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The Role of Neural Networks in Improving Construction Project Scheduling

Milad Torabi Anaraki [1]*, Akbar Alidadi Shamsabadi [2]*, Iman Pishkar [3]

[1] Department of Civil and Environmental Engineering, Amirkabir University of Technology,Tehran, Iran, Milad.torabianaraki@gmail.com
[2] Department of Energy & Environment, Science and Research Branch, Islamic Azad University, Tehran, Iran, a.alidai@srbiau.ac.ir
[3] Department of Mechanical Engineering, Payamenoor University (PNU),P.O.Box 19395-4697,Tehran,Iran.

Abstract

As delays in construction projects escalate costs, timely project completion stands as a pivotal criterion for success in construction endeavors. Accurate scheduling duration estimates play a vital role in averting additional expenses and mitigating the risk of disputes among employers, contractors, and clients. Experts assert that delays are a common occurrence in the majority of civil engineering projects, emphasizing the critical role of time management in these endeavors. Project scheduling often faces constraints related to activity precedence relationships, project completion time, budget, and various resources like tools, equipment, machinery, or limited human resources. In the realm of construction project control, neural networks emerge as potent and innovative tools. Leveraging machine learning capabilities and analyzing intricate data, these tools contribute significantly to enhancing the management and control of construction processes. This article introduces a model for addressing project scheduling challenges, proposing a novel application of the Long Short-Term Memory (LSTM) neural network. Results demonstrate that LSTM outperforms other Recurrent Neural Networks (RNNs) in handling time series problems. Furthermore, this study advances our understanding of GPT models' application, offering insights into research prospects for implementing GPT models within the construction industry.

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1. Introduction

Currently, artificial intelligence plays a crucial role in automating and seamlessly connecting the physical and digital realms across diverse domains of science, technology, and engineering. The global artificial intelligence market size was $93.50 billion in 2020 and is projected to reach $997 billion by 2028 [1,2]. The statistics indicate that this market experiences an annual growth of 40.2%, demonstrating that the majority of companies have started using artificial intelligence tools for effective data management [3]. In essence, artificial intelligence adeptly handles substantial data volumes in real-time [4]. Additionally, it significantly aids large companies through automation, intelligent decision-making, faster processes, reduced human errors, and resource optimization. This empowers companies to redirect their focus from manual tasks like time management, performance evaluation, resource allocation, item scoring, anomaly detection, to other critical priorities [5]. Considering these advantages, global revenue from artificial intelligence was $34.87 billion in 2021, projected to soar to $15.70 trillion by 2030 [1]. Figure (1) illustrates human-centric artificial intelligence and its automation levels, which are categorized as follows:

(a) Partial automation: AI offers decisions/actions to the user based on learned preferences and can restrict them according to user preferences.

(b) Conditional automation: With a user-defined set of decisions/actions, AI suggests alternatives to enhance user performance.

(c) High level automation; When artificial intelligence is enabled and capable of implementing an alternative (or set of alternatives) that is expected to improve user performance. This degree of automation necessitates user confirmation and is commonly acknowledged as the most advanced manifestation of human centric AI.

(d) Complete automation: After learning user preferences, artificial intelligence executes alternative options without user confirmation. In this level of automation, artificial intelligence may indicate to the user which decision/action has been modified and why.

In the construction industry, one of the areas that has witnessed the most artificial intelligence (AI)-based innovation is construction planning [6,7]. Until recently, this was a specialized field that had not seen significant support for the introduction of new technologies over the decades. Traditionally, scheduling was done using old tools such as P6 or Microsoft Project [8]. For many construction companies, scheduling has been a painful point. It is a manual and error-prone process that impacts the outcome of the work. If done poorly, the domino effect can lead to costly damages and a decrease in site safety. By incorporating artificial intelligence into the construction planning process, project risks can be managed, workflow improved, safety increased, and ultimately tasks completed on time and within budget [9].

In 2023, Obianyo et al. conducted an in-depth examination of the application of artificial intelligence in construction scheduling for efficient project management of a two-story residential structure. This study served as a case study for designing and evaluating scheduling and cost performance indicators [10]. Yu and Zuo In in 2022, proposed a project scheduling management method based on a fuzzy logic neural network algorithm for construction projects [11]. Yu et al. (2021) proposed an active dynamic construction scheduling model based on fuzzy earned value management (F-EVM) and back propagation neural network (BP-NN) [12]. Elmousalami in 2020, investigated the suitability of computational intelligence techniques, including neural computing, fuzzy logic, and evolutionary computation, for refining the evaluation of parametric cost prediction models [13]. Georgy et al. (2005) utilized a neuro-fuzzy computational software method for predicting engineering performance in construction projects [14].

Artificial intelligence technology can now assist employers and contractors in creating and testing various construction plans to find the most efficient way to build and construct.

While it's crucial to incorporate human-centered AI tools to ensure maximal human oversight across all scientific and engineering domains, the architectural, engineering, and construction (AEC) industry has yet to fully embrace this approach. In this sector, task success heavily relies on the collective knowledge, experience, and collaboration among architects, engineers, managers, workers, and decision-makers. However, existing AI methodologies often overlook the integration of such human-centric information into automation and optimization processes. Human-centered AI holds the potential to address challenges related to real-time Big Data processing and analysis.

Human-centered AI tools are also anticipated to effectively communicate with individuals, understanding their language, behaviours, interests, and preferences, and discerning applicable inputs for specific tasks. Additionally, these tools can extract pertinent human-related data from diverse file formats in past projects' Big Data repositories, streamlining and enhancing processes across architecture, design, engineering, contracts, and construction endeavours.

The innovation in the study lies in the novel application of the Long Short-Term Memory (LSTM) neural network for addressing project scheduling challenges in construction endeavors [15]. This innovative approach leverages machine learning capabilities to enhance the management and control of construction processes, outperforming other Recurrent Neural Networks (RNNs) in handling time series problems. Additionally, the study explores the unique advantages of GPT models, which offer a more comprehensive understanding of the complexities associated with construction project planning and procurement by effectively acquiring and analysing textual information. This innovative integration of LSTM and GPT models showcases a dynamic and effective solution for improving project management and decision-making in the construction industry.

2. The Role of AI in Project Management

In the domain of project management, generative artificial intelligence has the capability to automate mundane tasks such as scheduling and resource allocation. This liberation from routine tasks enables project managers to dedicate more time to strategic and higher-value activities [16,17]. Moreover, it has the potential to analyze extensive datasets, pinpointing potential issues and minimizing risks. According to Polonevych, artificial intelligence simplifies processes and enhances project outcomes in project management applications [18]. Despite its unique capabilities, human decision-making remains pivotal for project success. Project managers possess a set of skills and characteristics that pose challenges for independent artificial intelligence systems. These include essential features such as decision-making, problem-solving, creativity, and communication skills. Especially in complex and dynamic project

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environments where flexibility, insight, and social intelligence play a crucial role, these human capabilities are highly valuable.

Understanding overall human intelligence provides a comprehensive view of the interplay between generative artificial intelligence and human decision-making in project management. The results of a study have revealed that only 35% of projects today reach successful completion, and one of the reasons for this discouraging rate is the minimal growth in existing technologies for project management. [19]. However, this narrative is changing as researchers, startups, and innovative organizations increasingly adopt artificial intelligence, Machine learning and other up-to-date technologies for project control and management. AI programs enhance data quality and expedite decision-making [20,21].

Effectively recognizing and harnessing the synergy between AI capabilities and human expertise for project planning requires a strategic approach that integrates the strengths of both [22]. Identify Project Goals and Objectives, Assess AI Capabilities, Leverage Human Expertise, collaborative Approach, Training and Education, and Data Integration, and etc. by following these steps and fostering a collaborative environment between AI systems and human experts, organizations and stakeholders can effectively harness the synergy between AI capabilities and human expertise to ensure efficient and comprehensive project planning.

3. Human and artificial intelligence interactions in the field of project management

Various comparative studies have been conducted to increase the understanding and deepen the understanding of the effectiveness of artificial intelligence and human judgment in project management [23]. For example, in one study, it was shown how generative AI systems can help with decision-making and process optimization in project management, along with identifying the unique strengths and perspectives offered by a human project manager [24].

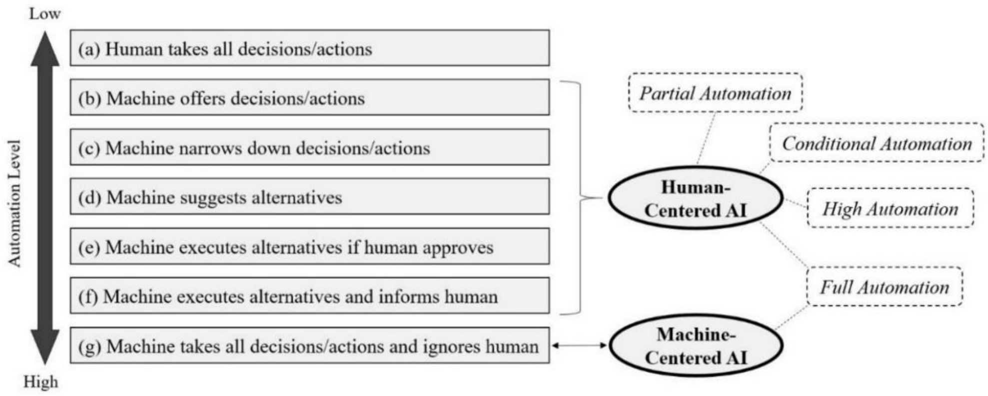

Fig. 1. levels of human centered AI automation.

Another research effort provided valuable data stemming from an experiment that directly compared the performance of human and artificial process managers. Such comparative analyses contribute to understanding the areas where generative artificial intelligence or human expertise excels, opening avenues for potential synergies in effective project management [25].

While there are arguments asserting that artificial intelligence cannot entirely replace the human mind, establishing trust and fostering collaboration between artificial intelligence systems and human project managers is considered crucial for successful cooperation in project management. In a specific study, the examination of the participant's identity and performance in trust and collaboration in human-AI cooperation revealed insights into how the perception of artificial intelligence as a collaborator influences the likelihood of cooperation and trust in its decisions [26,27].

Given the potential benefits of integrating artificial intelligence into project management, persistent challenges exist [28,29]. This includes ethical and technical challenges in the implementation of artificial intelligence systems, a lack of understanding and skills among project managers for effective use of artificial intelligence, and resistance to overall changes.

By examining the findings of this study, insights can be gained into how trust in artificial intelligence systems can be strengthened and how collaboration between humans and artificial intelligence can be optimized to maximize project outcomes.

Optimizing the collaborative approach between project plans created by artificial intelligence and those created by humans involves leveraging the unique strengths of each while mitigating their weaknesses. Here are several strategies for achieving this optimization:

- Utilize artificial intelligence for data analysis and prediction
- Combine human expertise for contextual understanding
- Facilitate collaboration and communication
- Integrate automation with human judgment
- Address bias and ethical concerns
- Promote learning and adaptability
- Balance speed and accuracy
- Integrate feedback loops.

By implementing these strategies, organizations can optimize the collaborative approach between project plans created by artificial intelligence and those created by humans, leveraging the unique strengths of each while addressing their respective weaknesses to achieve more effective and comprehensive project outcomes.

4. The Impact of AI in the Construction

Due to the dynamic nature of the construction industry, the success of any activity in this field significantly relies on the experience and knowledge of architects, engineers, managers, workers, and decision-makers, as well as proper communication between these sectors. Effective communication among these interconnected elements plays a crucial role in achieving success. The interaction between humans and machines is essential for creating work environments that prioritize human needs and optimizing project locations. Machines, including software, tools, and AI technologies, have traditionally been at the forefront of automation and optimization in construction. However, they frequently encounter limitations in integrating human knowledge, expertise, and preferences into their processes [30].

Common concerns among engineers about human centric AI posing a threat to their jobs are prevalent. However, it should be viewed as an opportunity to enhance traditional methods and replace repetitive tasks in areas where machine-centric tools may not effectively respond. AI technologies, by automating tasks, are expected to foster workforce creativity and increase labor productivity by up to 40% [18].

Human-centric artificial intelligence simplifies contractual processes and enhances project construction and operation, playing a crucial role in advancing the construction sector. This form of artificial intelligence empowers users to rapidly and accurately define project-related information. The gathered information is subsequently cross-referenced with past projects, codes, and standards to identify any inaccuracies in contracts and document processes. Furthermore, as a substantial contributor to construction sites, human-centric AI is expected to identify human-related information on project sites, thereby preventing occupational accidents and health hazards and prioritizing safety and health concerns.

Furthermore, by accurately understanding human needs and preferences, the collection and analysis of specific human information through human centric AI enable the precise automation of advanced technologies (such as robots and drones) and the management of machinery and tools on project sites.

AI functions as a powerful tool for the analysis and interpretation of extensive datasets in diverse aspects of the construction industry. AI is used as an important tool for the analysis and correct interpretation of big data in various sectors of the construction industry, which can lead to data-based project management and control, improved collaboration, employee health, increased safety and reduce waste of time and materials [31,32].

5. Project Control in the Construction Industry Using Neural Networks

As the global economy undergoes rapid growth, a significant portion of the workforce and financial resources are annually allocated to construction projects. The key benchmarks for a successful project include achieving desirable quality and meeting planned objectives. However, discrepancies between predictions and actual outcomes in quality and scheduling can emerge during a project's progression due to two primary reasons. On one hand, as inherent quality risks and uncertainties in a project are unavoidable, and the complexity and dynamics of a construction project increase, the frequency of quality-related risk events also rises, leading to delays and reduced project quality. On the other hand, developing a project schedule can be constrained by various internal and external factors. Failure to identify the relationship between the project schedule and the quality risk of the project results in a mismatch, causing delays and compromising project quality [33].

Quality and project scheduling are influenced by diverse factors such as the construction environment, technology, team experience, and capital recovery pressures, among others [34]. Reducing the construction project duration can expedite recovery and yield more economic benefits for construction companies. Enhancing project quality can reduce rework time and maintenance costs. However, an excessively compressed construction period can have adverse effects on project quality, jeopardizing sustainability, long-term operation, and social benefits. Stringent quality standards require preventive actions and inspection stages, leading to an increase in construction period and costs [35]. Therefore, quality and scheduling must be carefully considered based on the specific circumstances of each project to achieve positive economic and social outcomes.

Due to the intricate nonlinear relationship between project quality and scheduling, quality and scheduling control measures devised by project managers based on their experience tend to be subjective. This subjective satisfaction with quality and planning goals introduces challenges and results in a mismatch between quality requirements and schedules [36]. To solve these problems, traditional phenomenological models, which are based on detailed, logical and systematic relationships, are often adopted to create more complex models [37]. Consequently, researchers and managers need insight and prior knowledge about the specific system. However, due to the complexity of these relationships, such models cannot always be derived. With the continuous enhancement of information levels in the construction industry, heterogeneous multi-source data generated during project development are rapidly expanding [38].

Most of the available data is inactive and lacks meaningful utilization from the perspective of quality risk and schedule control. For example, most project risk assessment methods depend on the opinion and experience of managers and experts, and the accuracy, stability, and speed of such expert opinion are very important for the validity of the results [39,40]. However, the content of various historical project records, such as engineering drawings, contract documents, engineering reports, weather data, and daily construction records, is rarely used to optimize the performance of experts. Behavioural models, which do not necessarily require insight into mechanisms or fundamental theory, can be expanded by identifying relationships between input variables and outputs through an analysis of historical project data [41]. In the era of big data, behavioural modelling techniques find applications across various fields [42]. Historical project data extraction to create a model for the relationship between project quality and scheduling, as well as providing support for optimizing quality control and scheduling, requires fundamental innovation and systematic changes. In the following, we will discuss the role of neural networks in project control:

Estimating the time until the completion of a project is a challenging variable due to its complexity, uncertainty, and the limited information currently available. Most project control managers in the construction industry currently estimate this variable using their past experiences in budget planning. However, this method is expensive and highly prone to inaccuracy. Artificial neural networks are widely utilized for scheduling problems and have been applied to address engineering problems, particularly in the field of construction management [43]. The technique of artificial neural networks is favoured by many researchers due to its strong capability to learn effectively from unknown datasets [44].

The simplest type of neural network model is the Feedforward Neural Networks (FNNs). Nevertheless, this model frequently falls short in delivering highly accurate predictions for time series problems due to its structure's inadequate capture of sequential information over the project duration.

The LSTM Neural Network model was devised to tackle the prevalent scheduling challenges in the construction field and formulate a network structure that integrates both sequential and non-sequential factors.

While the Feedforward Neural Network (FNN) model excels in generating accurate predictions for non-time series factors, the Recurrent Neural Network (RNN) model is more proficient at producing precise predictions for time series factors. Therefore, this study combined the strengths of both neural networks to create a new forecasting model that simultaneously processes time series and non-time series factors. The framework of the proposed model is shown in Figure 2, where independent time-independent input variables Xi are incorporated into the Feedforward Neural Network (FNN), and time-dependent inputs X_t along with outputs from the previous memory state ht-1 are integrated into the Recurrent Neural Network. Subsequently, the outcomes of the Neural Network (NN) and Long Short-Term Memory models are interconnected to yield the final prediction values.

The Long Short-Term Memory Neural Network is developed using the Theano library, implemented in Python. This library facilitates the effective definition, optimization, and evaluation of mathematical expressions, including multi-dimensional arrays. The utilization of Theano aids in optimizing parameters in the Long Short-Term Memory Neural Network model throughout the training process. The subsequent sections delineate the sub-processes of the Long Short-Term Memory Neural Network, encompassing the Feedforward Neural Network and the Recurrent Neural Network.

5-1- Feedforward Neural Network (FNN)

In this section, the Feedforward Neural Network (FNN) within the LSTM model is responsible for handling independent inputs, operating similarly to conventional FNNs. It consists of three types of layers: the input layer, hidden layer, and output layer. The input layer receives the independent input features and propagates them through the hidden layer. Neurons within the hidden layer process the input signals and transmit the generated outputs to the subsequent layer. The output layer then processes these input signals and produces the FNN outputs. For this study, the FNN was configured with two hidden layers, each containing three neurons. The governing equation for the neural process in neural networks is as follows:

$$y_j = f\left(\sum w_{ji}x_i + b_{j0}\right) \tag{1}$$

In which y_j, the output of the neuron, is calculated by the inputs x_i of the neuron; w_{ji} represents the connection strength (weight) from node (or neuron) j to node (or neuron) i; b: the node threshold value; and f is an activation function that uses a sigmoid function with a slope coefficient.

One of the key features of Recurrent Neural Networks (RNNs) is the presence of a recurrent memory unit that enables the storage and utilization of past information. This memory unit, known as the "hidden state," is received as input at each time step, combined with the current information, allowing the network to learn long-term relationships and sequences.

Historical records suggest that Long Short-Term Memory (LSTM) networks exhibit superior performance compared to other Recurrent Neural Networks (RNNs) when dealing with time series problems. As a result, LSTM was integrated into modeling time sequences and their long-term dependencies within the NN-LSTM model. LSTMs consist of specialized units known as memory blocks, which substitute the hidden layer present in conventional neural networks. Memory blocks containing memory cells with their connections store the temporal state of the network and facilitate constant error flow through internal states and control the flow of information in addition to special multiplication units called gates.

A memory cell is characterized by gates that act as sigmoid functions with different weights adjustable through gradient descent that control the flow of information. These gates, by transforming information into values within the range of 0 to 1, determine what enters the cell and what gets blocked. A value of 0 signifies that something should not enter the cell, while a value of 1 implies that everything should enter. Figure 3 depicts the architecture of a memory block.

The LSTM structure comprises input, forget, output gates, and input modulation gates, as illustrated in Figure 3. For this study, two hidden layers were employed, each featuring three memory cells [45].

$$\begin{aligned}
i_t &= \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i)\\
f_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f)\\
g_t &= \sigma(W_{xc}x_t + W_{hc}h_{t-1} + b_c)\\
c_t &= f_t\, c_{t-1} + i_t g_t\\
o_t &= \sigma(W_{Xo}x_t + W_{ho}h_{t-1} + b_o)\\
h_t &= o_t \tanh(c_t)
\end{aligned} \tag{2}$$

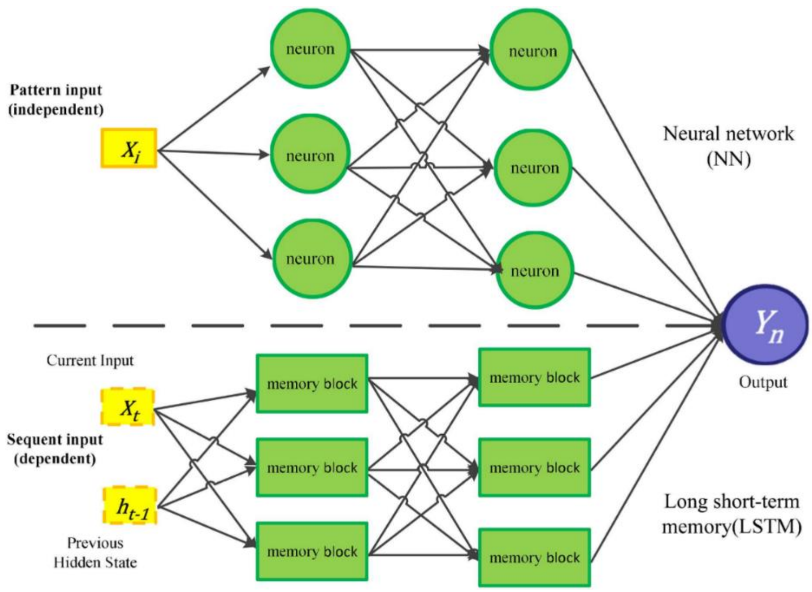

Fig. 2. LSTM Neural Network.

In this equation: h_{t-1}: the previous hidden state, x_t: current input, σ: represents the logistic sigmoid function, i_t, f_t, o_t, g_t, ct, c_{t-1}, and h_t: the input gate, forget gate, output gate, input modulation gate, cell state, previous cell state, and current hidden state, respectively. W_{xi}, W_{xf}, W_{xo}, W_{xc}, W_{hi}, W_{hf}, W_{ho}, and W_{hc}: weight matrices, and b_i, b_f, b_c, and b_o: biases.

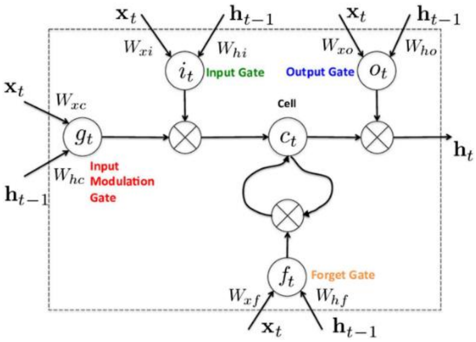

Fig. 3. Illustrates a single unit structure of LSTM [45].

The Forget Gate plays a crucial role in deciding which information should be discarded from the memory cell. By examining ht-1 and xt, it produces a number between 0 and 1 for each element in the previous cell state. A value of 0 blocks all incoming information, while a value of 1 allows all information to enter the cell. This process is crucial, as not all information in the network is considered essential and, therefore, not worth retaining.

Simultaneously, the Input Gate determines the extent to which new information should be stored in the cell state. This decision is influenced by the Input Modulation Gate. In the memory cell, the outcomes from the Forget Gate and Input Gate, as expressed in Equation 5, are combined to facilitate the update of the current cell state. This integration is significant for managing the flow of information within the network and selectively incorporating relevant details. Furthermore, the Output Gate regulates the flow of output activations from the cell to the rest of the network. This LSTM feature effectively addresses issues related to gradient vanishing and exploding, contributing to the network's ability to handle long-term dependencies and sequential data effectively.

6. Results

Project management planning is critical to the successful delivery of projects, as inadequate planning can lead to increased costs, time, and quality problems. Machine learning-based approaches have shown promising results for construction projects. However, the performance of most methods depends on the availability of data and the user's technical and infrastructural data processing capacity. Previous research has employed a combined approach using Mixed-Integer Linear Programming (MILP) and machine learning (ML), particularly emphasizing the use of Long Short-Term Memory (LSTM) models. The LSTM method, as a subset of recurrent neural networks, enables access to all past values in time series, making it a powerful tool for predicting events with complex nonlinear relationships over time. The LSTM architecture is a type of recurrent neural network capable of considering long-term dependencies, and it was employed to forecast the progress trend of the project. Nevertheless, GPT models demonstrate unique advantages compared to conventional techniques. Unlike MILP and LSTM, which often work on structural and numerical data, GPT models have the ability to effectively acquire and analyze textual information, thereby facilitating a more comprehensive understanding of the complexities associated with construction project planning and procurement. Unlike mathematical optimization problems described in MILP models, GPT models use learned patterns and representations derived from existing data. Often this approach can reduce the need for explicit mathematical modelling and enable a more flexible and clear approach to addressing the planning and logistical challenges of construction efforts. In addition, the use of GPT can be used to implement critical path method (CPM) and schedule evaluation and review technique by entering the project schedule. Creating an accurate Recurrent Neural Network (RNN) for predicting the precise completion time of a project involves various stages, including preprocessing data, building the model, training, and evaluation. Below is a simplified Python code using TensorFlow and Keras libraries, leveraging GPT 3.5, based on a set of effective data to determine the completion time of a construction project. However, this is a basic example, and it may be necessary to adapt it to the specific dataset and requirements of the project. This code provides a fundamental framework for building an LSTM model for predicting project completion time, and adjustments may be required to fine-tune hyperparameters, optimize the model architecture, and manage potential overfitting based on the project dataset features.

7. Conclusion

While human-centric AI tools are fundamentally needed to provide the highest level of human control in any scientific and engineering field, such tools have not been well-received in the construction industry. In this industry, the success of any work relies on knowledge, experience and communication between architects, engineers, managers, workers and decision makers. However, current AI practices largely fail to consider and integrate such human information into automation and optimization processes. Human centric AI has the potential to address the challenge of real-time processing and analysis of large datasets. These tools are expected to engage effectively with humans, understanding their language, behavior, interests, and preferences to identify usable inputs for specific tasks. Additionally, they can retrieve necessary human-related information from Big Data in various file formats from past projects, thereby facilitating and optimizing construction processes and project control.. AI, alongside neural networks, can contribute to improving strategic and tactical decision-making, resource optimization, and predicting potential issues. These tools empower construction projects with dynamic and flexible management capabilities to cope with various variable changes. The use of neural networks in construction project control, in addition to increasing productivity, can lead to cost reduction and service quality improvement. By analyzing various data, including geographical information, history of similar projects, and environmental conditions, neural networks make better decisions throughout the project lifecycle. As a result, neural networks are widely used as innovative and effective tools in the control of construction projects, assisting managers and decision-makers in enhancing performance and making informed decisions. The research showcased the reliability and precision of NN-LSTM. With additional historical records, NN-LSTM becomes an invaluable resource for project managers, contractors, and clients, aiding in well-informed decision-making regarding program and planning management. FNN effectively handles time-independent variables, while LSTM excels in capturing enduring time dependencies associated with time-dependent variables.

Based on the findings presented in the text, here are several suggestions for future research directions or practical applications that can enhance the impact and relevance of linear versions:

- Integration of human-centric artificial intelligence in construction management.
- Acquisition and processing of advanced data for artificial intelligence models.
- Combination approaches merging GPT models with other techniques.
- Fine-tuning and optimization of artificial intelligence models.
- Real-time decision support systems.
- Integration of environmental and geographical data: Investigating the incorporation of environmental and geographical data into neural network models for construction project control.

By addressing these research directions, future studies can contribute to advancing the application of artificial intelligence and neural network technologies in project management, ultimately enhancing project outcomes, performance, and sustainability.

```python
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense

# Load your dataset
data = pd.DataFrame({
    'project_area': [value_1],
    'number_of_workers': [value_2],
    'financial_resources': [value_3],
    'project_complexity': [value_4],
    'history_of_similar_projects': [value_5],
    'geographic_conditions': [value_6],
    'time_data': [value_7],
    'Legal_and_Regulatory_Challenges': [value_8],
    'Supplier_and_Material_Delays': [value_9],
    'Technological_Advancements': [value_10],
    'Market_Conditions': [value_11],
    'Labor_Market_Dynamics': [value_12],
    'Public_Opinion_and_Relations': [value_13],
    'Environmental_Impact_Assessments': [value_14],
    'Unforeseen_Risks_and_Emergencies': [value_15],
    'Political_and_Economic_Stability': [value_16],
    'Contractual_Disputes': [value_17],
    'Project_Management_Efficiency': [value_18],
    'End_Time': [target_end_time]  # Your target variable
})
```

```python
# Extract features and target variable
X = data[['project_area', 'number_of_workers', 'financial_resources', 'project_complexity',
          'history_of_similar_projects', 'geographic_conditions', 'time_data',
          'Legal_and_Regulatory_Challenges', 'Supplier_and_Material_Delays',
          'Technological_Advancements', 'Market_Conditions', 'Labor_Market_Dynamics',
          'Public_Opinion_and_Relations', 'Environmental_Impact_Assessments',
          'Unforeseen_Risks_and_Emergencies', 'Political_and_Economic_Stability',
          'Contractual_Disputes', 'Project_Management_Efficiency']]

y = data['End_Time']

# Normalize the data
scaler_X = MinMaxScaler()
X_scaled = scaler_X.fit_transform(X)

scaler_y = MinMaxScaler()
y_scaled = scaler_y.fit_transform(np.array(y).reshape(-1, 1))

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_scaled, test_size=0.2, random_state=42)

# Reshape data for LSTM input
X_train = np.reshape(X_train, (X_train.shape[0], 1, X_train.shape[1]))
X_test = np.reshape(X_test, (X_test.shape[0], 1, X_test.shape[1]))

# Build the LSTM model
model = Sequential()
model.add(LSTM(units=50, input_shape=(X_train.shape[1], X_train.shape[2])))
model.add(Dense(units=1))
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
model.fit(X_train, y_train, epochs=50, batch_size=32)

# Evaluate the model
loss = model.evaluate(X_test, y_test)
print(f'Mean Squared Error on Test Data: {loss}')
# Make predictions
predictions_scaled = model.predict(X_test)
predictions = scaler_y.inverse_transform(predictions_scaled)

# Evaluate the predictions as needed for your specific problem
```

Fig. 4. A simplified Python code using TensorFlow and Keras libraries, leveraging GPT 3.5, based on a set of effective data to determine the completion time of a construction project.

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