input and output data are structured and interpreted [97]. Rogers [98] proposed guidelines for designing and training a neural network to simulate a structural analysis program and reduce the amount of time it takes an optimization process to converge to an optimum design. Mukherjee and Deshpande [99] used ANNs to model an initial design process. They developed a multi-layer feed-forward network model for the initial design of reinforced-concrete single-span rectangular beams. The design moment resistance and secant stiffness of steel connections was calculated by Anderson et al. [100] using an ANN method. The buckling load of cellular steel beams was estimated by Abambres et al. [101] adopting the ANN technique. The analysis of beam-to-column connections was carried out by Trung et al. [102] using the ANN approach. Zhou et al. [103] calculated the shear capacity of masonry walls with reinforced concrete grouting by applying a neural network with neuro-fuzzy system models. The shear strength of FRP-reinforced concrete flexural members without stirrups was calculated by Lee and Lee [104] with the help of an ANN. The tensile strength of corroded steel was calculated by Karina et al. [105] with the help of ANN. Post-tensioned concrete road bridges were designed by García et al. [106] using the ANN method. Space trusses' safety factors were determined by Yadollahi et al. [107] using the ANN method. An intelligent system model was developed by Terenchuk et al. [108] for the estimation of the technical state of construction structures based on the Takagi–Sugeno–Kang fuzzy neural network.

3.5. Sustainable Construction Management

The construction industry is one of the biggest sectors, and while it is beneficial in terms of value creation and employment opportunities, it also has significant negative impacts on socioeconomic and environmental conditions [109]. Sufficient prediction of construction project management, such as financial planning (project and overhead costs, cash flow), planning and scheduling of the project, temporary structure planning, productivity, safety issues, etc., increases the transition process of sustainability in construction engineering. The ability to adapt to a changing environment is essential to continued progress in the construction sector. The construction industry must rethink its existing management approaches and find new management tools [110]. Organizations that are active in construction are being challenged by three significant shifts, namely, the growing demand for workers with knowledge, the expansion of markets, and the digital revolution [111]. The construction industry should frame new strategies with long-term comprehensive action plans and guide resource allocation to accomplish the goal of sustainable competitive advantage [112]. The construction industry's market environment is extremely sensitive to the state of the economy and the level of success achieved by other industries, as the interdependence between industries drives construction initiatives [113]. Neural networks are proven to be an encouraging management tool for the fast development of sustainability in the construction industry by increasing automation efforts for the designing, planning, construction, and management of infrastructures [114]. Artificial Neural Networks have found wide applications in various branches of civil engineering, including studying the performance of construction materials and structural characterization and control, in soil engineering regarding soil liquefaction potential, in construction management regarding forecasting schedules and costs of construction, and in construction services regarding analyzing the water distribution network, etc. [115] A comprehensive review of published literature was conducted by Araujo et al. [116] using the meta-analysis methodology to assess the sustainability of the construction industry in reducing the economic, environmental, and social impacts of the consumption of large amounts of resources. A scientometric review related to the application of ANNs in construction project management was presented by Xu et al. [117]. They found that there are still numerous obstacles to overcome in ANN applications, such as the necessity for systematic platform design, data collection, cleaning, and storage, and the coordination of efforts across many stakeholders, researchers, and nations/regions. A critical evaluation and future development of Artificial Intelligence

including the ANN in construction engineering and management was outlined by Pan and Zhang [118]. A construction project's success relies on its planners' ability to predict various project phases accurately and reliably. Prediction and forecasting provide early warnings of project challenges during execution. ANN models can be used to predict project performance factors such as cost/budget variance and risk analysis based on observations made in the project environment [119]. An ANP model, named the EnvironalPlanning system, was developed by Chen et al. [120] for environment-conscious construction planning to control construction's negative impacts on the environment. Rizzo et al. [121] presented a new ANN-based site characterization method, SCANN (Site Characterisation using Artificial Neural Networks), to plot discrete spatially distributed fields.

Construction scheduling problems were addressed by Ansari and AbuBakar [122] using Artificial Intelligence techniques. Bhokha and Ogunlana [123] used a three-layered back-propagation-based ANN technique to predict the construction schedule at the pre-design stage when very little project information is available. The application of an artificial neural network (ANN) to forecast the schedule of a residential construction project from the pre-design stage to completion was performed by Al-Zubaidi et al. [124]. The linear regression and multilayer perceptron neural network model was developed by Petruseva et al. [125] to predict the duration of a construction project using time and cost construction data of contracted and actual values. The time estimation of concrete operations in a construction project was carried out by Maghrebi et al. [126] using the ANN method. The time contingency in Egyptian construction projects was evaluated by Yahia et al. [127] using the ANN model.

Shi [128] used the ANN model to estimate the earthwork quantities of construction projects. The construction project cost flow was anticipated by Boussabaine and Kaka [129] using the ANN approach. A study related to project tender offers with the application of an ANN was performed by Minli and Shanshan [130]. The ANN method can be used to analyze the dispute resolution practices of construction projects [131]. Yitmen and Soujeri [132] studied the effect of frequent change orders on dispute resolution. A predictive model based on an ANN for time and cost claims in construction projects was prepared by Yousefi et al. [133]. An optimal risk allocation model for the 3P project delivery method adopting an ANN was developed by Jin and Zhang [134]. The project performance of design-build contract projects was studied by Ling and Liu [135], while the performance of general contract projects was studied by Waziri [136] by applying the ANN method. A project's risk management for construction quality was evaluated on the basis of a rough set and a neural network by Liu and Guo [137]. A framework to predict multi-project resource-conflict risk was proposed by Bai et al. [138] adopting the ANN technique. The critical-success-factor-based ANN model was recommended by Costantino et al. [139] for project selection in project portfolio management. The contractor prequalification framework was prepared by Lam et al. [140] employing the fuzzy neural network approach.

3.6. Infrastructure Functional Performance

The performance of infrastructure in the construction industry in accordance with planning and design directly influences the sustainability of the industry sector, as non-compliance with the standards has a negative impact on the environment and the socio-economic system. The behavior of a compression member was simulated by Oztekin [141] using the ANN technique. The application of the ANN technique was employed by Yadollahi et al. [142] to examine the performance of repaired structures made of a glass-fiber-reinforced polymer (GFRP) that had been damaged by high temperatures. Earth seismic disturbance and earthquake prediction using an ANN were performed by Xie et al. [143]. Chen et al. [144] developed a back-propagation neural network controller for active control of structures under dynamic loading. Lee and Sterling [145] developed an ANN model for the identification of probable failure modes of underground openings from prior case history information. Watson et al. [146] used ANN for the development of a

pile integrity testing system. A framework for multi-dimensional fragility relationships in skewed concrete bridge classes was generated by Mangalathu et al. [147] using the application of the ANN technique. The long-term performance of the Fei-Tsui arch dam was carried out by Kao and Loh [148] with help of ANN-based approaches. ANN and multiple linear regression models were used by Mata [149] to study the performance of a concrete dam. An ANN model based on a multilayer perceptron (MLP), a radial basis neural network (RBNN), a generalized regression neural network (GRNN), and multi-linear regression (MLR) and multi-nonlinear regression models (MNLR) was developed by Pinar et al. [150] to forecast the backwater through arched bridge constructions.

3.7. Sustainable Maintenance Management

Best construction maintenance and management practices must be followed to reduce the wastage of energy and resources and introduce sustainability into the construction industry [151]. ANN-based models are implemented to develop structural health-monitoring benchmark studies [152], which can be utilized to enhance the sustainability of structures. The development of applications of Artificial Intelligence methods, including the ANN, for structural performance in structural engineering was reviewed by Salehi and Burgueno [153]. A technique based on the hybrid ant colony algorithm using the Hooke–Jeeves pattern search without the need for an initial dataset was proposed by Shakya et al. [154] for the damage prediction of structures. Advanced quality-control models for incorporating sustainability aspects in concrete were proposed by Choi et al. [155], applying pattern-recognition-based ANNs and data-driven and self-adaptive functions. Facility management maintenance methods are mostly corrective, and a shortage of funds limits preventive maintenance to the minimum level [156]. Davtalab et al. [157] developed a construction defect detection system utilizing the convolutional neural network technique (CNN) for construction 3D printing. Shi [158] uses an artificial neural network (ANN) model and an unascertained system to evaluate the quality of construction projects. Stephens and VanLuchene [159] explored the use of ANNs for damage assessment in determining the safety condition of a structure following a seismic event. The reinforcement corrosion assessment model using ultrasonic tests and an artificial neural network for reinforced concrete construction was developed by Xu and Jin [160]. Begum et al. [161] developed an ANN system for the testing of concrete surfaces. The output of the network is the overall probability of the defect interface occurring within a given depth range. The structural damage monitoring system of a five-story steel frame was proposed by Elkordy et al. [162] to identify the damage level and class using the ANN approach based on observations of other researchers and physical and analytical model-based results. The damage identification of truss structures using the ANN technique was performed by Chiwiacowsky et al. [163]. Applications of ANN and anti-resonant frequencies for the vibration-based damage assessment of a beam were outlined by Meruane and Mahu [164]. The CNN-based structural health assessment technique was developed by Sony et al. [165]. Dung [166] applied a deep CNN to find cracks in concrete structures. The ANN-based approach was used by Neves et al. [167] to determine the damage to bridge structures.

The application of ANN models for forecasting the service life of concrete sewer pipes in a corrosive environment was performed by Li et al. [168]. The detection of sewer pipe defects using a CNN was performed by Cheng and Wang [169]. ANN models were used by Ganesapillai et al. [170] to achieve self-sustainability in sanitation engineering. A predictive model for construction waste prediction using an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based waste analytics system (A-WAS) was developed by Akinade and Oyedele [171].

4. ANN Application in Economic Aspect of Sustainable Development of Construction Industry

4.1. Financial Management

The construction industry should implement effective financial management to promote long-term economic growth in the construction industry and increase positive impacts on the social, environmental, and cultural aspects of the community. A project's financial management is a critical factor in the smooth functioning and timely completion of the construction project. Additional financial burdens on construction projects due to poor financial management can cause serious problems for stockholders and the environment and even require interruption of the work due to a lack of resources [172]. An extensive survey of research work on Artificial Intelligence and cost estimate modelling was provided by Elmousalami [173]. Kumar and Gururaj [17] presented financial planning prediction models using the neural network approach for sustainable construction projects. The life-cycle costs of existing buildings were assessed using the ANN technique by Oduyemi et al. [174]. ANN models were employed by Chao and Kuo [175] to estimate the minimum rate of overhead and markup. Shiha [176] utilized artificial neural networks (ANNs) to predict the cost of building materials in the context of the Egyptian construction industry. The total project cost was assessed by Alshahethi and Radhika [177] using ANN procedures. Nonparametric cost estimation problems faced in the application of the ANN method were discussed by Juszczyk [178]. The final cost of construction projects in the context of Iraqi projects using the ANN approach was predicted by Abdul et al. [179]. The cost prediction model consisted of 11 variables, namely building height, average inter-floor height, average perimeter, usage area of the building, roof area, bathroom area, the value of the open space, number of floors, types of floor structures, types of roof structures, and the ground slab. An analytical model based on a multilayer perceptron ANN, capable of estimating the project construction costs for a building project, was presented by Pessoa et al. [180]. An ANN cost forecasting model for government buildings was developed by Sitthikankun et al. [181]. An ANN cost-forecasting model was prepared by Bala et al. [182] for Nigerian educational building projects. Residential buildings' conceptual costs were estimated by Juszczyk [183] using the ANN method. Highway engineering costs were estimated by Wang and Duan [184] using the ANN method. An ANN model was developed by Arafa and Alqedra [185] to estimate the early-stage building construction costs. The structural costs of building projects were valued by Roxas and Ongpeng [186] employing the ANN approach.

Lesniak and Juszczyk [187] forecasted the site overhead costs by applying the ANN model. A hybrid expert system and artificial neural network approach was applied by Li and Love [188] to estimate the markup for construction projects. A two-step neural network-based formulation was developed by Lhee et al. [189] to forecast the construction cost contingency. The identified cost-significant items were included by Alqahtani and Whyte [190] to improve the life-cycle costs of construction projects using an ANN. The order of magnitude cost estimation in construction using the ANN was performed by El-Sawah and Moselhi [191]. The cost estimation of engineering services by applying the ANN technique was prepared by Matel et al. [192]. The estimation of cost for BIM implementation in construction projects was performed Hong et al. [193]. Alex et al. [194] used an ANN for cost computations of water and sewer-line services. The cost of quality achievement in the construction project was estimated by Jose and Ambili [195] using the ANN technique. The earthworks' execution time and costs were forecasted by Hola and Schabowicz [196] using the ANN.

4.2. Construction Productivity

Productivity-boosting digital technologies such as the ANN technique can help to decrease construction production costs, the greenhouse gases released, and the intensity of production process resources. Construction productivity was assessed by Portas and AbouRiz [197] using ANN-based forecasting models. ANN models were used by Nasirzadeh et al. [198] to forecast a construction project's labor productivity and by Gol-

naraghi et al. [199] to forecast concrete formwork labor productivity. El-Gohary et al. [200] used the ANN technique to improve the productivity of construction workers under different conditions. Al-Zwainy et al. [201] proposed an ANN-based productivity prediction model for floor finishing works. An ANN estimation model was built by OK and Sinha [202] to forecast construction equipment productivity. The ANN technique was used by Sinha and McKim [203] to identify the level of organizational performance in the construction industry. The technique conceptualized 14 variables from 4 general criteria of organizational characteristics pertinent to reviewing effectiveness, namely, person-oriented practices, structural perspectives, strategic means and ends, and organizational flexibility and guidelines.

5. ANN Application in Social Aspect of Sustainable Development of Construction Industry

5.1. Society and Human Values in Construction Industry

Improved sustainability in the construction industry can be achieved via social coordination such as market correspondence and increased accessibility to public services and through the solution of health and safety issues in construction. Artificial Neural Networks (ANNs) may be utilized for social behavior research carried out within the framework of the construction industry [204]. The relationship between human values and the motivations of construction stakeholders using an ANN application was explored by Wang et al. [205]. The prediction of building-occupant complaints employing the neural network approach was modelled by Assaf and Srour [206]. In terms of unsafe behavior and posture detection, Patel and Jha [207] used an ANN to predict employees' safe work behaviors and identified the main influencing factors of safe behaviors. Construction projects' risk management for participants' behavioral risk was examined on the basis of an ANN by Xiang and Luo [208]. The application of an ANN for the detection of human errors in an engineering system was performed by Amiruddin et al. [209]. D'Oca et al. [210] emphasized the need for further study to incorporate human factors into building design and operation procedures with the aim of improving occupant comfort and productivity. An ANN model was developed by Albahussain [211] to study the influence of corporate social responsibility (CSR) on the competitive advantage (CA) of the industry.

5.2. Health and Safety Issues in Construction Projects

Artificial neural networks are up-to-date interdisciplinary fields that are used to find solutions to a wide range of engineering challenges that traditional modeling and statistical techniques have failed to address. Occupational Health and Safety (OHS) is the most important aspect of any construction project. The performance of construction safety management systems was analyzed by Goh and Chua [212] using the ANN method. An accident prevention system was developed by Ayhan and Tokdemir [213] using ANN-based models for the prediction and consequences of construction project accidents. A back-propagation (BP) neural-network-based model was designed by Shen et al. [214] to predict the safe conditions of building construction. Analyses of accident severity in construction were performed by Ayhan and Tokdemir [215] by adopting the ANN approach. A risk prediction model based on the neuro-fuzzy methodology was presented by Jahangiri et al. [216] regarding falling from temporary structures. Zhang et al. [217] proposed using a smartphone as a data collection tool to detect and identify near-miss falls based on an ANN. This method helps to identify hazardous elements and vulnerable workers. ANN-based crowd evacuation modelling was developed by Testa et al. [218] for building construction safety. Wen et al. [219] presented an early warning system as a surveillance method for working in hot and humid environments, safeguarding frontline labor health and safety. Ren and Cao [220] employed a fast prediction method by considering a low-dimensional linear ventilation model (LLVM)-based ANN model to forecast the indoor pollutant concentrations for safe and healthy building environments.

6. Review Outcome

From the review of literature for the application of ANNs presented in the preceding sections, it is very clear that the ANN technique is a multi-disciplinary and multi-task approach with a high degree of accuracy and is equally applicable to quantitative and qualitative datasets, even with its variability and complexity. It is also clear that ANNs can be successfully used for optimization, estimation, prediction, and decision making. The comprehensive literature survey shows that ANN applications can be utilized to develop relationships between construction material composition and product properties. It is also clear from the literature survey that ANNs can be applied for energy and material optimization, cost-effective production processes, effective project management, and effective hazard and safety management in infrastructure development in the construction sector. It is observed that ANNs have applications in all three aspects of sustainability, i.e., environmental, socio-economic, and social, with reference to construction phases and construction industry segments (application in the development of sustainable construction materials, energy management, material testing and control, infrastructure analysis and design, sustainable construction management, infrastructure functional performance, sustainable maintenance management, financial management, construction productivity, societal and human values, and health and safety issues), and can be utilized in the sustainable development of the construction industry. However, the success of ANN method applications depends on the availability of real data for the training and validation of models. Further research is certainly needed to reduce the dependency of ANN applications on the input dataset. Research is also needed to apply ANN to construction management, life-cycle assessment of construction projects, and social aspects in relation to sustainability concerns. From this research review, we conclude that a holistic research approach with comprehensive input data from various phases of construction and segments of the construction industry is required for the sustainable development of the construction industry.

7. Conclusions

The construction sector is a high-energy and natural-resource-demanding field with high greenhouse gas emissions and waste generation. The sustainable development of the industry is essential for minimizing the exploitation of Earth's natural resources and preventing the destruction of its ecosystem. Artificial Neural Networks (ANNs) constitute the most popular and effective technology used for optimization, decision making, and forecasting, which can be fruitfully applied to the sustainable development of the construction industry. The study presents state-of-the-art applications of ANNs to attain environmental and socio-economic perspectives of sustainability in the construction industry. It is evident from the review that a holistic research approach with comprehensive input data from various phases of construction and segments of the construction industry is needed to implement sustainable development of the construction industry. Further research is certainly needed to apply ANNs to construction management, life cycle assessment of construction projects, and social aspects in relation to sustainability concerns of the construction industry. It can be concluded that ANNs can be applied to high-performance material development, energy and material optimization, cost-effective production processes, effective project management, and effective hazard and safety management in infrastructure development in the construction sector.

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