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Applying Hybrid Machine Learning for Construction Material Price Prediction and Procurement Cost Optimization

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***Abstract*— Construction material cost is the major component of construction project costs. Among the material cost categories, construction material price fluctuation is the major risk that causes construction cost estimation to be different from actual cost in many countries. In addition, unable to consider the construction material price in construction material procurement cost optimization is uneconomical because may lead to the material being ordered at a period when the price is high. Therefore, a two-staged method for construction material price prediction and a strategic economical construction procurement method is proposed. In the first stage, the Multilayer Perceptron (MLP) is used to predict construction material prices. Then in the second stage, the predicted price of the MLP model was taken as input along with procurement data for the Deep Q Network (DQN) to identify ordering time and quantity at a minimum cost. The application of the proposed method in the Ethiopian construction industry shows that MLP has better performance in predicting cement prices than linear regression. Besides, the DQN algorithm procurement strategy for the nonpolynomial hard problem is < 1% in cost performance than the exact mixed integer linear programming (MILP) method with reasonable solution time. The proposed hybrid model can help construction practitioners to make material-related data-driven decisions.**

Keywords*— *Construction Material, DQN, Machine Learning, MLP, Price Prediction, Procurement Cost Optimization

I. INTRODUCTION

The cost of construction materials is greater than 50% of the construction project cost [1]. It contains costs due to the price of construction material [2], shortage cost [3], ordering costs during procurement, and holding of inventory [4]. Construction material price fluctuation is the main risk that causes time and cost overrun of construction projects in developing and less developed countries [5-7]. Tang et al. highlight having reliable construction material price prediction tools helps to better estimate construction costs instead of using previous historical data that don't consider price fluctuation due to time and economic market [8]. Moreover, it helps to know the best time for the procurement of materials.

Project cost reduction can be maintained by using an economically strategic material procurement. Kumar, alongside with and Patil & Pataskar emphasize construction companies using the mathematical Economic order quantity (EOQ) model can decrease costs that incur during ordering and inventory holding by directing the optimal order quantity, order interval, and the available inventory [4,9]. In addition, construction material availability in construction projects before the commencement of work improves productivity by 8-10% and decreases delay [10]. However, EOQ has limitations because in reality cost per unit of purchase of material fluctuates over time, so the ordering period may lay in time when the actual price of the material is uneconomical [4]. To capture the variability Khondoker et al. have proposed a mixed integer linear programming (MILP)-based procurement plan for 32 time steps [11]. However, Urbanucci outlines MILPs have difficulty optimizing high dimensional problems [12].

In addition, many simulation researches were done to form a model that considers the variability in construction materials procurement parameters in the construction industry such as [13-15]. Apart from that for prefab manufacturers, Du et al. have proposed a genetic algorithm-based material procurement model that considers construction price prediction [13]. The model optimizes the procurement cost for monthly construction material requirements of prefab components based on the site's installation plan. But Kulkarni & Halder mentioned that heuristics algorithms like genetic algorithms rarely find global optimum but are better at finding near optimum values [14]. Besides construction projects may take several months to finish. These increase the complexity and broadness of the problem, so there is a need for a machine-learning procurement model to give insight [16]. In the construction industry project delays, cost overruns and contractual disputes are common due to resource planning, risk management, and logistic difficulties. These challenges encourage the use of advanced machine learning algorithms to analyze the cause and preventive measures. The use of recent technology and analyzing its accuracy can help to make an improved prediction for stakeholders in the construction industry [17].

Given that, the objective of this study is to propose a hybrid machine learning-based procurement model for construction projects scheduled material requirements that considers fluctuation of construction material price based on predicted construction material price. The proposed MLP model is used for the prediction of construction material price then the predictions are taken as input to the procurement DQN model environment. Then DQN agent is used to identify the period for strategic procurement and optimum construction material quantity to order at minimum cost.

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II. Literature Review

A. Construction Material Price Prediction

Past Prediction methods can be grouped into two. These are either qualitative or quantitative forecasting. Qualitative forecasting depends on the expert's judgment. Whereas, quantitative forecasting uses causal past data to predict future value. The types of quantitative forecasts are causal methods using regression or time series [18].

Many studies have been done on the prediction of construction cost index including [18]. However, it may not accurately predict construction cost as Hwang et al. highlight, total construction material cost fluctuation is the sum of each construction material price fluctuation because construction materials prices increase or decrease at different rates [19]. Besides Shiha et al. state construction materials can have different leading indicators within the same countries depending upon the economic condition [20]. The author also stated that the construction cost index contains many assumptions, so predicting individual construction material prices helps to reach a more accurate prediction.

Akintoye et al. highlight leading indicators help to project future trends of construction price movements [18]. Shiha et al. using macroeconomic indicators in Egypt developed an Artificial neural network (ANN) for the prediction of steel and cement prices [20]. The identified leading indicators by correlation analysis for the prediction of the steel reinforcement bar prices were GDP, CPI, unemployment rate, foreign reserves, PPI, lending rate, and US dollar to Egyptian pound exchange rate. But, for the cement price prediction the indicators were, all the indicators for steel reinforcement bar price except the lending rate. The validation of the model results with multiple linear regression prediction model shows that ANN is suitable to predict price fluctuation during economic instability.

For the Ghana construction industry, Bediako et al. have developed a multiple linear regression model to predict Portland cement [21]. From the analysis, it was concluded that cement price was not affected due to inflation and monetary policy rate but was affected by trends of an exchange rate with a positive relationship. In addition, Ernest et al. have identified key economic indicators that affect the building construction industry that construction planners should give attention to [22]. From indicators identified through the literature review top 5 factors refined using statistical methods were CPI, PPI, currency exchange rate, GDP, and interest rate.

Afolabi & Abimbola developed a web-based linear regression machine learning model for cement price prediction in the Nigerian construction industry to assist construction firms during tendering and planning construction material procurement [23]. The predictors used were the bank's interest rate, exchange rate to the dollar, petrol prices, and diesel prices. The model developed has 80% accuracy. However, the method has limitations as the predictors are estimated first to predict the dependent variable.

Dilip & Jesna assessed the macroeconomic indicators of India and performed a test method same as Shiha et al. to identify potential predictors for cement and steel prices from June 2010 to June 2020 in lagged months of 0, 1, 3, 6 and 12 [24,20]. The result shows Bank Lending Rate, PPI, Inflation Rate, and outputs from steel manufacturing industries are potential predictors of cement price prediction for a lag of 6 months among lagged months with a correlation coefficient of 0.7. A 6-month lag is also identified as best for steel price prediction with predictors with a correlation coefficient of 0.697.

B. Construction Material Procurement Management

Efficient material procurement is essential to the successful completion of the project by making material to be accessible at their point of use when required. Construction project cost saving during procurement of construction materials is one role of construction material management. Because construction materials are a key expense in construction; reduced construction material procurement costs increase the opportunities to lower the total project cost [9].

The Traditional mathematical EOQ model can be used for construction material procurement cost optimization [9]. It is an optimization of ordering cost and carrying cost to obtain economic order quantity and interval [25]. In terms of cost structures, carrying costs and ordering costs are essentially in contradiction with one another. For instance, the overall cost of carrying inventory lowers when the order quantity drops. However, as several orders must be placed to meet the demand, the overall cost of ordering will increase. Contrarily, when order quantity is raised, the overall cost of orders will decrease since fewer orders are issued, but the total cost of carrying inventory will rise because the average cyclical inventory in the system will grow. Planning and controlling inventory will revolve around striking a balance between these two opposing expenses [26]. However, the traditional EOQ model is uneconomical because it does not consider shortage, price breaks, and inflation [25].

Zhang et al. created an MS Excel add-in that uses a linear programming (LP) approach to reduce the overall cost of construction material supply chain for building projects under warehouse size limitation and site restriction [27]. The method is simple to apply because it doesn't call for any specialized software or even the users' technical proficiency in quantitative procedures. However, LP has the intrinsic drawback of being unable to take fluctuating variables into account like demand for construction material.

Kulkarni & Halder developed a PERT-based simulation model, that is used to determine the optimal re-order point and order size for the procurement of building materials [14]. It aims to reduce the average inventory level and downtime caused by material unavailability. The STROBOSCOPE simulation framework, created by the University of Michigan academics, was used to execute the material procurement simulation. Each phase of the procurement process was modeled using the duration data gathered from a building project. Then the simulation result was compared with the traditional EOQ model. The study finds that the simulation has maintained safety stock but the EOQ methods construction material inventory level falls below the minimum threshold of safety stock. This is because of the uncertainty in delivery and change in demand fluctuation on the site.

Some studies use meta-heuristic algorithms to optimize construction material logistics and handling [13,15]. Son et al.

have combined the dragonfly algorithm (DA) and particle swarm optimization algorithm (PSO) to optimize the cost of construction material through logistic planning from a contractor perspective [15]. To verify the advanced searching ability of the DA–PSO algorithm, the algorithm was compared with the gray wolf and the genetic algorithms. The input parameters to the model were discount to purchase of the bulk material, interest rate, schedule penalties, and cost for transport and site layout. The output of the model is an optimized fixed order period and warehouse size for each construction stage of the structure basement, superstructure, and finishing. The researcher took steel to study the developed model's performance and concluded that the DA-PSO model is more suitable to achieve optimum results in a limited time than the gray wolf and the genetic algorithms. The drawback of the model is it doesn't consider the future price of the construction material. Several studies have been conducted to solve the NP-hard material cost optimization problems in the construction industry. However, in this study, a two-staged strategic construction material procurement method is proposed for onsite construction. The Procurement method includes the predicted price of material depending on the macroeconomic condition of the country and restricted warehouse capacity. In addition, despite the previous studies having limitations in terms of validation of their proposed models with the exact method, in this study with the hope of gaining a better solution by comparing against the exact method, a deep reinforcement algorithm is proposed to solve the NP-hard problem with reasonable solution time.

III. METHODOLOGY

In this section, the two staged MLP-DQN-based methods problem to solve the problem are described. The methodology flow chart in Figure I illustrates the stages. Section III.A describes the MLP model which is the first stage of the method to make price prediction. Then the DQN model used in the second stage is described in detail in Section III.B to show how it was used in construction material procurement cost optimization.

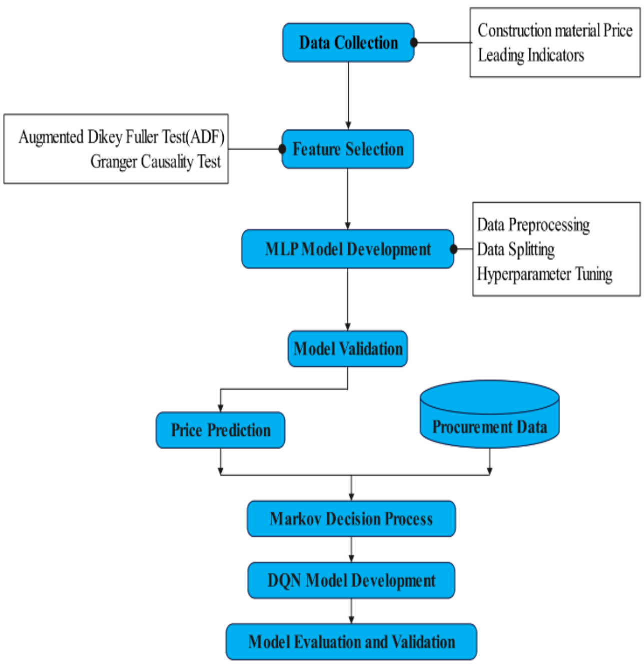

FIGURE I. RESEARCH METHODOLOGY FLOWCHART

A. *Construction material Price Prediction Using Multilayer Perceptron*

1. *Data Collection and Data Source*

Depending on the literature review on the leading indicators and the availability of data, potential leading indicators that are identified in Ethiopia are shown in Table I. The data collected is monthly from Sep 2010 to May 2022.

TABLE I. POTENTIAL LEADING INDICATORS FOR CEMENT

Indicator	ID	Description	Data Source
Net Foreign Assets	NFA	Shows the country's economic condition and equity-debt imbalance. It gives attraction to investors in the construction sector [20].	NBE
Consumer Price Index	CPI	The consumer price index is a way to gauge the cost of a representative basket of products and services that urban consumers would typically buy [28].	CSS
Inflation Rate	IR	Inflation causes the rate of change in the price of construction materials to vary over time [29].	CSS
Export	EX	The export of goods gives a country additional foreign currency.	NBE
Lending Rate	LR	To finance their projects, construction stakeholders would be dependent on loans from financial organizations. The rate of interest changes would influence the party's readiness to invest, which would have an impact on the demand for new development [20].	NBE
Exchange Rate	ER	Affects the decision to invest in the country's construction industry by foreign investors [20].	NBE
Money Supply	M2	It is a metric that shows the sum of money that circulates in the country's economy [28].	NBE

2. *Input variable selection*

In this step among the available potential leading indicators collected, input variables that are cause for cement price fluctuation were identified. Leading indicators have a relationship with the dependent variable with a margin period. So, to identify the leading indicators for cement price in the Ethiopian construction sector it was tested for a lag period of 1, 3 and 7 months using the Granger Causality test. The test is a theory of causality based on statistics and prediction. The variable under test is a leading indicator if, previous values of its contain information to predict the dependent variable in addition to the dependent variable's past values [30]. However, the test needs stationary data of the variables. So, the stationarity of the data was tested by the Augmented Dickey-Fuller (ADF) method. To transform the time series data to stationary differencing technique was adopted. For the variables that show test result data is nonstationary, differencing stops when the null hypothesis is rejected or the time series is stationary. Then granger causality test was performed between the leading indicators that have the same order of cointegration with the dependent variable for the specified lag length.

3. Model Development

Multilayer Perceptron (MLP) is an important class of neural network that uses a feed-forward supervised learning algorithm to bring a set of outputs from the given set of inputs. The network is composed of an input layer, more than one hidden layer, and an output layer. During the forward pass input vector is applied to the input neuron of a network then it propagates into the subsequent layer of the MLP network to give a prediction. According to Parmezan et al. [31], mathematically the forward pass is expressed as:

$$y_m = f\left(\sum_{i}^{m} w_{lm} y_l + b\right) \tag{1}$$

where, y_m = the m_{th} output layer predicted output, y_l = the output at the previous(l) hidden layer, b = is the bias, w_m = the weight at the m^{th} output layer, f = activation function, i = the input layer, m = the output layer

Then the difference between the actual and predicted values is backpropagated to adjust the weights and bias. MLP can solve complex problems, and handle datasets with a large number of features especially non-linear ones [32].

TABLE II. HYPERPARAMETERS PURPOSE LITERATURE REVIEW

HyperParameters	Description
Learning rate	Too small a learning rate may cause overfitting. Excessive large learning rates cause divergence in training. Choosing an appropriate learning rate will increase the model's performance [35].
Window size	It is the number of time steps in a reframing of time series problems as supervised machine learning. There is no ideal window size [36]. So it is necessary to test the performance of the model using different window sizes.
Epoch Size	Epoch size is a hyperparameter that controls the number of times the learning algorithm will operate over the full training dataset [37].
Activation function	It helps the artificial neural network to learn the complex and nonlinear relationships between inputs and outputs [38].
Hidden layer	To get a good performance of the model, the number of hidden layers depends on the complexity of the problem [39]. Therefore, it is mandatory to test the performance of the model with a different number of hidden layers.
Number of neurons	It affects the performance of the model. If the number of neurons is small the model prediction error is high because, information from the input grid cannot be conveyed to the next layers correctly [40].
Batch Size	It is the size of data samples that are used to update a neural network weight. Searching for the optimal value helps to identify what works for the problem [37].

Feature scaling

Data contain features with different ranges of values. This makes features with large values more dominant in influencing the convergence of the result than features with small values. It also decreases the speed of the learning process. Feature scaling techniques help to change the data into the same range. Among the techniques Min-Max, Z-Score, and Median Normalization can be listed [33]. In this model, the min-max method was selected.

$$Normalized\ Value = \frac{unscaled\ value - \min(range)}{\max(range) - unscaled\ value}$$

Hyperparameter tuning

The accuracy of the model depends on the hyperparameter values. Hyperparameter value setting needs experience and exploration. In this model gird search method was employed to tune the set value of hyperparameters and search the optimal set of hyperparameters as specified by [34]. The hyperparameters and search space of the grid search are illustrated in Table II and Table III.

TABLE III. LIST OF HYPERPARAMETERS AND GRID SEARCH SPACE FOR TIME-SERIES MODELS

HyperParameters	Search Space
Learning rate	0.1,0.01,0.001,0.0001,0.00001,0.000001
Epoch Size	7000
Activation function	Relu, Sigmoid, Tanh
Number of Hidden layers	2,4,8
Number of neurons	2,4,6,8,10
Batch Size	4,8,16,32,64

Train, Test, and Validation Split

Samples were generated and divided into train and test sets using ratios of (90, 10), (80, 20), (70, 30), and (60, 40) to train the model and validate the model by setting early stopping of 10.

Measurement of Prediction Performance

Metrics used for model performance evaluations were the most commonly used methods. These are mean squared error(MSE), root mean squared error(RMSE), and mean absolute percentage error(MAPE). Eq. 3 to Eq. 5 illustrates the performance evaluation metrics formula as highlighted by Steurer et al. [41].

MSE is a Squared-difference measure that is particularly helpful in circumstances when it is necessary to reduce significant forecast mistakes.

$$\mathbf{MSE} = \frac{\mathbf{1}}{\mathbf{N}} \sum_{\mathbf{n=1}}^{\mathbf{N}} (\mathbf{Actual\ Value} - \mathbf{Predicted\ Value})^{\mathbf{2}} \tag{3}$$

The MSE may be monotonically transformed into the RMSE as shown in Eq. 4. RMSE has an advantage over MSE because it produces smaller numbers that are simpler to compare and thus simpler for the user to interpret.

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N} (Actual\ value - Predicted\ value)^2}{N}} \tag{4}$$

Mean Absolute Percentage Error (MAPE) is a prediction error measured as ratios of predicted and actual values.

$$\boldsymbol{MAPE} = \frac{1}{N}\sum_{n=1}^{N}\left(\left(\frac{\textit{Predicted value}}{\textit{Actual value}}\right) - \mathbf{1}\right) \quad (5)$$

Residual Normality Test

The residual Normality test is applied to assess the model's fitness for the data. If the residuals are normally distributed it can be concluded that the model has captured the relevant information from the input data for the prediction. In this study distributed histogram is used for testing the normality of residuals.

B. Construction Material Procurement Using The DQN Model

Reinforcement learning is used to solve problems that contain dynamic sequential systems by the interaction of the agent with the dynamic environment. The expression of the problem suitable for reinforcement learning as state and action is called the Markovian Decision Process (MDP) [42]. While learning the agent explores and exploits by making an action to navigate from the current state(S) to a new state(S+1). Then the agent gains a reward (r+1) that gives temporal credit to the state (S) [43]. The temporal credit that the agent gives to the state is given by the Bellman equation in Eq. 6.

$$Q^*(S_t, A_t) = r + \gamma\max_a Q^*(S_{t+1}, A_{t+1}) \quad (6)$$

Where γ is the discount rate to give less value for future rewards?

The exploration and exploitation dilemma of the agent is avoided by epsilon value which ranges from 0 to 1. As the agent trains epsilon value decreases from 1 to the minimum set value by the given epsilon decay rate. When the epsilon value decreases the exploration, rate decreases but exploitation increases. The agent's fastness in learning is monitored by the learning rate in the temporal difference or error between the state(s) action value and the next state(s+1) action value plus the reward the agent gets when making the action as shown in the Eq. 7. This method helps to avoid the need to wait until the end of the episode to compute the optimal value and policy [43].

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma\max_a Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)] \quad (7)$$

One of the known reinforcement learning is q learning. However, it needs tables to map the state and the action [44]. This causes high memory requirements of computers for computing large problems. Besides the agent needs to visit the states frequently. To avoid those problems, Mnih et al. proposed a deep reinforcement learning technique (DRL) called a Deep Q Network (DQN) algorithm that uses the value function approximation method [45]. The error between the q network prediction and the target action-value function shown in Eq. 8 is a temporal difference that the DQN agent learns using the backpropagation algorithm [45,46].

To avoid instability of learning during training Mnih et al. use experience replay and target q network. The experience replay allows agents to sample from the experience buffer which breaks the relationship between sequential action by sampling from different episodes and sequences of action to avoid instability [45]. Besides, the target q network in addition to the online q network is used to maintain stability by fixing the q values for some episodes to avoid divergence and oscillation.

$$TD \leftarrow (R_{t+1} + \gamma max_a Q(S', a'; \theta_i^-) - Q(S, a; \theta_i))^2 \quad (8)$$

Where Θ_i^- is target network parameter and Θ_i is the online network parameter.

1. *Problem Formulation as a Markov Decision Process (MDP)*

States

The model possesses the Markov property, the state is solely determined by the state that came before it and the selected action. State *(s)* in the MDP contains a tuple of (d, P, D, I_t) where

d is a colander day that accounts for preparation for procurement of material and construction project duration.

P is the predicted price of the construction material on day d

D is the demand for construction material at the day d depending on construction planning.

I_t is the current inventory in the warehouse that is available at the end of day d.

Action

Actions available in a given state (a_t) consist of [0, 1]. Where 0 represents the action of not to procure and action of 1 represents the action to procure bulk units of material. The bulk material procurement amount is with a maximum limit of warehouse capacity and a minimum set amount according to convenience. The choice of action depends on the agent's decision by observing the available current inventory (k_t) and price of construction material in the state of the environment. The action tuple is (Q, P, d_{del}) where Q is the quantity ordered, P is the price of construction material on the day of procurement, and d_{del} is a delivery day on the calendar days.

Rewards

State(S_t) in MDP has reward(r_t) for being in itself plus expected total rewards in future states(S_{t+1} to S_n) of the environment. For strategic construction material procurement, MDPs consist of a negative reward or penalty for ordering(k), unit material purchasing price at the lead time (P_{t-L}), holding cost(h) per unit of inventory(I_t), storing cost(T) per unit of holding inventory(I_t) beyond the storage capacity of the warehouse(W), lead time(L), Safety stock(S), and large liquidated damage assumed as a result of construction material shortage in the warehouse(M) on day d. For the first n timesteps (n days) the shortage cost occurs when the inventory is less than the safety stock. However, for the last n timesteps, shortage cost arises when the inventory is less than the demand for the material.

For the first n steps the equations and functions that are used in the step function are illustrated Eq. 9 to Eq. 18.

In case 1 when the DQN agent does not make a procurement (action = 0) during the lead time and:

a) if the current inventory (I_t) is within a range of safety stock(S) and warehouse capacity(W) as illustrated in

Eq. 9, the reward at time t is the holding cost for the inventory as shown in Eq. 10.

$$S \leq I_t \leq W \tag{9}$$

$$r_t = (I_{t-1} - D_t) * h \tag{10}$$

b) if the current inventory (I_t) exceed the warehouse capacity(W), the reward is the holding cost of the material with the maximum warehouse capacity plus the penalty for excess storage as illustrated in the Eq. 11.

$$I_t > W \tag{11}$$

$$r_t = W * h + (I_{t-1} - D_t - W) * T \tag{12}$$

c) if the current inventory is less than the safety stock, the reward at the time step is a shortage cost as indicated in Eq. 14:

$$I_t < S \tag{13}$$

$$r_t = (S - I_{t-1} - D_t) * M \tag{14}$$

But in case 2 when the action at the lead time is to procure (action = 1), the order arrives and;

a) if the inventory is within a range of safety stock and warehouse capacity, the reward at time t is the sum of the purchasing price, ordering cost, and the holding cost for the inventory given by Eq. 15.

$$r_t = P_{t-L} * (Q) + k + (I_t) * h \tag{15}$$

b) if the inventory at time t is greater than the warehouse capacity, the reward at time t is the sum of the purchasing price, ordering cost, holding cost, and penalty for excess storage as illustrated in the Eq. 16:

$$r_t = P_{t-L} * (Q) + k + W * h + (I_t - W) * T \tag{16}$$

c) if the inventory storage is less than the safety stock, the reward at time t is the sum of the purchasing price, ordering cost, and shortage cost as shown in Eq. 17.

$$r_t = P_{t-L} * (Q) + k + (S - I_t) * M) \tag{17}$$

Where inventory at time t (I_t) is the sum of inventory at the previous timestep (($\boldsymbol{I_{t-1}}$) plus the arrived material minus the planned demand for the material on day d as illustrated in Eq.18.

$$I_t = (I_{t-1} - D_t + Q) \tag{18}$$

For the remaining last timesteps, the if conditions safety stock(S) of Eq. 9, Eq.13, Eq.15 and Eq.17 are replaced with the demand for the material at time t (D_t). This enables the agent to make procurement decisions that eliminate inventory upon completion of the project.

IV. RESULT AND DISCUSSION

Depending on stage one and the methodology stated in the previous chapter using Python programming language, potential leading indicators were tested to identify indicators for cement price prediction. First, the retail cement price and the indicators were investigated for stationarity by the ADF unit root test. As shown in Table IV cement price and all the indicators are not stationary because the ADF t-statistics is greater than a critical value of -2.88.

Then to avoid the nonstationarity of the macroeconomic indicators and retail cement price data the first difference was performed. The ADF unit root test result for the first difference shows cement price, lending rate, foreign reserve, and inflation rate become stationary as demonstrated in Table IV. But money supply(M2), Consumer Price Index, and export don't come stationary at first differencing so it needs another differencing. However, the variable for the Granger causality test is to be in the same order of integration with the dependent variable of cement price, variables that become stationary at first difference were used for further investigation of causality and lag length determination.

TABLE IV. RESULT OF ADF UNIT ROOT TEST FOR CEMENT PRICE AND ALL INDICATORS

Variable	ADF t-statistic	Variable	ADF t-statistic
Cement	2.42	ΔCement	-5.73*
CPI	2.82	ΔCPI	2.73
M2	2.45	ΔM2	0.62
NFA	-1.70	ΔNFA	-3.36*
LR	0.05	ΔLR	-11.91*
IR	-1.46	ΔIR	-4.83*
EXP	3.53	ΔEP	-1.25
ER	4.93	ΔER	-2.76

Granger causality test was conducted to examine the relationship between differenced cement price to itself, a net foreign asset to cement price, lending rate to cement price, and inflation rate to cement price for a lag period of 1,3 and 6 months with the confidence of 90%. The net foreign asset is accepted as a Granger cause of cement price for the lag periods. This is because the result of the Granger causality is not less than the critical value for F-statistics and the null hypothesis is rejected. However, for the cement price itself, the lending rate to cement price and inflation rate to cement price is not a granger cause for lags specified because the null hypothesis is accepted as shown in Table V.

TABLE V. RESULT OF GRANGER CAUSALITY TEST BETWEEN CEMENT PRICE AND LEADING INDICATORS

Null Hypothesis	F – Statistics		
	1-Month lag	3-Month lag	6-Month lag
ΔCement doesn't Granger cause ΔCement	0	0	0
ΔNFA doesn't Granger cause ΔCement	5.26*	3.13*	3.25*
ΔLR doesn't Granger cause ΔCement	0.10	0.89	0.59
ΔIR doesn't Granger cause ΔCement	1.22	1.71	1.4

A. Model Development and Evaluation

Using the methodology specified in the previous chapter, a model of MLP was developed by using the predictor of net foreign assets of the country which is the Granger cause of cement price for three-month lag duration. By using hyperparameter tuning of grid search and performance evaluation metrics as shown in Table VI, the MLP model that gives better performance contains a training validation split of 60:40 with a lookback window size of 5 months. Besides, the best hyperparameter combinations are learning rate, epoch, activation function, hidden layer, number of neurons, the batch size value of 0.00001,720, Tanh,4,10, and 32 respectively.

TABLE VI. RESULTS FOR MLP MODEL

Model	**Metrics**	**Data Sets**		
		Training	Validation	Testing
MLP	MAPE	14.6	13.6	13.01
	MSE	1274.5	1650.79	8328.9
	RMSE	35.7	40.66	91.26

The developed model performance was compared with linear regression model prediction performance. The linear regression model has a RMSE of 36.4 in the training set and 206.26 in the testing set. Whereas in terms of MAPE, it has 20.6% in training and 47.24% in testing set. This shows the developed model can learn the trend of cement prices using the leading indicator.

Furthermore, as illustrated in Figure II below from the distributed residual histogram plot, the residuals are normally distributed. This indicates the model has captured the relevant information from the data.

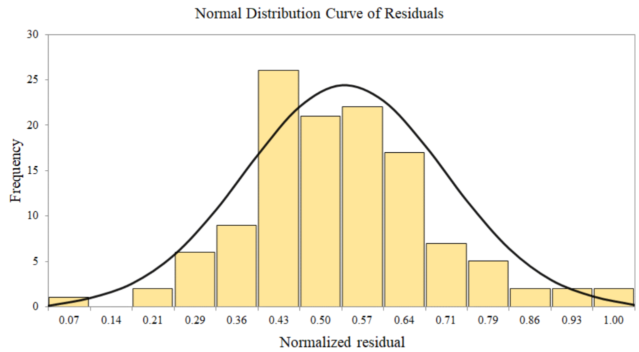

FIGURE II. DISTRIBUTED RESIDUAL HISTOGRAM

B. *Simulated example of DQN model performance*

This study takes a building construction project located in Addis Ababa city with storage space limitations. It is a private project which is under construction with a total project cost of 120 million birrs and a total project duration of 90 days. The demand for cement in quintals from the 6th of Dec-2022 to the 6th of Mar-2022 for structural work based on the material requirement planning is in alignment with the predicted construction material price. The project time to assess for procurement of cement price to the project is 90 Days and the warehouse capacity to carry cement is 1200 Qtls with a safety stock of 200 Qtls. The ordering cost per order to cover the cost related to dealing, market assessing, and inspection costs for cement collected from the site is 500 birr. To cover the cost related to storage, security, obsolescence, interest cost, and insurance, the estimated cost for cement is 136 birr per year. Other project data-related inputs to procurement are a leading time of 6 days, a penalty of 40 birrs per quintal of cement for excess inventory, and 300,000 birr per shortage quantity.

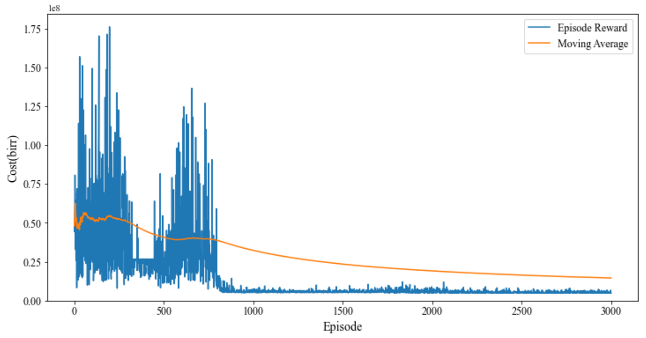

FIGURE III. EPISODE REWARD AND MOVING AVERAGE REWARD OF DQN MODEL

1. *Deep Q Learning (DQL) Model*

The DQN agent was trained with the optimization algorism of Adam, the activation function of ReLU, the number of neurons of 30, hidden layer of 2, Batch size of 32, the learning rate of 0.0006, the number of episodes of 3000, minimum epsilon value of 0.008, epsilon decay rate of 0.995 and replay buffer size of 20000 to find the optimal quantity and ordering period for the project in the custom environment. In Figure III, the episode reward plot shows the total procurement cost at the end of each episode. As the episode increases the agent is trained to learn action to perform in a given state which decreases the cost because it is negative reinforcement learning. The red moving average line indicates the cumulative rewards or total cement procurement, holding cost, and other penalties starting from the first up to the episode under consideration divided by episode number. The moving average cost decreasing as episodes increase implies that the agent is learning through time as it decreases exploration and exploits more. The optimal policy is the policy that has lower cost as a result of the agent's decision on when and how much cement to procure. In this case, it is the lowest point in the episode reward line given the indicated episode number.

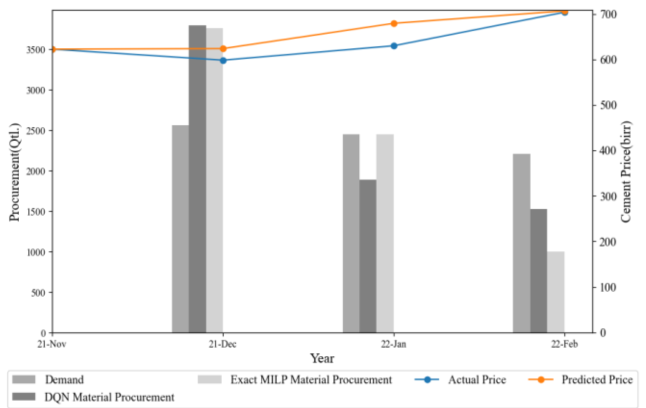

FIGURE IV. PROCUREMENT USING DQN'S AGENT AND THE EXACT MILP METHOD

To validate the DQN Procurement model's performance, the problem was optimized using the exact MILP method which gives the global minimum value. It was implemented on an Intel(R) Core (TM) i3-3120M CPU @ 2.50GHz laptop like the DQN method, using the MIP python package and CBC solver [47]. As shown in Figure IV for the three-month duration of the construction project, during the December month the rate of increase for cement price is lower than

January and February. But as the price increases the total procured cement quantity by both the DQN agent and the exact MILP optimization becomes less than the total demand of material in the given month. Because it is valuable to procure and hold materials in December to cover the demand in the following months.

In addition to 90 time steps, sample tests were performed for 30 and 60. In all of the tests, the agent learns to make a decision which is less than 1% starting from around 1000 Episodes. As shown in Table VII the GAP for the total 3000 episode value indicates that the proposed method quality of best solution is slightly less than the exact MILP method. However, as the timestep increases the time taken for the MILP method increases at a higher rate than the proposed DQN method. This is because in MILP to find the exact solution it needs assessment of all available spaces. But, in DQN the agent can learn the environment through exploration and exploitation so that by approximating the experience using bootstrapping it decreases the time for searching near optimal value. This implies the proposed DQN method can be used to execute material procurement strategy optimizations to projects with longer duration in less time than the exact MILP method.

TABLE VII. OPTIMAL SOLUTION AND GAP BETWEEN MILP AND DQN

Number of Steps	MILP Exact Optimization		DQN Optimization		
	Optimal Cost	Time per Step	Optimal Cost	Time per Step	GAP
30	1605074.989	0.22 Sec	1606486.521	156 Sec	0.088 %
60	3206842.311	23 Sec	3,213,704.953	178 Sec	0.214 %
90	4739536.468	482 Sec	4,754,892.56	212 Sec	0.324 %

V. CONCLUSION

Construction material cost is the major cost for construction projects. The costs include direct purchasing, procuring, and holding costs. An inaccurate estimate of construction materials costs leads actual cost of construction to be over or under the initial estimate. The underestimation causes project time and cost overrun and overestimation decreases developers willingness to invest and also the contractor's competitiveness. In this research, two staged hybrid machine learning models are proposed for predicting construction material prices and for optimizing construction material procurement costs.

To show the performance of the proposed algorithms, in the first stage, using the most significant indicator identified in the Ethiopian Construction Industry three months ahead cement price is predicted by the MLP model. The performance of the prediction model is better than the alternative linear regression model in both MAPE and MSE. Then, in the second stage, price prediction is used as input to the DQN procurement model environment. The DQN agent interacts with the procurement model environment and learns to make a procurement action in the appropriate quantity and period. This implies that because the material procurement problem is NP-hard, the optimization process needs DQN's algorithm to solve the formulated problem as MDP. The developed two-staged hybrid model is helpful to construction project practitioners to know early the optimized likely cost associated with construction material and its timely order.

However, the study has some limitations. First, it includes one construction material but increasing the material types and solving it using multiagent could be future research direction. The objective of this study is also to decrease project costs. However, in construction projects, time is another significant factor. So, integrating multi-material ordering and renewable resources with project scheduling can create multiobjective problems that can be solved by a multiagent DQN algorithm. In addition, in the procurement stage, the agent is punished for storing material above storage capacity. This method is helpful for the agent to learn to make material ordering with a reasonable amount. But, in some of the best solutions in the episodes having less than 1 percent cost deviation with the exact method, it was observed that there is an inventory level above the storage capacity. This has an impact on training time requirements to get the constrained inventory level in the material reorder point. Future research can extend this study by adding techniques to compel the agent in the selection of valid procurement actions.

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DATA AVAILABILITY

The data supporting the findings of this study are available upon request from the authors.

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AUTHORS' CONTRIBUTIONS

All authors contributed equally to this work.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

ETHICAL STATEMENT

In this article, the principles of scientific research and publication ethics were followed. This study did not involve human or animal subjects and did not require additional ethics committee approval.

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