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Evaluation of Buildings Structure Alternatives Using Life-Cycle Cost Prediction Model

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KEYWORDS:
Life cycle cost (LCC), LCC criteria, Analytic Hierarchy Process (AHP), Deep learning, Prediction model.

Abstract— A life-cycle-cost (LCC) is a powerful tool used to make economic decisions for construction building. LCC is a practice of accounting for all expenditures incurred over the lifetime of a particular structure. Costs at any given time are discounted back to a fixed date, based on assumed rates of inflation and the time-value of money. This study investigates the feasibility of obtaining an accurate deep learning prediction model of building LCC by applying historical data of similar projects. The applied LCC input and output criteria are gathered from previous literature studies. The input criteria are building area, floor height, no. of floors, structure & envelope type, building age, and year of built. The output categories include the relevant costs initial cost, operating and maintenance cost, environmental impact cost, and the end of life, each of them have its criteria. An electronic questionnaire of analytical hierarchy process (AHP) is developed to weight the selected criteria to be ready for the prediction model. Only 37 responses were received from Egypt and from outside Egypt and we excluded five of them to achieve the consistency. The Deep Belief network is developed with Restricted Boltzmann machine hidden layers based on 312 training data set of input and output criteria. Three case studies are devoted to validating on the assumption modelling procedures. The probability distributions of each case study predicted outputs are investigated by using statistical regression methodology.

I. Introduction

THE needs to assess building expenses and create financial methodologies to evaluate life cycle costs is expanding, the initial capital cost was considered the only investment choice for many clients. A number of reports have upheld the necessity to think through the long-term cost of project choices. Therefor a systematic methodology is applied to evolve LCC deep learning prediction model. An electronic questionnaire of analytical hierarchy process (AHP) is established. This questionnaire is divided into three sections; the first section provides the selected life cycle cost criteria and categories from previous literature studies and its definition. These categories include [1, 2, 3]: initial cost, operating and maintenance cost, and environmental impact cost, and end of life cost. The second section provides the calculated relative weights based on the pairwise matrix and the scale ranges between one and nine provided by experts. The third section is to find the consistency analysis of responses.

Structure judgments, prediction costs, and a massive amount of calculations go into life cycle costing. The key issue is determining a quick manner to represent the LCC. Deep learning machine is a fast and a clever optimization learning is used to predict LCC. Deep learning is an artificial intelligence (AI) method for developing complex prediction algorithms and models in the field of predictive data analytics. Deep learning is a type of machine learning algorithm that employs multiple

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layers to extract higher-level features from raw data. These analytical models enable data analysts to uncover hidden insights, predict future values, and produce reliable, repeatable decisions through learning from historical relationships and trends in the data.

The main objective of this paper is to develop LCC deep learning prediction model for new buildings in Egypt. This paper is prepared as follows. The literature review focuses on the literature defining the objectives of AHP process and life cycle cost (LCC) criteria concept and analysis of LCC prediction models for construction buildings. The two-phase research methodology is explained in the following section. Investigations and the results are explained in the validation and statistics analysis. The conclusion explains the contribution of the article.

II. Literature Review

The AHP approach was created by a mathematician named Thomas L. Saaty [4-5-6]. This method provided a framework for operative decision-making on difficult sections by simplifying and speeding up the decision-making process for resolving issues into sections. The importance of each variable was assigned by private numerical values, and these various considerations were gathered to determine which variable had the highest superiority and performance to influence the outcome of the status [7]. The AHP method helped in solving complicated problems by a framework hierarchy of criteria. The AHP also integrated the strengths of the various issues of reasoning, and then aggregates the various results that were consistent with our estimates as previously presented [8-9]. Saaty used AHP to tackle the problem, relying on three principles: the hierarchy framework, the prioritization principle, and the logical consistency principle [4-5]. In the investigation, the AHP was a hierarchy of issues that needed to be resolved while taking into account the factors that supported the achievement of the goals [9].

It is critical to ensure that all aspects used in making decisions to achieve the needed objectives are covered at the criterion selection step for each object. To aid decision-makers in grasping the offered choices, each of these criteria should be defined. We develop disciplined standards based on the desired goal [9-10] to avoid any criterion with the same meaning. Building judgments about the proportional weight of two criteria at a given level in relation to the levels above is referred to as comparative judgement. This assessment is at the heart of the AHP, as it will influence the criteria's preference criterion. To determine the evaluation results, the pairwise comparison matrix is used [10]. When comparing two criteria, you want to use effective measurements. According to Saaty, the scale of comparative importance in pairs was completed using the benchmark reference in Table 1.

A. Life cycle cost concept and analysis of construction buildings

Early decisions in the construction process have the greatest impact, necessitating the use of life cycle costing [1, 2, 3]. A life cycle costing is an economic, quantitative estimation tool [1, 11, 12]. This considers a building's total cost over its entire operational life [2, 13, 14]. Initial capital expenses, maintenance costs, running costs, and the asset's final disposal at the end of its life are all included in the operating life [15, 16].

In the LCCA study, determining the economic effects of alternatives is a crucial step. To extract and coordinate Common independent factors associated to LCCA, literature research was undertaken [17 -21]. The variables that applied for our LCC prediction model were building area, floor height, no of floors, structure and envelope type, building age, and year of built.

B. LCC prediction models

The review included a broad overview of the various features and models of LCC. Web-based conceptual cost estimated for construction projects using Evolutionary Fuzzy Neural Inference Model [22]. AI methods were used in the field of forecasting model analytics [17, 23 - 25]. Predictive modeling for commercial building energy used a comparison of existing statistical and machine learning algorithms [26]. Subsequently the Cost estimation model was investigated for building projects [21, 27, 28]. Life cycle costs played a key role in the decision making of green building projects [29].

TABLE 1
THE FUNDAMENTAL SAATY RATING SCALE [4-5-6]

Scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgment strongly favor one activity over another
5	Essential or strong importance	Experience and judgment strongly favor one activity over another
7	Very strong importance	An activity is strongly favored and its dominance demonstrated in practice
9	Extreme importance	The evidence favoring one activity over another is of tile highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgments	When compromise is needed

III. Methodology Of Evaluating Building LCC Criteria By Using The AHP

AHP questionnaire is applied to weight the selected criteria of LCC for buildings. Therefore, this study looked for the most affective LCC criteria from previous studies. In order to rank and weight the selected criteria, to choose the best priorities (Fig. 1), a 37 expert evaluated the chosen criteria by saaty scale and, the relative weights are calculated by using the pairwise comparison matrix.

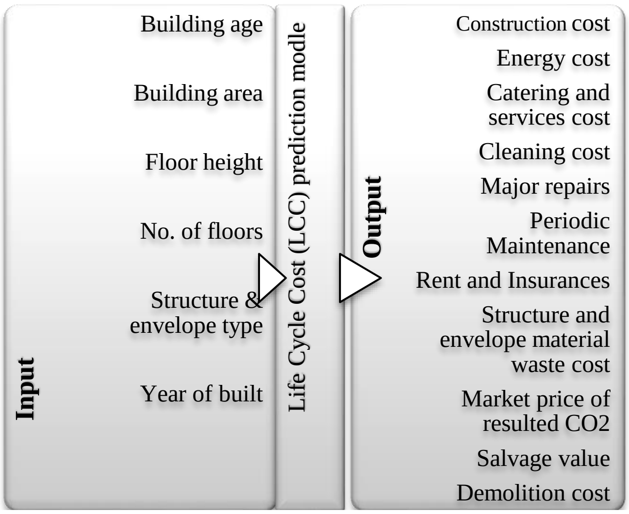


Fig. 1: Accord-framework of LCC selection criteria needed for prediction model

A. Selection Framework

The selected criteria are introduced to govern the LCC of buildings. The selected LCC criteria definitions and preparation are provided in Table 2.

B. Calculations of sample size

The required sample size is statistically calculated according to the following Equation of Montgomery [35] as follows in (1). Where, n is sample size, $Z\alpha/2$ is a critical value from statistical tables, P is a percentage of the target sample population to the total population, and d is accepted error percentage.

$$n = \frac{\left(z_{\alpha/2}\right)^2 * p * (1-p)}{d^2} \tag{1}$$

For a target sample population of 10,000 and 22,729 for contractor and consultant, respectively, and a total population of 182,703 civil engineers (all registered civil engineers in all departments as the Egyptian Engineers Syndicate), the assumed accepted error percentage in this method questionnaire is 10%; $Z\alpha/2$ = 1.645 and the minimum sample size is calculated to be 15. The participated experts in my research are 37 experts.

TABLE 2
Categories and criteria description and preparation related to Building life cycle cost

Category and Criteria	Description	Data preparation.
Initial Cost (IC)	Equivalent of total development costs in NRM 1[1], including: site costs, ownership, finance charges, construction and infrastructure costs, and etc.	From manufactures such as Modern4concrete Company's group [30] in Egypt.
Operating and Maintenance (O&M)	Referred to as hard facilities management costs. Cleaning and energy expenditures, as well as maintenance and other costs, are included in these prices.	From industrial board of Companies such as Modern4concrete industrial board in Egypt.
Energy cost	Energy used for heating and lighting [31].	From standard energy and simulation.
Catering and services	General support services, communications and security services, letting fees, facilities management fees, caretaker and janitorial services, service transport, IT services, and laundry and linen services, e.g., internal deliveries.	From industrial board of Companies such as Modern4concrete industrial board in Egypt.
Cleaning	Waste management and disposal [32].	
Major repairs	Redecoration, renovation, rehabilitation, replacement.	
Periodic maintenance	Contractors' (or system employees') costs for skilled jobs such as sanitation and HVAC services [33].	
Rent and insurances	Insurance rates and other local taxes and charges.	
Environmental impact cost (EIC)	The environmental impact cost is a reference to the cost of greenhouse gas (GHG) emissions, which produced during construction of concrete and which has effects on the environment.	From environmental **i**mpact estimators
waste of Structure and envelope material co sulted st	Emissions of GHG come from stages such as production of raw materials, manufacturing concrete, placing concrete in the location, and demolition.	From industrial board of Companies such as Modern4concrete industrial board in Egypt.
Market price of reCO2	Cost of controlling gas emissions.	From carbon market (point carbon website [34])
End of life cost (EoLC)	This includes disposal and demolition, but specifically includes the worth of alternatives at the end period of LCCA.	From industrial board of Companies such as Modern4concrete industrial board in Egypt.
Salvage and recycling	Recycling, the conversion of waste of the building into new objectives.	
Demolition cost	Building demolition wastes such as materials, aggregate, concrete, wood, and metal...	

C. Survey study

A web-based survey is applied considering a pilot study feedback, and then distributed it to about hundreds of experts in Egypt and out of Egypt. This study was conducted in the English language. Building managers, consultants, academics, and contractors. Only 37 response was received and then five of them were excluded. The responses were collected electronically, primarily from experts via a web-based system.

D. Evaluation and weighting criteria using the AHP

The decision makers weight the criteria in the AHP by using pairwise comparison matrices. Starting with asking the experts to fill out half of the matrix of the questionnaire about a preference scale ratio from 1 to 9. After that, the filled values in the other half of the matrix were reversed. This method evaluates and quantifies the relative weights for the criteria gathering set. The average of 32 responses calculation matrixes are presented in Tables 3-7, and its weights are calculated at the last column of each matrix.

TABLE 3.
THE PAIR-WISE COMPARISON MATRIX OF LCC OUTPUT CATEGORY

LCC output category	initial costs	Operating and Maintenance	Environmental Impact cost	End of life cost	WIGHT
initial costs	1.00	2.00	2.00	3.00	0.40
Operating and Maintenance	0.50	1.00	2.00	2.00	0.27
Environmental Impact cost	0.50	0.33	1.00	4.00	0.23
End of life cost	0.50	0.50	0.25	1.00	0.10
				sum	1.00

TABLE 4.
THE PAIR-WISE COMPARISON MATRIX OF LCC INPUT CRITERIA

LCC input criteria	Building area	Floor height	No. of floors	Structure & envelope type	Building age	Location city	Year of built	WIGHT
Building area	1.00	2.00	3.00	2.00	2.00	4.00	4.00	0.27
Floor height	0.50	1.00	3.00	2.00	2.00	4.00	2.00	0.21
No. of floors	0.33	0.50	1.00	3.00	3.00	4.00	3.00	0.18
Structure & envelope type	0.33	0.50	0.50	1.00	4.00	3.00	3.00	0.14
Building age	0.50	0.33	0.33	0.25	1.00	2.00	3.00	0.09
Location city	0.25	0.25	0.25	0.33	0.33	1.00	2.00	0.05
Year of built	0.25	0.50	0.33	0.50	0.33	0.50	1.00	0.05
							sum =	1.00

TABLE 5.
THE PAIR-WISE COMPARISON MATRIX OF OPERATING AND MAINTENANCE COST CRITERIA

Operating and Maintenance criteria	Energy consumption cost	Catering and services	Cleaning	Major repairs	Periodic Maintenance	Rent and Insurances	WIGHT
Energy cost	1.00	3.00	1.00	2.00	3.00	4.00	0.29
Catering and services	0.33	1.00	2.00	4.00	4.00	3.00	0.26
Cleaning	1.00	0.50	1.00	3.00	4.00	4.00	0.22
Major repairs	0.50	0.25	0.33	1.00	3.00	3.00	0.11
Periodic Maintenance	0.33	0.25	0.25	0.33	1.00	2.00	0.06
Rent and Insurances	0.25	0.33	0.25	0.33	0.50	1.00	0.05
						sum =	1.00

TABLE 6.
THE PAIR-WISE COMPARISON MATRIX OF ENVIRONMENTAL IMPACT COST CRITERIA

Environmental Impact Cost Criteria	Structure and Envelope Material Waste Cost	Market Price of Resulted CO2	WIGHT
Structure and envelope material waste cost	1.00	2.00	0.67
Market price of resulted CO2	0.50	1.00	0.33
		sum =	1.00

TABLE 7.
THE PAIR-WISE COMPARISON MATRIX OF THE END-OF-LIFE CRITERIA

End of life cost criteria	Salvage value	Demolition cost	WIGHT
Salvage and recycling	1.00	3.00	0.75
Demolition cost	0.33	1.00	0.25
		sum =	1.00

E. The Consistency Analysis of Responses

The consistency test is passed by all responses. Divide the consistency index value (CI) by the random consistency index value (RI) to get the consistency ratio (CR = CI / RI). The confidence interval (CI) is calculated as follows: CI = (λmax – n) / (n -1), while the RI value is obtained from Table 8, and this value depends on a size n matrix. If CI equal 0, it refers to that the matrix is consistent. The inconsistency of the responses is still regarded acceptable when the CR value of any matrix is less than 10% [36]. Due to their high consistency ratio, five of the 37 responses were eliminated. The value of max is calculated by dividing the vector weight by the relative weight of each criterion, as shown in Table 9. The consistency index value (CI), and consistency ratio (CR) for all the previous matrixes.

TABLE 8.
RANDOM INCONSISTENCY INDEX (*RI*) FOR *N*=1, 2…10

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.27	1.32	1.41	1.54	1.49

There are different consistency ratios CR and the value of λmax and CI for all the previous matrixes in table 9. When consistency ratio of matrixes responses of LCC output category, LCC input criteria, Operating and Maintenance criteria are 0.082, 0.098, 0.085 respectively which less than 0.1 [35], the consistency is considered acceptable. When the CR decreased to zero, the comparison matrix is completely consistent as in Environmental impact cost criteria and End of life cost criteria comparison matrix.

IV. THE LCC PREDICTION MODEL METHODOLOGY

The scope of this study is to predict the LCC of construction buildings through deep learning. The research proposes LCC approach that collects the historical building data generated and analyzes the data with deep learning techniques to predict the future costs of the new buildings, and thus to achieve the best decision-making in building design, refurbishment, and renovations. Therefore, Deep Belief network is developed [23] with Restricted Boltzmann machine hidden layers based on 315 historical gathering data input and output criteria. A belief net is a directed acyclic graph composed of stochastic variables.

- Getting to observe some variables to solve two problems:
- The inference problem: Infer the states of the unobserved variables.
- Adjusting the interactions between variables to make the network more likely to generate the observed data is the learning problem.
- Two types of generative neural network can learn deep Belief nets:
- If binary stochastic neurons are connected in a directed acyclic graph a Sigmoid Belief Net was getting.
- A Boltzmann Machine is created when binary stochastic neurons are connected using symmetric connections. [23].

Therefor the connectivity was restricted in a special way, because a Boltzmann machine is simple to be learned.

A. Data analysis

The study has training data set of 312 values for 6 input and 11 output criteria. All gathering data were collected in excel sheet in seventeen columns of input and output criteria. The input criteria are building area, floor height, no of floors, structure & envelope type, year of built, and building age. The output criteria are initial cost, energy cost, catering and services, cleaning, major repairs, periodic maintenance, rent and insurances, structure and envelope material waste cost, market price of resulted CO2, salvage value, and demolition cost respectively for 312 raw training data set value. Basic statistics are applied to the variables as shown in Table 10.

TABLE 9.
THE VALUE OF ΛMAX, CI, CR FOR ALL THE PREVIOUS MATRIXES

Matrix name	LCC output category	LCC input criteria	Operating & Maintenance criteria	Environmental impact criteria	End of life criteria
λmax	4.22	7.76	6.35	2	2
CI	0.074	0.13	0.106	0	0
CR	0.082	0.098	0.085	0	0

TABLE 10.
THE BASIC STATISTICS INFORMATION OF THE DATA GATHERING VARIABLES

Basic statistics	Area (m^2)	floor height (m)	no of floors	structure and envelope type	building age (year)	year of built	Initial cost (LE)
Maximum	40,000	8	5	3	18	2021	39,172,350
Minimum	1470	3	1	1	1	2003	3,051,251
Mean	12,952	5.4	3	1	11.3	2013	16,005,482
Median	17,250	5	3	2	13	2015	12,582,253

B. Data Derivation

The LCCA of the prediction model is studied over a period of 25 years. To compare the LCCs of the construction buildings during the past 25 years, several hypotheses are considered. The initial costs, O&M costs, EIC, and EoL costs of all buildings are converted to the "present values" in 1996. Assuming that for each building, the changes in cost over time are proportional to the rate of inflation from Egypt Inflation Rate, (1960-2021) site [37].

The present value of the initial cost is calculated according to the following equation (2):

$$PV_{IC} = IC \times \Pi^{t}_{i=1} (1 + r_i) \quad (2)$$

Where:

PV_{IC} is the present value of the initial cost.

IC is the amount of initial cost.

t is the building age.

r_i is the annual inflation rate of i years ago.

The present value of the operation and maintenance cost is calculated according to the following equation (3):

$$PV_{OM} = \Sigma^{n}_{j=1} ((EC_j + C\&S_j + CC_j + MR_j + PM_j + R\&I_j) \times \Pi^{j}_{i=1} (1 + r_i)) \quad (3)$$

Where:

PV_{OM} is the present value of operation and maintenance cost.

EC_j is the annual Energy cost j years ago.

$C\&S_j$ is the annual Catering and services cost j years ago.

CC_j is the annual cleaning cost j years ago.

MR_j is the annual Major repairs cost j years ago.

PM_j is the annual Periodic maintenance cost j years ago.

$R\&I_j$ is the annual Rent and insurances cost j years ago.

n is the length of the study period in years.

The present value of the Environmental impact cost is calculated according to the following equation (4):

$$PV_{EIC} = \Sigma^{n}_{j=1} ((MWC_j + Rco_{2j}) \times \Pi^{j}_{i=1} (1 + r_i)) \quad (4)$$

Where:

PV_{EIC} is the present value of Environmental impact cost.

MWC_j is the annual Structure and envelope material waste cost j years ago.

Rco_{2j} is the annual Market price of resulted CO2 j years ago.

The present value of the End of life cost is calculated according to the following equation (5):

$$PV_{EoLC} = \Sigma^{n}_{j=1} ((DC_j - SV_j) \times \Pi^{j}_{i=1} (1 + r_i)) \quad (5)$$

Where:

PV_{EoLC} is the present value of End of life cost.

DC_j is the annual Demolition cost j years ago.

SV_j is the annual Salvage value cost j years ago.

C. Configuration of the Deep Belief Network DBN

This involves the following steps for LCC deep learning prediction model.

1. Setting required parameters for creating deep belief network DBN.

A training set of 312 values for 6 input and 11 output. DBN was created with 2 hidden Layers of restricted Boltzmann machines with 10 hidden neurons in each hidden layer (Fig. 2).

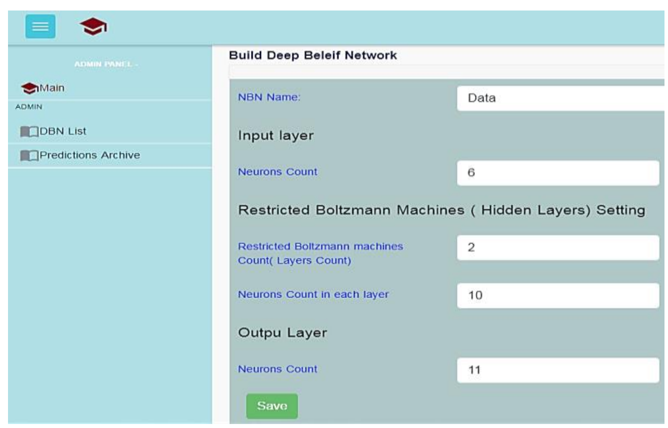


Fig. 2. Setting required parameters for Creating DBN

2. Setting the required parameters for the Training operation Code:

There are double Learning Rate from 0 to 1, 20000 number of training Epoch, and 312 data set size (Fig. 3).

3. loading training data set.

From (choose file), file data set can be uploaded document file (.txt) then click save (Fig. 3).

Fig. 3. setting the required parameters for the Training operation Code

D. *Training of the Network.*

First train deep network layer of features that receive input directly from the pixels.

• It can be proven that adding another layer of features improves a variation lower bound on the log likelihood of the training data by treating the activations of the trained features as if they were pixels and learning features of features in a second hidden layer.

– The proof is a little tricky. – However, it is based on a simple analogy between an RBM and a deep directed model (described later)

Each hidden RBM layer transforms its data distribution into a posterior distribution that is aggregated.

• This splits the task of data modelling into two parts:

– Task 1: Discover generative weights for converting the aggregated posterior distribution over hidden units back to the data distribution.

- Task 2: Acquire knowledge of how to model the aggregated posterior distribution over hidden units.

– The RBM does a good job with task 1 and a fair job with task 2.

• Task 2 is simpler than modelling the original data (for the next hidden RBM layer) because the aggregated posterior distribution is closer to a distribution that an RBM can model precisely (Fig 4).

The weights, W, in the bottom level RBM define $p(v|h)$ and they also, indirectly, define $p(h)$. So, we can express the RBM model as in equation (6).

$$p(v) = \Sigma_h \; p(h)\, p(v|h) \qquad (6)$$

If we leave $p(v|h)$ alone and improve $p(h)$, we will improve $p(v)$. To improve $p(h)$, we need it to be a better model of the aggregated posterior distribution over hidden vectors produced by applying W of the data.

E. *Prediction values of LCC parameters from DBN input simulations*

LCC outputs could be predicted by choosing prediction archive then click create prediction an input page will appear as in Fig. 5 (a). All required input could be filled as in Fig. 5(b) then click predict. All output results of the prediction model will appear as shown in Fig. 5 (c).

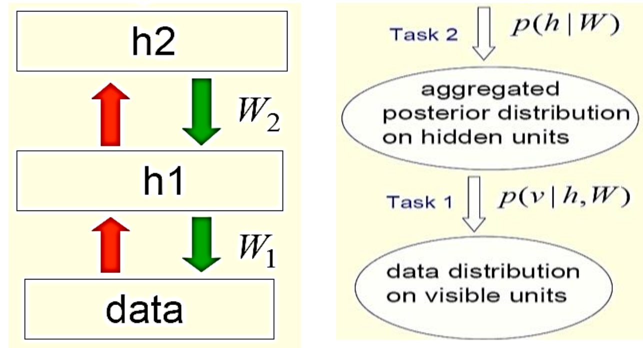
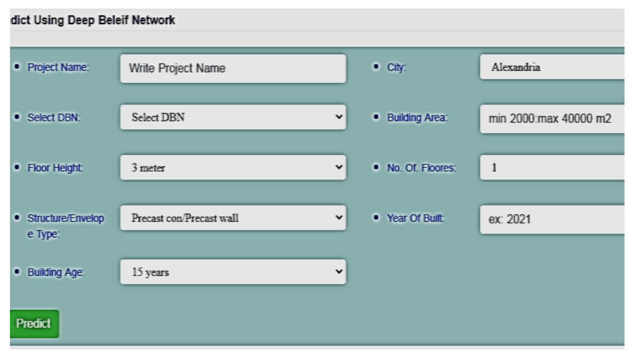
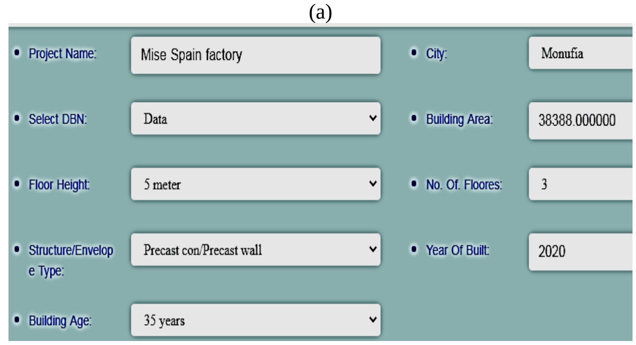


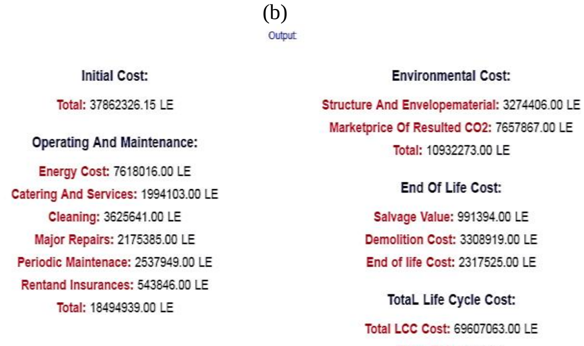
Fig. 4. The developed structure of Deep Belief Network DBN with restricted boltzmann machine RBM hidden layers for LCC prediction model.



(a)



(b)



(c)

Fig. 5 shows the Prediction values of LCC parameters of DBN input and output.

V. VALIDATION

The validity of the processes employed in the LCC model is a crucial concept. Therefore, three case studies in this section are devoted to validating on the assumption modelling procedures. The inputs of the three case studies are gotten from Modern4concrete Company's group in Egypt mentioned in table 11. The values are forecasted for twenty-five years building age from the year of 1996 to 2021. The actual costs of LCC criteria and the predicted values, which extracted from deep belief learning input simulations after twenty-five years, are collected in table 12. The prediction model calculates an error ratio for each case study as shown in Table 12.

TABLE 11
DATA COLLECTION OF THE THREE CASE STUDIES.

No.	Project Name	City	Input building parameter			
			Area (m2)	Height (m)	No. of. Floors	Structure & Envelope Type
1	**Case 1**	10 of Ramadan	12635	8	1	S/ M
2	**Case 2**	10 of Ramadan	13160	5	3	PC/ PC
3	**Case 3**	El Obour	17200	3	5	C/ M

Where: (C/ M) is reinforced concrete frame with masonry wall alternative, (PC/ PC) is precast concrete frame with precast concrete walls alternative, and (S/ M) is steel frame with masonry wall alternative

TABLE 12.
THE TRADITIONAL METHOD CALCULATION COSTS (ACTUAL) OF LCC CRITERIA IN 2021 AND THE PREDICTED VALUES, WHICH EXTRACTED FROM DEEP BELIEF LEARNING INPUT SIMULATIONS, AFTER 25 YEARS

Project Name		Actual LCC cost after 25 years (L.E)			Predicted LCC Cost after 25 years (L.E)		
		Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
IC		16450250	23831000	27967500	13844146	23099754	22787784
O&M	*EC*	2510509	3645335	2351722	2151722	3983835	3870192
	C&S	675865	997217	601724	591724	1095555	1064303
	CC	1301755	1827667	1175861	1075861	1991918	1935096
	MR	735553	1172600	655517	645517	1195151	1161058
	PM	852828	1355367	763103	753103	1394342	1354567
	R&I	191063	278950	171379	161379	298788	290264
EIC	*MWC*	1148129	1539723	906551	896551	1659931	1612580
	RCO2	2454301	3506020	2191952	2091952	3873173	3762687
EoLC	*SV*	452057	662099	331260	321260	564525	577593
	DC	1260143	1725248	986168	996168	1844368	1791756
				Error Ratio %	4.63	4.07	4.92

Where: (O&M) Operating and Maintenance Cost, (EIC) Environmental impact cost, and (EoLC) End of life cost.

VI. STATISTICS ANALYSIS

Each of case studies predicted output probability distributions is investigated by using some descriptive Statistics, regression, mean square error and autocorrelation. The statistical methodology Refers to the relation between two or more quantitative variables with the assistance of SPSS Statistics v22.

A. Descriptive Statistics

Basic statistics information is studied for the three case studies. Table 13 shows the mean and stander deviation of each case study.

TABLE 13.
THE MEAN AND STANDER DEVIATION OF EACH CASE STUDY.

	Case 1	Case 2	Case 3
Mean	2091037	3812393	3712260
Std. Deviation	3899868	6641599	6500772

B. Regression and Mean Square Error Results

The correlation between outputs and targets is measured using regression values. A close association has an R-value of 1, whereas a random relationship has an R-value of 0. The bigger the regression coefficient, the smaller the difference between the projected and real time series. The average squared difference between outputs and targets is known as the MSE. The regression and mean squared findings for each case study are shown in Table 14.

TABLE 14.
THE REGRESSION AND MEAN SQUARED RESULTS FOR EACH CASE STUDY

	Case 1	Case 2	Case 3
R	0.942	0.903	0.970
*Mean Square Error * E14*	1.027	4.350	4.896

The next stage in verifying the network is to generate a regression plot, which depicts the relationship between the network's outputs and the actual, as seen in fig. 6. The network outputs and the actual would be exactly equal if the training was perfect, but in practice, the relationship is rarely perfect. For each case study, the network outputs are plotted against the actual in the following regression plots. The fit is reasonably good for all data sets, with R-value in each case of 0.903 or above.

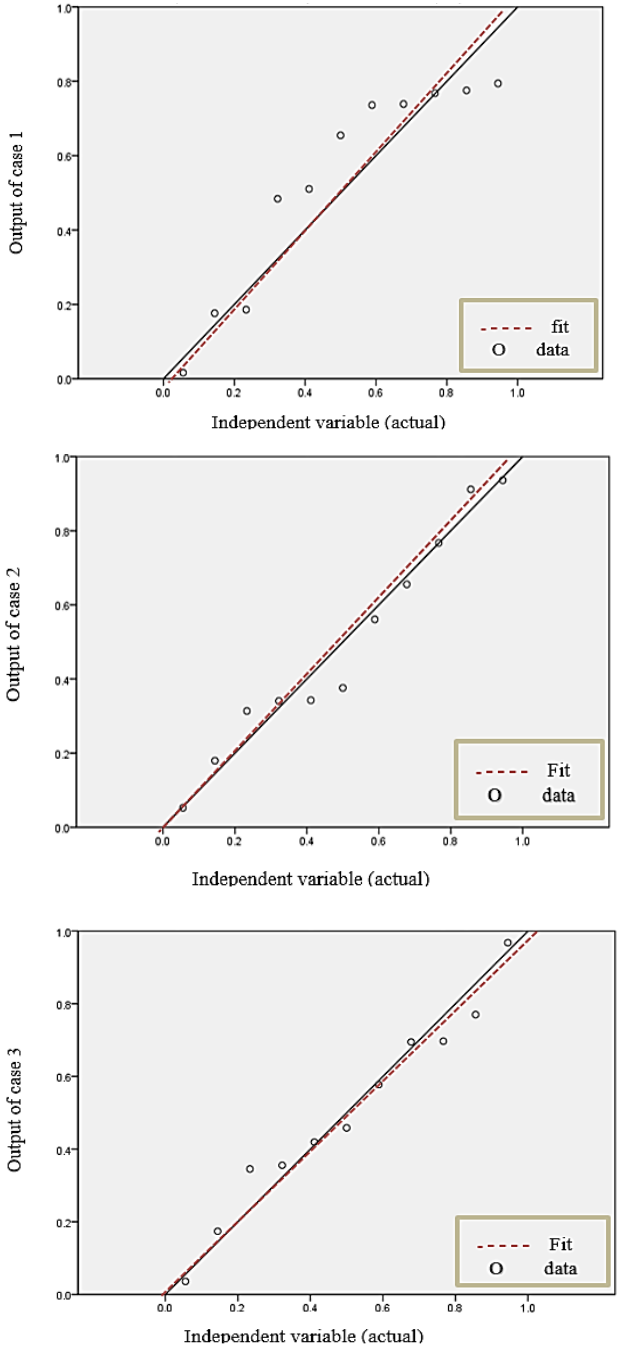


Fig. 6. Network validating with a regression plot for the three case studies

C. *Autocorrelation Test (Durbin-Watson)*

The Durbin-Watson statistic has a value between zero and 4. Values from zero to less than 2 indicate positive autocorrelation and values from 2 to 4 indicate negative autocorrelation. There is a positive autocorrelation in case 1 which less than 2. While, case 2 and 3 have negative autocorrelation as it is greater than 2. Table 15 shows Durbin-Wa tson autocorrelation for each case study.

TABLE 15.
DURBIN-WATSON AUTOCORRELATION FOR EACH CASE STUDY

	Case 1	**Case 2**	**Case 3**
Durbin-Watson	1.305	2.541	2.692

CONCLUSION

This research contributes to the economic sustainability. As the paper presents a Deep learning prediction model for LCC of construction buildings in Egypt. The study applied a strategic methodology divided into evaluating building LCC criteria by using the analytical hierarchy process AHB and LCC prediction model methodology.

The first methodology begins with collecting LCC criteria through the previous reviews. The AHP questionnaire was put up to compare corresponding input and the output criteria according to the fundamental Saaty Rating Scale, and 37 experts voted in. The weights of the input and the output criteria were calculated by using the AHP method, which help in developing the prediction LCC model of construction buildings in Egypt. As well as, the consistency of each paired matrix was calculated. Five responses were excluded due to their high consistency ratio. Finding that, When the consistency ratio of matrixes responses of LCC output category, LCC input criteria, Operating and Maintenance criteria are 0.082, 0.098, 0.085 respectively which less than 0.1, the consistency is considered acceptable.

The second approach of methodology presents modelling the historical costs and forecasting costs of buildings. This based on a deep learning network, which a combination of Deep Belief network and Restricted Boltzmann machine. A training data set of 312 value was developed for 6 inputs and 11 outputs to predict LCC of the building after 25 years. The prediction model was validated by experiment three case studies of construction buildings on a study period of 25 years from the year of 1996 to 2021. Where, the comparison between the actual and the predicted values from the model was done statistically. The prediction model calculates error ratio between 4.07 and 4.92. This approach is significantly more reliable in predicting long-term construction costs. A statistical methodology was utilized to validate the outputs of the network by using some descriptive Statistics, regression, mean square error and autocorrelation. The fit is reasonably good for all data sets, with R-value in each case of 0.903 or above. The network outputs and the actual values are exactly equal, but the relationship is rarely perfect in practice.

AUTHORS CONTRIBUTION

M. Basiouny

He provided the final approval for the version to be published.

El-Dash K. M.

He is a supervisor of our work, project administrator, and contributed in investigation, methodology, and article revision.

Ahmed Nouh

He substantially contributed in conception or design of the work, investigation, methodology, continuous supervision, and critical revision of the article.

Omia S. El Hadididi

She determined the tools, data collection, methodology innovation, data analysis and interpretation, finding resources, drafting the article, and critical revision of the article.

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ARABIC TITEL

تقييم بدائل الهيكل الإنشائي للمباني باستخدام نموذج تنبؤ بتكلفة دورة حياة المباني

ARABIC ABSTRACT

تكلفة دورة الحياة (LCC) هي أداة قوية تستخدم في اتخاذ القرارات الاقتصادية لبناء المباني. هذه هي الممارسة المحاسبية لجميع النفقات المتكبدة على مدى عمر هيكل معين. يتم خصم التكاليف في أي وقت إلى تاريخ محدد، بناءً على معدلات التضخم المفترضة والقيمة الزمنية للنقود. تساوي تكلفة دورة الحياة تكلفة البناء بالإضافة إلى القيمة الحالية للمرافق المستقبلية والتشغيل والصيانة وتكاليف تأثير الذيل اللاحق على مدى عمر المبنى، وتبحث هذه الدراسة في جدوى الحصول على نموذج دقيق للتنبؤ بالتعلم العميق لمبنى LCC من خلال تطبيق البيانات التاريخية لمشاريع مماثلة. إن معايير المدخلات والمخرجات LCC المطبقة مستمدة من الدراسات السابقة. معايير الإدخال هي مساحة المبنى، وارتفاع الطابق، وعدد الطوابق، والهيكل ونوع المغلف، وعمر المبنى، وسنة البناء، والموقع (المدينة). تشمل فئات المخرجات التكاليف الأولية ذات الصلة، وتكلفة التشغيل والصيانة، وتكلفة الأثر البيئي، ونهاية العمر الافتراضي، ولكل منها معاييره الخاصة. تم تطوير استبيان إلكتروني لعملية التسلسل الهرمي التحليلي (AHP) لوزن المعايير المختارة لتكون جاهزة لنموذج التنبؤ. تم استلام 37 ردًا فقط من مصر ومن خارج مصر واستبعدنا خمسة منهم لتحقيق الاتساق. لذلك تم تطوير شبكة Deep Belief باستخدام طبقات مخفية لآلة Boltzmann المقيدة بناءً على 312 مجموعة بيانات تدريب لمعايير المدخلات والمخرجات. تم تخصيص ثلاث دراسات حالة للتحقق من صحة إجراءات نمزجه الافتراض. تم التحقيق في التوزيعات الاحتمالية لكل من المخرجات المتوقعة لكل دراسة حالة باستخدام منهجية الانحدار الإحصائي.