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Implementation of a Life Cycle Cost Deep Learning Prediction Model Based on Building Structure Alternatives for Industrial Buildings

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Abstract: Undoubtedly, most industrial buildings have a huge Life Cycle Cost (LCC) throughout their lifespan, and most of these costs occur in structural operation and maintenance costs, environmental impact costs, etc. Hence, it is necessary to think about a fast way to determine the LCC values. Therefore, this article presents an LCC deep learning prediction model to assess structural and envelope-type alternatives for industrial building, and to make a decision for the most suitable structure. The input and output criteria of the prediction model were collected from previous studies. The deep learning network model was developed using a Deep Belief Network (DBN) with Restricted Boltzmann Machine (RBM) hidden layers. Seven investigation cases were studied to validate the prediction model of a 312-item dataset over a period of 30 years, after the training phase of the network to take the suitable hidden layers of the RBM and hidden neurons in each hidden layer that achieved the minimal errors of the model. Another case was studied in the model to compare design structure alternatives, consisting of three main structure frames—a reinforced concrete frame, a precast/pre-stressed concrete frame, and a steel frame—over their life cycle, and make a decision. Precast/pre-stressed concrete frames were the best decision until the end of the life cycle cost, as it is possible to reuse the removed sections in a new industrial building.

Keywords: life cycle cost (LCC); precast structure building; deep learning; prediction model; deep belief network (DBN); restricted boltzmann machine (RBM); industrial building; precast/pre-stressed (PC/PS)

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1. Introduction

There is a growing need to raise awareness with respect to the economic sustainability of industrial buildings, as this is considered one of the key aspects of buildings that can contribute to economic recovery and end stagnation. Therefore, this study proposes an initiative to assess the life cycle costing of industrial buildings by developing a deep learning prediction model.

Life Cycle Costing (LCC) is a sustainable economic tool. This study applies LCC to measure the economics of alternative-construction buildings that have different structures and envelope types, in terms of their cash flows over a building's total lifespan [1–3]. This is considered to be an intelligent design process for controlling the initial and running costs of construction and building ownership. The LCC method shows clearly that we could achieve savings when the higher initial cost of a building reduces long-term running costs, such as operation, maintenance, and environmental impact costs [2]. In contrast, a lower initial cost could lead to increased running costs and repeal the initial savings throughout the building's lifespan. Life cycle costing is a combination of structural judgments, prediction of costs, and a huge amount of calculations.

The main problem is to figure out a fast method to represent the LCC. Therefore, this study presents a fast tool from deep machine learning. Deep machine learning is a clever form of optimization learning used to predict LCC. Deep learning is an artificial intelligence (AI) method for developing complicated prediction algorithms and models [4–6]. Deep learning comprises a class of machine learning algorithms [7] that use multiple layers to extract progressively higher level features of the raw input; 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 [8].

The objective of this research is to develop software [9] for a deep learning prediction model of historical building data, so as to predict the Life Cycle Cost (LCC) of a new industrial building after n years (building age), and to evaluate structure and envelope-type alternatives to make a decision for any given industrial building.

2. Literature Review

2.1. Life Cycle Costing Elements

Rather than focusing just on the initial cost, Figure 1 shows how the allocation differs when LCC is taken into account [10]. Initial costs, running costs, energy, maintenance, and cleaning charges, as well as other rates, are all factored in. LCC allocation differs depending on the types and purposes of the constructions [10–12].

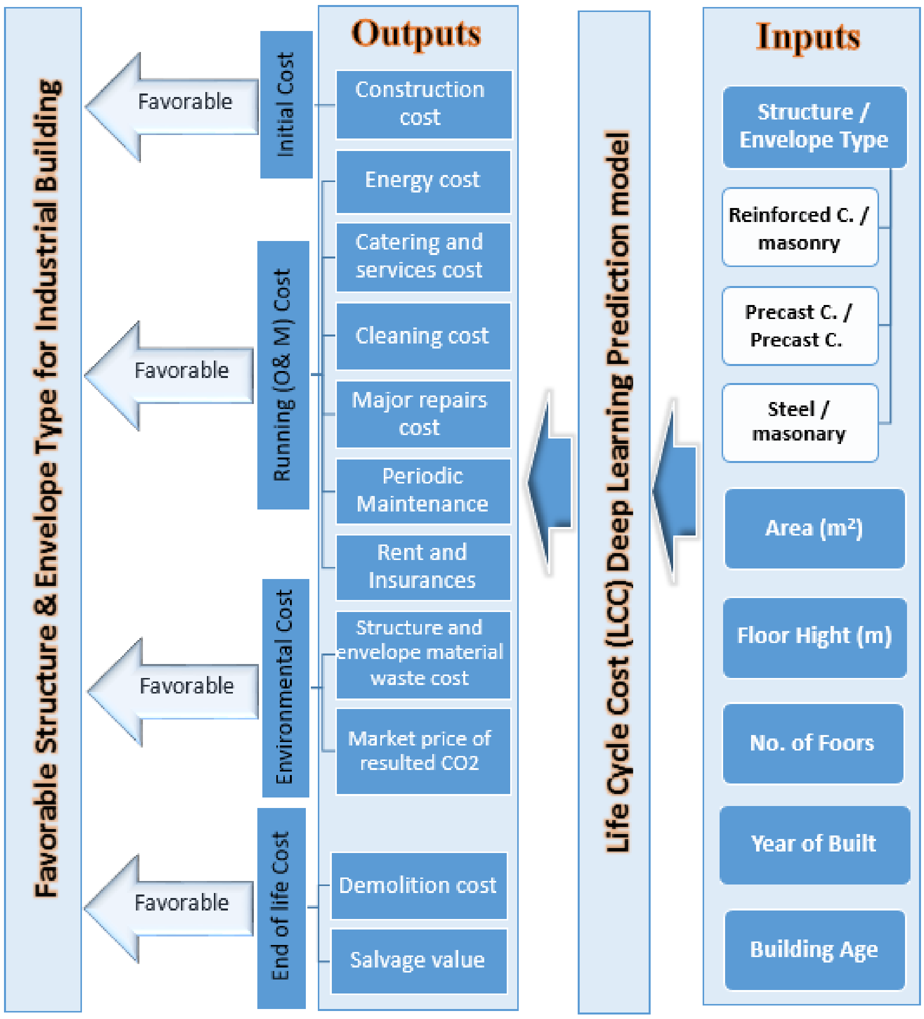


Figure 1. Applied LCC prediction model framework needed for selecting the favorable structure and envelope type of industrial buildings.

Early decisions in the construction of a structure have the greatest impact, necessitating the consideration of life cycle cost. Life cycle costing is an economic quantitative estimation method [2,13] that examines the total cost of a building throughout its entire operational life. 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 [14–16].

In other words, an economic comparison takes into account not only the project's initial capital expenses, but also its operating costs and disposal production costs [8]. The LCC method can also provide information for the calculation of a construction's economic feasibility, as well as the identification of cost drivers [17–19].

Life cycle costs play a key role in the decision making of green building projects [20]. Determining the economic effects of alternatives is an important step in the LCCA study. The literature review was conducted to extract and coordinate common independent variables related to LCCA [21–24]. The variables that applied for our LCC prediction model were building area, floor height, number of floors, structure and envelope type, building age, and year of construction [25–28].

2.2. Implementations of LCC in the Construction of Buildings

LCC is used in a variety of construction projects, including office buildings, infrastructure, and residential and commercial constructions. The author of [29] evaluated the issues of LCC implementation and the limitations of LCC in building projects. The benefits of LCC should be applied in construction projects, as determined by government authorities and consultants [30]. Life cycle costing is the only approach to anticipate the full cost of basic purchasing decisions [31]. Previous studies produced models to predict office building life cycle cost as part of the basic design process [32–34]. LCC has a wide use in infrastructure building research [35–37]. LCC studies on educational buildings are reported in [38–41], and others were carried out in commercial buildings [12,42,43].

Most previous studies in the field of industrial buildings were more concerned with environmental evaluation than with economic evaluation, which is called life cycle cost assessment [44–46]. Only a few studies that illustrate the LCC distribution of industrial buildings have been published. In Sri Lanka, a study of LCC contrasted green and traditional industrial buildings [47]. Kovacic et al. [48] created a decision-making tool for assessing the economic and environmental effects of industrial buildings. Reisinger et al. [49] provided a model for the economic benefit and flexibility of industrial buildings.

2.3. Artificial Intelligence Prediction Modelling in the Construction of Buildings

Artificial intelligence (AI)-related research has exploded with the development of computer science [50] (e.g., machine learning and deep learning), and appears not only in the field of computer science, but also regularly in the engineering sector [51,52]. Machine learning (ML) is the process of analyzing data and learning from them to aid prediction and decision making [53]. ML with transfer learning is a technique to obtain information on the properties of buildings from photos [54,55]. Deep learning is a branch of machine learning, and not an autonomous learning approach [56]. Several implications of deep learning—particularly in the construction industry—have yet to be explored, including site management and planning, safety, and cost estimation. Previous studies have applied deep learning to common construction issues such as structural health monitoring, worksite safety, building utilization modelling, and energy usage forecasting [57–60].

3. Methodology

The applied methodology of this research introduces data collection to develop a tool to predict LCC and assist in industrial construction to select the most favorable structure and envelope type for new industrial buildings.

The conducted research applies deep learning to predict the LCC through developing deep belief networks with restricted Boltzmann machines. This research consists of three structure alternatives and envelope types: a reinforced concrete frame, a precast/pre-stressed concrete frame, and a steel frame. Table 1 summarizes various structure and envelope types that are commonly used in the design of industrial buildings in Egypt [61].

Table 1. Structure and envelope types.

Alternatives	Frame Type	Wall Type	Floor Type	Roof Type
C/M	Reinforced concrete	Masonry	Solid concrete slab	Solid concrete slab
PC/PS	Precast/pre-stressed	Precast concrete panels	Pre-stressed slab	Hollow core slab
S/M	Steel frame	Masonry	Concrete/metal deck/open joists	Concrete/metal deck on open web joists

The selected framework introduces the inputs and outputs of the deep learning prediction model to achieve the best decision making with respect to the favorable structure frame for industrial buildings, with minimal LCC (Figure 1).

3.1. Required Data for LCC Model

3.1.1. Data Preparation

The input and output criteria of the LCC model were collected from existing literature and civilian experience. The inputs were building area, floor height, number of floors, structure and envelope type, building age, and year of construction [42,43,61]. The outputs were initial cost, operation and maintenance cost (energy costs, catering and services, cleaning, major repairs, periodic maintenance, and rent and insurance), environmental impact cost (structure and envelope material waste costs, and market price of resulting CO_2), and end-of-life cost (residual value and demolition cost). Table 2 describes the model inputs and outputs, the main sources, and references of data collection related to building life cycle cost.

Table 2. Description and preparation of input and output criteria related to building life cycle cost.

	Selected Criteria	Descriptions	Data Preparation
Inputs	Building area	The total area of the building, which is one of the basics of the building footprint.	The capital planning and investment control system. Some digital spreadsheets that record the design and construction costs from manufactories such as Modern4concrete in Egypt.
	Floor height	The height of each building story in unit length, which is one of the basics of the building footprint.	
	Numbers of floors	Number of building stories (e.g., 1, 2, 3, . . .), which is one of the basics of the building footprint.	
	Structure and envelope type	These include steel, concrete, wood, and precast concrete, in various combinations.	

Table 2. *Cont.*

	Selected Criteria	Descriptions	Data Preparation
	Building age	The study period, in years (e.g., 15, 25, 30, . . . years).	
	Year of construction	This parameter includes the projects built within the study period.	
Outputs	Initial Cost (IC)	Construction Cost	
	Operation and Maintenance Cost (O&M)	This refers to hard facility-management costs These costs include operating costs such as cleaning and energy costs, maintenance costs, and other costs [1,2].	Computerized maintenance management systems of industrial boards of construction companies in Egypt.
	Energy Cost (EC)	Energy used for heating and lighting [27].	From standard energy and simulation. The building energy management systems.
	Catering and Services (C&S)	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 [1].	From the industrial boards of construction companies, such as the Modern4concrete industrial board in Egypt.
	Cleaning (C)	Waste management and disposal.	
	Major Repairs (MR)	Redecoration, renovation, rehabilitation, and replacement.	
	Periodic Maintenance (PM)	The cost of contractors who perform skilled jobs, such as the sanitation and HVAC services [1].	
	Rent and Insurance (R&I)	Insurance rates and other local taxes and charges.	
	Environmental Impact Cost (EIC)	The environmental cost refers to the cost of controlling gas emissions, and of structural and envelope material waste costs [41].	From environmental impact estimators in Egypt [62].
	Structure and envelope Material Waste Cost (MWC)	Waste gathered from all stages, such as production of raw materials, manufacturing of concrete, placing concrete at the location, and demolition.	From the industrial boards of construction companies and their computerized maintenance management systems.
	Market price of resulting CO_2 (RCO_2)	Cost of controlling gas emissions.	From the carbon market (Point Carbon website) [63].
	End-of-Life Cost (EoLC)	This includes disposal and demolition, but specifically includes the worth of alternatives at the end period of LCCA [64].	The capital planning and investment control system. Some digital spreadsheets that record the design and construction costs. Some physical documents related to building design and construction.
	Residual Value (RV) or Salvage Value (SV)	Salvage value, recycling, the conversion of waste from the building into new objectives.	
	Demolition cost (DC)	Building demolition waste such as materials, aggregates, concrete, wood, and metal.	

3.1.2. Data Analysis

We used a dataset of 312 values, with 6 input and 11 output criteria. All gathered data were collected in an excel sheet. Basic statistics were applied to the variables, as shown in Table 3.

Table 3. The basic statistical information about the data collection variables.

Basic Statistics	Area (m^2)	Floor Height (m)	Number of Floors	Structure and Envelope Type	Building Age (Years)	Year of Construction	Initial Cost (LE)
Maximum	40,000	8	5	1	20	2020	43,172,350
Minimum	820	3	1	1	1	2000	3,261,480
Mean	18,052	5.2	3	1	11.3	2013	17,005,149
Median	16,200	5	3	1	13	2015	15,582,100

3.1.3. Data Derivation

The LCC of the prediction model was been studied over a period of 30 years. To compare the LCCs of the industrial buildings over the past 30 years, several hypotheses were considered. The initial costs, O&M, EIC, and EoL costs of all buildings were converted to the "present values" in 1991. We assumed that that for each building, the changes in cost over time were proportional to the rate of inflation [65]. The present value of all costs was calculated according to the following equations [66]:

The present value of the initial cost was calculated according to the following equation:

$$PV_{IC} = IC \times \prod^{t}{}_{i=1} (1 + \mathrm{r}_i) \tag{1}$$

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 was calculated according to the following equation:

$$PV_{OM} = \Sigma^{\mathrm{n}}{}_{\mathrm{j}=1} ((\mathrm{EC_j} + \mathrm{C\&S_j} + \mathrm{CC_j} + \mathrm{MR_j} + \mathrm{PM_j} + \mathrm{R\&I_j}) \times \prod^{\mathrm{j}}{}_{i=1} (1 + \mathrm{r}_i)) \tag{2}$$

where:

PV_{OM} is the present value of operation and maintenance costs;
$\mathrm{EC_j}$ is the annual energy cost j years ago;
$\mathrm{C\&S_j}$ is the annual catering and services cost j years ago;
$\mathrm{CC_j}$ is the annual cleaning cost j years ago;
$\mathrm{MR_j}$ is the annual major repairs cost j years ago;
$\mathrm{PM_j}$ is the annual periodic maintenance cost j years ago;
$\mathrm{R\&I_j}$ is the annual rent and insurance costs j years ago;
n is the length of the study period in years.

The present value of the environmental impact cost was calculated according to the following equation:

$$PV_{EIC} = \Sigma^{\mathrm{n}}{}_{\mathrm{j}=1} ((\mathrm{MWC_j} + \mathrm{Rco_{2j}}) \times \prod^{\mathrm{j}}{}_{i=1} (1 + \mathrm{r}_i)) \tag{3}$$

where:

PV_{EIC} is the present value of environmental impact cost;
$\mathrm{MWC_j}$ is the annual structure and envelope material waste cost j years ago;
$\mathrm{Rco_{2j}}$ is the annual market price of resulting CO_2 j years ago.

The present value of the end-of-life cost was calculated according to the following equation:

$$PV_{\mathrm{EoLC}} = \Sigma^{\mathrm{n}}{}_{\mathrm{j}=1} ((\mathrm{DC_j} - \mathrm{SV_j}) \times \prod^{\mathrm{j}}{}_{i=1} (1 + \mathrm{r}_i)) \tag{4}$$

where:

PV_{EoLC} is the present value of end-of-life cost;
DC_j is the annual demolition cost j years ago;
RV_j is the annual residual value cost j years ago.

3.2. Development of the LCC Deep Learning Prediction Model

This study presents new software using a library built in a .NET framework—asp.net core MVC; database: Microsoft SQL Server Database; programming language: C#. The deep learning network is applied by a deep belief network with restricted Boltzmann machine hidden layers, based on 312 historical data of input and output criteria. A belief network is a directed acyclic graph made up of random variables [9,67].

We were able to observe some variables in order to fix two major problems:

- The inference problem: Inferring the configurations of the unobserved parameters.
- The learning problem: Adjusting the connections between variables of the network to be more likely to produce the desired results.

Two types of generative neural network can learn deep belief nets:

- A sigmoid belief net is formed when binary stochastic neurons are coupled in a directed acyclic graph.
- A Boltzmann machine is created when binary stochastic neurons are coupled utilizing symmetric connections.

As a result, the connectivity is restricted in a special way by simple learning with Boltzmann machines.

3.2.1. Configuration of the Deep Belief Network (DBN)

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

Step 1: setting the required parameters for creating the DBN.

The model has a dataset of 312 values, with 6 inputs and 11 outputs. After the network training, 3 hidden layers of restricted Boltzmann machines with 6 hidden neurons in each hidden layer are reached to achieve minimal error in the prediction model (Figure 2).

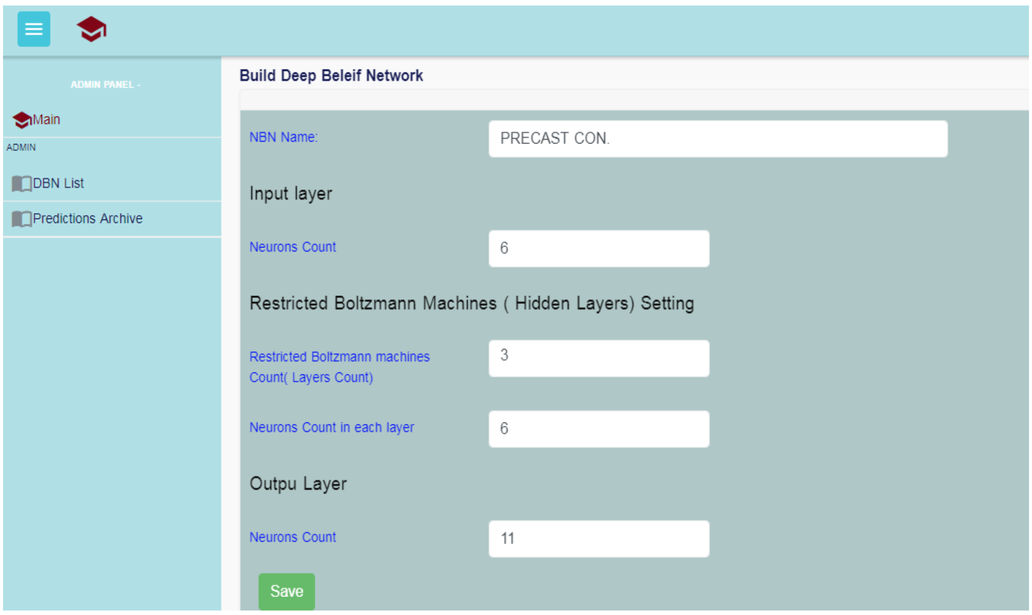


Figure 2. Setting the required parameters for creating the DBN in the interface program.

Step 2: setting the required parameters for the training operation.

The model has a double learning rate that varies from 0 to 1, based on the number of training epochs and dataset size (Figure 3).

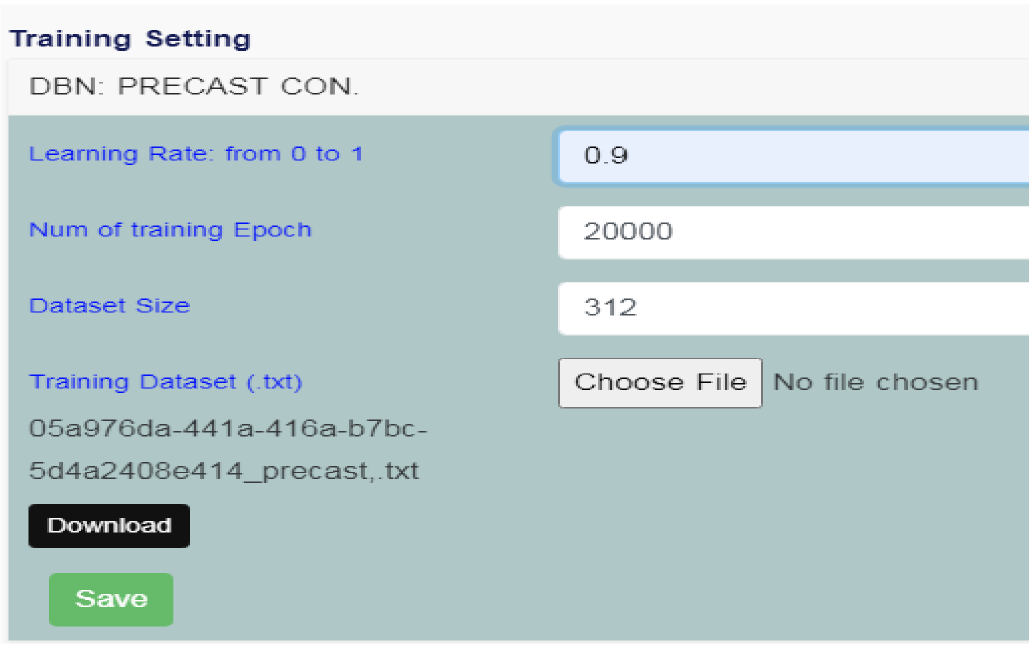


Figure 3. Setting the required parameters for the training operation code.

Step 3: loading the training dataset.

From (choose file) we can upload the dataset as a document file (.txt), and then click "save" (Figure 3).

3.2.2. Training of the Network

A dataset of 312 values, with 6 inputs and 11 outputs, is used in the training phase to choose the best numbers of hidden layers and neurons until the model establishes weights that achieve minimal errors.

- DBNs are trained using greedy learning methods. For learning the top-down, generative weights, the greedy learning algorithm employs a layer-by-layer approach [9].
- On the top two buried layers, the DBNs follow Gibbs sampling steps. The RBM described by the top two hidden layers is sampled in this stage.
- DBNs use a single pass of ancestral sampling through the rest of the model to generate a sample from the visible units.
- DBNs learn that the values of the latent variables in each layer can be inferred using a single bottom-up pass.

Finally, three hidden layers of the RBM, with six hidden neurons in each hidden layer, achieve the minimal errors of the model outputs during the training phase; Figure 4 shows an example of the DBN structure [9].

3.2.3. Predicted Values of LCC Parameters from DBN Input Simulations

LCC outputs can be predicted by choosing prediction archive and then clicking "create prediction", causing an input page to appear, as shown in Figure 5; we can fill all required inputs (Figure 5), and then click "predict". All output results will then appear; Figure 6 shows how the program works.

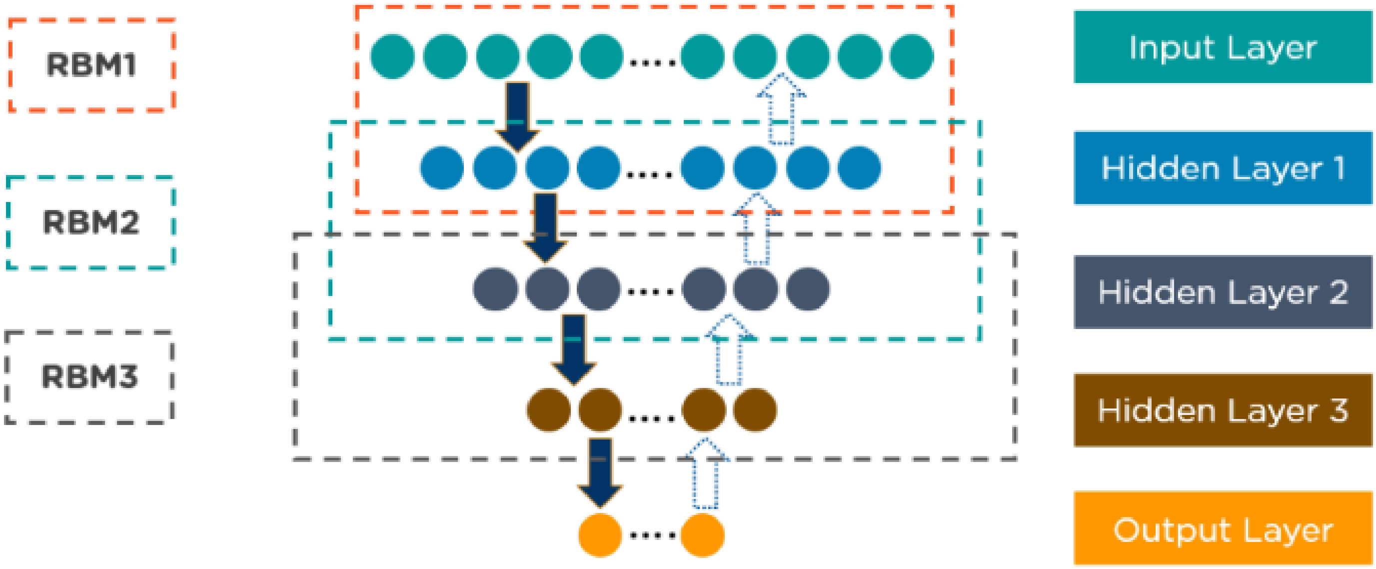


Figure 4. The developed DBN structure with multilayer RBM for the LCC prediction model.

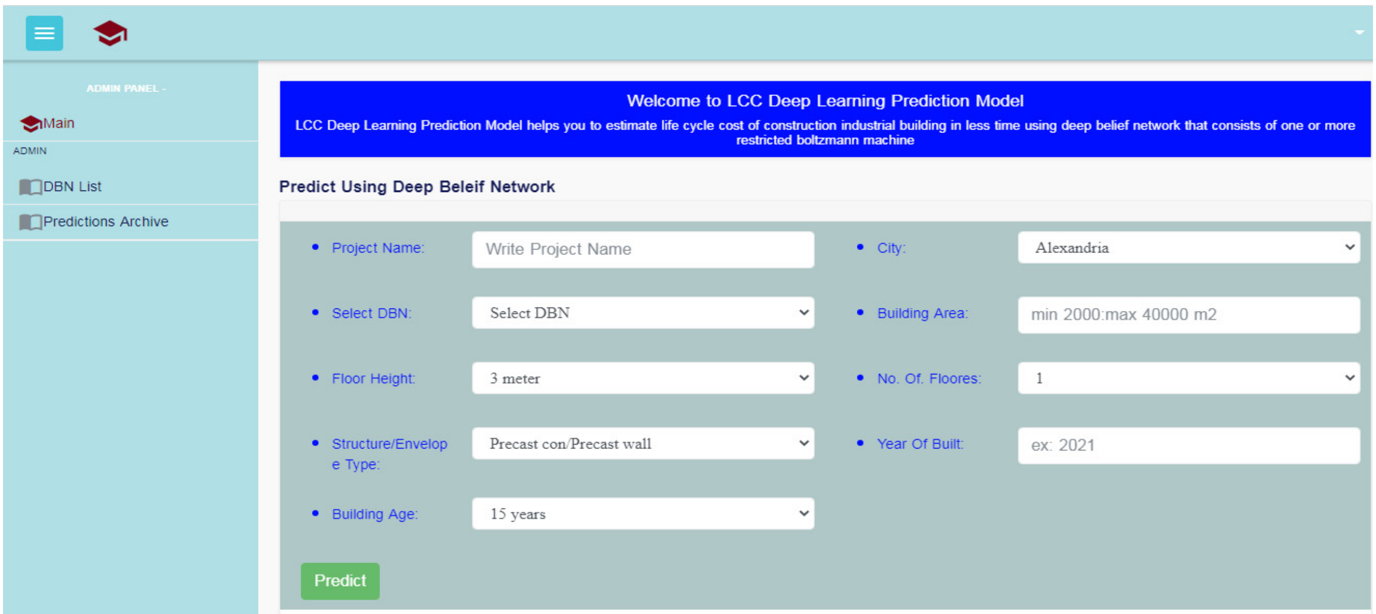


Figure 5. All required inputs of the model.

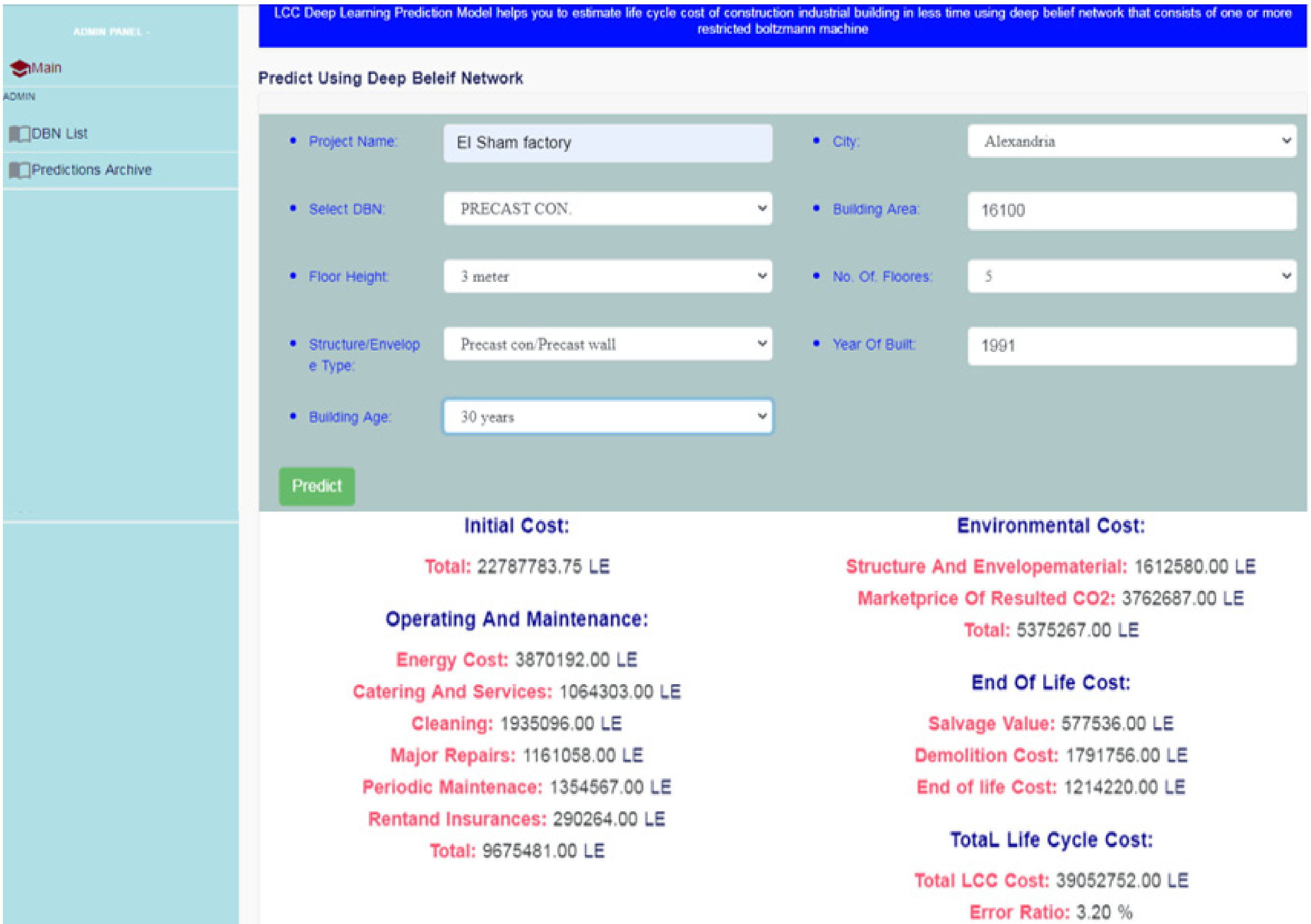


Figure 6. How the program works.

4. Validation and Implementation with Case Study

4.1. Validation of the Network

The validity of the utilized LCC prediction model is considered a crucial concept. Therefore, seven case studies of precast industrial buildings are devoted in this section to validating the prediction modelling procedures. The inputs and the actual LCCs of the seven case studies were obtained from the Modern4concrete group in Egypt, and are displayed in Tables 4 and 5 for the year of 2021.The values are forecasted for 30 years of building age from the year of 1991, extracted from deep learning input simulations, as shown in Table 6. The prediction model calculates an error ratio of each case between 3.2 and 3.82, as shown in Table 6.

Table 4. Data collection of the seven case studies.

No.	Project Name	City	Input Building Parameter		
			Area (m^2)	Floor Height (m)	Number of Floors
1	Frag Tex	10th of Ramadan	13,435	8	1
2	Shrbagy Textile	10th of Ramadan	11,560	5	3
3	El sham	El Obour	16,100	3	5
4	Basma Gee	10th of Ramadan	7784	8	1
5	Fitex	10th of Ramadan	11,344	6	2
6	Mise Spain Soinng factory	Sadat city	38,388	5	3
7	Exaust Store Robaeia	Sadat city	4672	8	1

Table 5. Actual LCC of the case studies in 2021 (L.E).

Actual Values of Buildings' LCC in 2021 (EGP)								
Project Name		**Frag Tex Factory**	**Shrbagy Textile Factory**	**El Sham Factory**	**Basma Gee Factory**	**Fitex Factory**	**Mise Spain Soinng Factory**	**Exaust Store Robaeia**
IC		15,450,250	22,831,000	26,967,500	7,394,800	20,702,800	40,891,065	4,947,413
O&M Cost	EC	2,410,509	3,545,335	4,228,111	1,178,026	3,240,058	6,385,139	774,764
	C&S	665,865	987,217	1,166,355	315,457	841,566	1,736,051	213,060
	CC	1,201,755	1,727,667	2,131,555	574,013	1,651,029	3,190,820	387,382
	MR	725,553	1,072,600	1,260,933	342,408	972,318	1,916,692	232,429
	PM	842,828	1,255,367	1,478,689	405,409	1,134,720	2,237,974	271,167
	R&I	181,063	268,950	316,233	86,352	247,154	473,923	58,107
EIC	MWC	1,048,129	1,439,723	1,709,629	452,511	1,392,858	2,612,683	322,818
	RCO2	2,354,301	3,406,020	4,235,802	1,185,858	3,153,001	6,198,260	753,243
EoL	SV	442,057	652,099	762,058	216,449	620,381	1,162,526	143,474
	DC	1,160,143	1,525,248	1,923,144	542,123	1,530,953	2,976,314	358,687

Table 6. The predicted values from the deep learning model after 30 years.

Predicted Values LCC of Buildings' after 30 Years (EGP) from the Year of 1991								
Project Name		**Frag Tex**	**Shrbagy Textile**	**El Sham**	**Basma Gee**	**Fitex**	**Mise Spain Soinng Factory**	**Exaust Store Robaeia**
IC		13,844,146	23,099,754	2,2787,784	7,296,579	19,416,808	39,286,999	5,061,459
O&M Cost	EC	2,151,722	3,983,835	3,870,192	1,201,967	2,837,209	6,792,340	757,467
	C&S	591,724	1,095,555	1,064,303	330,541	780,233	1,867,893	208,303
	CC	1,075,861	1,991,918	1,935,096	600,984	1,418,605	3,396,170	378,733
	MR	645,517	1,195,151	1,161,058	360,590	851,163	2,037,702	227,240
	PM	753,103	1,394,342	1,354,567	420,689	993,023	2,377,319	265,113
	R&I	161,379	298,788	290,264	90,148	212,791	509,426	56,810
EIC	MWC	896,551	1,659,931	1,612,580	500,820	1,182,170	2,830,142	315,611
	RCO2	2,091,952	3,873,173	3,762,687	1,168,579	2,758,398	6,603,664	736,426
EoL	SV	321,260	564,525	577,593	176,410	485,232	1,074,311	149,914
	DC	996,168	1,844,368	1,791,756	556,466	1,313,523	3,144,602	350,679
Error Ratio %		3.60	3.47	3.20	3.53	3.64	3.82	3.31

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

4.1.1. Descriptive Statistics

Basic statistical information was studied for the seven case studies. Table 7 shows the mean and standard deviation of each case study.

Table 7. The mean and standard deviation of each case study.

	Frag Tex	**Shrbagy Textile**	**El Sham**	**Basma Gee**	**Fitex**	**Mise Spain Soinng Factory**	**Exaust Store Robaeia**
Mean	2,139,035	3,727,394	3,655,261	1,154,888	2,931,741	6,356,415	773,432
Standard Deviation	3,933,869	6,532,598	6,447,773	2,067,754	5,530,462	11,103,635	1,439,142

4.1.2. Regression and Mean Square Error Results

The correlation between outputs and targets was evaluated using regression results. 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 predicted and real series. The average squared difference between outputs and targets is known as the MSE. For each case study, Table 8 provides the regression and mean square error results.

Table 8. The regression and mean square error of the seven case studies.

	Frag Tex	Shrbagy Textile	El Sham	Basma Gee	Fitex	Mise Spain Soinng Factory	Exaust Store Robaeia
R	1.00	0.996	0.998	1.00	0.997	0.998	0.995
Mean Square Error E14	1.547	4.260	4.156	0.427	3.058	12.30	0.207

The next step of the model validation is to plot the regression between the outputs and the actual values to find their relationship, as shown in Figure 7. The relationship seems perfect when the network outputs and the actual values are exactly equal, but it is rarely ideal in practice. For each case study, the network outputs are shown against the actual values in the following regression plots (Figure 7). The fit is satisfactory for all cases, with R values 0.995 or above. A regression model relates Y to a function of X and β, where β is the unknown parameter, X is the independent variable (actual), and Y is the dependent variable (output).

4.1.3. Autocorrelation Test (Durbin–Watson)

The Durbin–Watson statistic ranges from zero to four. Positive autocorrelation is defined as a value between zero and two, whereas negative autocorrelation is defined as a number between two and four. We have positive autocorrelation in Frag Tex, at less than 2. The rest of the seven case studies have negative autocorrelation, as the autocorrelation is greater than 2. Table 9 shows Durbin–Watson autocorrelation for each case study in the model, with all outputs correlated strongly.

Table 9. Durbin–Watson autocorrelation for the seven case studies.

	Frag Tex	Shrbagy Textile	El Sham	Basma Gee	Fitex	Mise Spain Soinng Factory	Exaust Store Robaeia
Durbin–Watson	1.138	2.969	2.790	2.118	2.599	2.735	2.833

4.2. Implementation with a Case Study

We applied the economic branch of sustainability in this case study by predicting the LCC of the three different alternative structural frames, so as to enable decision makers on industrial boards to select the best structures and envelope types for their new industrial buildings. The analyzed case study is a one-story industrial factory building built in El Mahalla city, El Garbiah, Egypt, in 2019. Table 10 shows the general parameters of the tested case study.

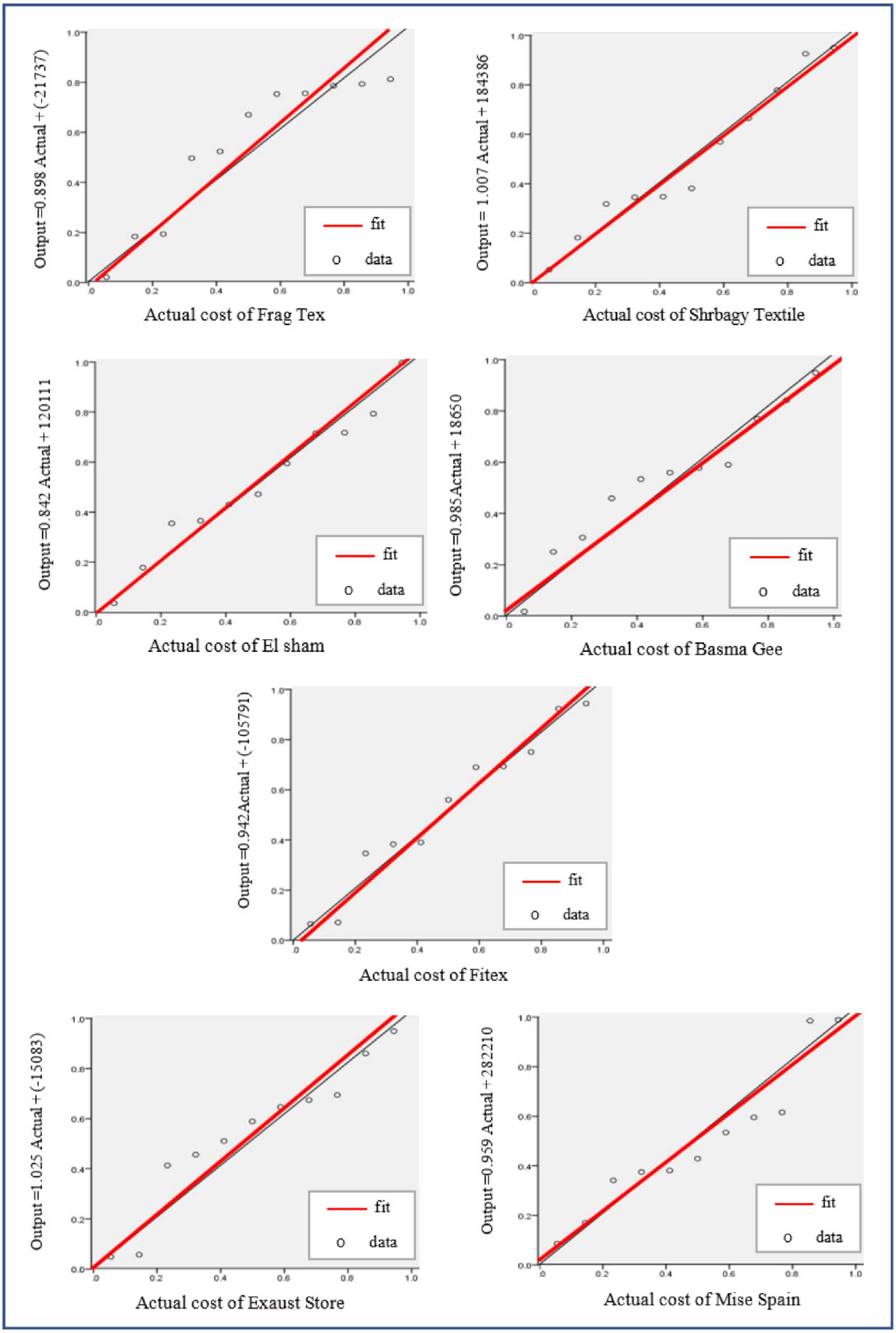


Figure 7. A regression plot between the independent variable (actual) and the dependent variable (output) for the seven case studies.

Table 10. General parameters of the tested case study.

Parameter	Description	Parameter	Description
Industry name	El Mahalla Spinning	City	El Mahalla
Area	53,398 (m^2)	Number of floors	1
Floor height	8 (m)	Structure type	Test all
Lifespan	30 years	Year of construction	2019

Meanwhile, we achieved the prediction model objectives shown in Table 11, which presents the total life cycle component costs for each alternative in Egyptian pounds (EGP), at an extremely constant error ratio of about 5%.

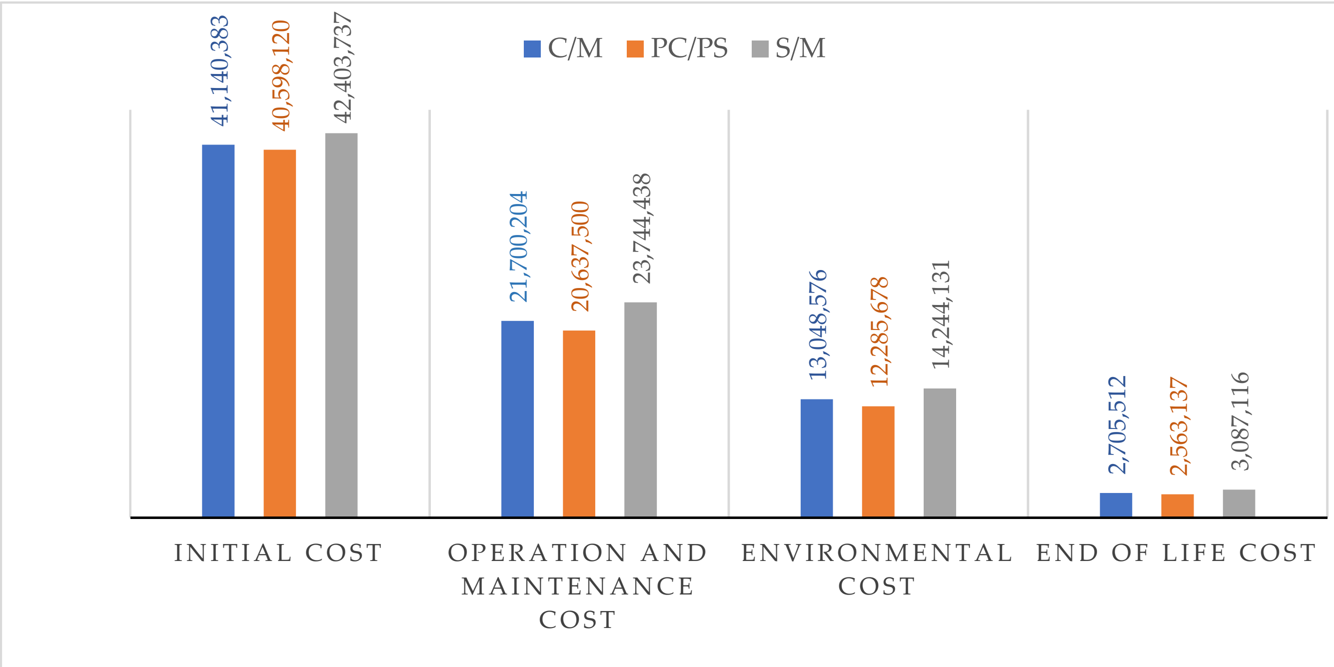
Table 11. Shows El Mahalla Spinning's predicted LCC over 30 years (EGP), with the three variables C/M, PC/PS, and S/M.

		C/M		PC/PS		S/M	
Initial Cost (IC)		41,140,383		40,598,120		42,403,737	
O&M Cost	EC	9,097,530	21,700,204	8,571,926	20,637,500	9,892,950	23,744,438
	C&S	2,310,490		2,212,022		2,539,439	
	CC	4,200,891		4,021,858		4,617,162	
	MR	2,520,535		2,413,115		2,770,297	
	PM	2,940,624		2,815,301		3,232,014	
	R&I	630,134		603,279		692,574	
EIC	MWC	3,914,573	13,048,576	3,685,694	12,285,678	4,273,239	14,244,131
	RCO2	9,134,003		8,599,953		9,970,892	
EoLC	SV	1,199,273	2,705,512	1,175,703	2,563,137	1,203,084	3,087,116
	DC	3,904,784		3,738,840		4,290,200	
Total LCC (EGP)		78,594,676		76,084,405		83,479,422	
Error Ratio %		5.05		5.03		4.99	

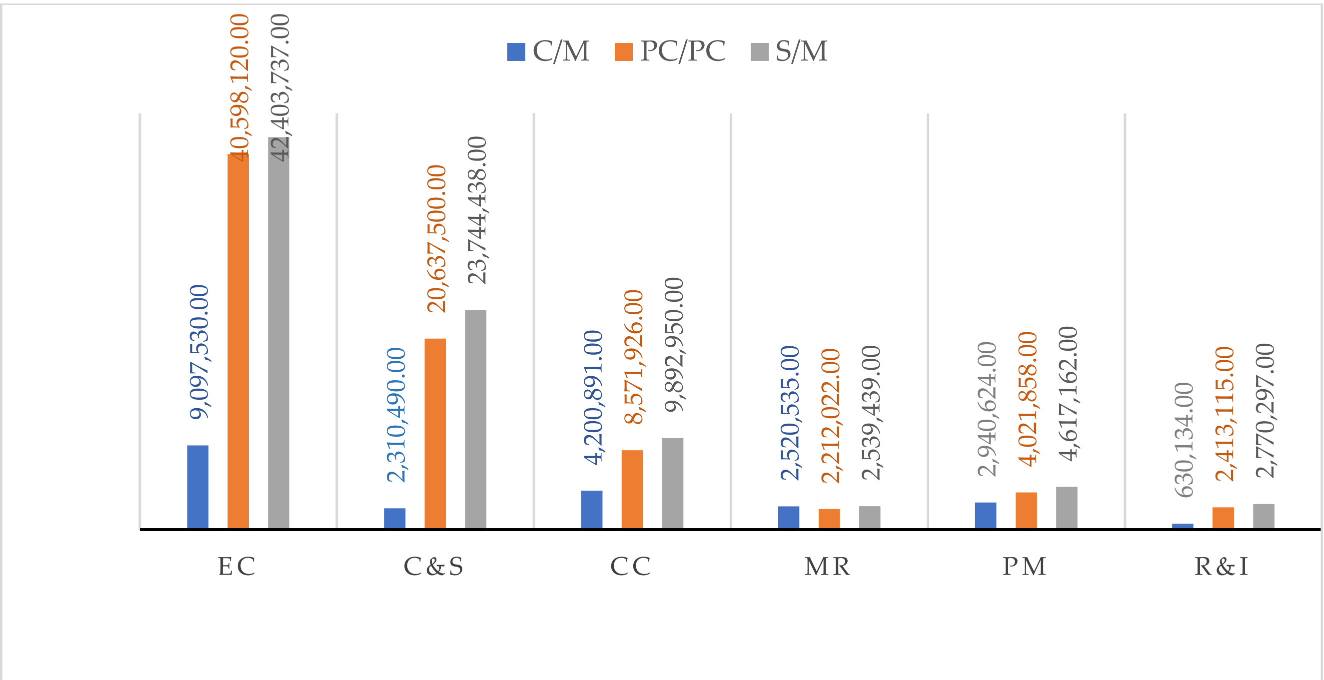
5. Results

The results of the case study demonstrate the effectiveness of the deep learning LCC prediction model framework for identifying the best structure frame between the three different alternatives, at an extremely constant error ratio of about 5%, where the LCC values of the precast concrete frame with precast concrete walls alternative (PC/PS) achieved the best scores, compared with the reinforced concrete frame with masonry wall alternative (C/M) and the steel frame with masonry wall alternative (S/M), which increased the costs by 3.2% and 8.9%, respectively. The lowest initial cost was recorded at 40.6 million LE for the PC/PS alternative, while the highest cost was 42.4 million LE for the S/M alternative. The O&M costs varied between 20.38, 21.7, and 23.74 million LE for PC/PS, C/M, and S/M, respectively, as shown in Scheme 1, while EIC and EoL cost achieved the highest scores in S/M and C/M, respectively, and the lowest in the PC/PS alternative.

As an alternative to cast-in-place and steel construction, pre-stressed/precast concrete construction can increase a building's overall sustainability in terms of both environmental and economic aspects. This was clear in terms of energy costs, catering and services, cleaning, major repairs, and periodic maintenance costs, as all of these values in PC/PS were the least cost, and increased in C/M by approximately 4% and in S/M by 11%. As such, PC/PS provides the opportunity to investigate the reuse of existing materials from a previous project several times in order to reduce operating and maintenance costs, as shown in Scheme 2.

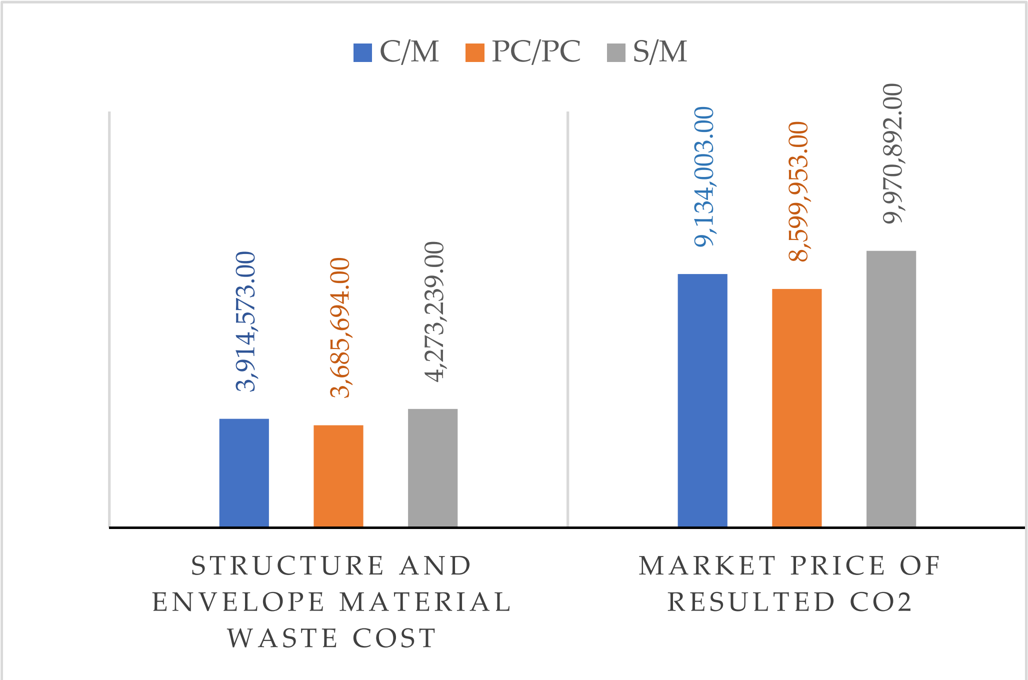


Scheme 1. The LCC component values of the various alternatives for the case study.



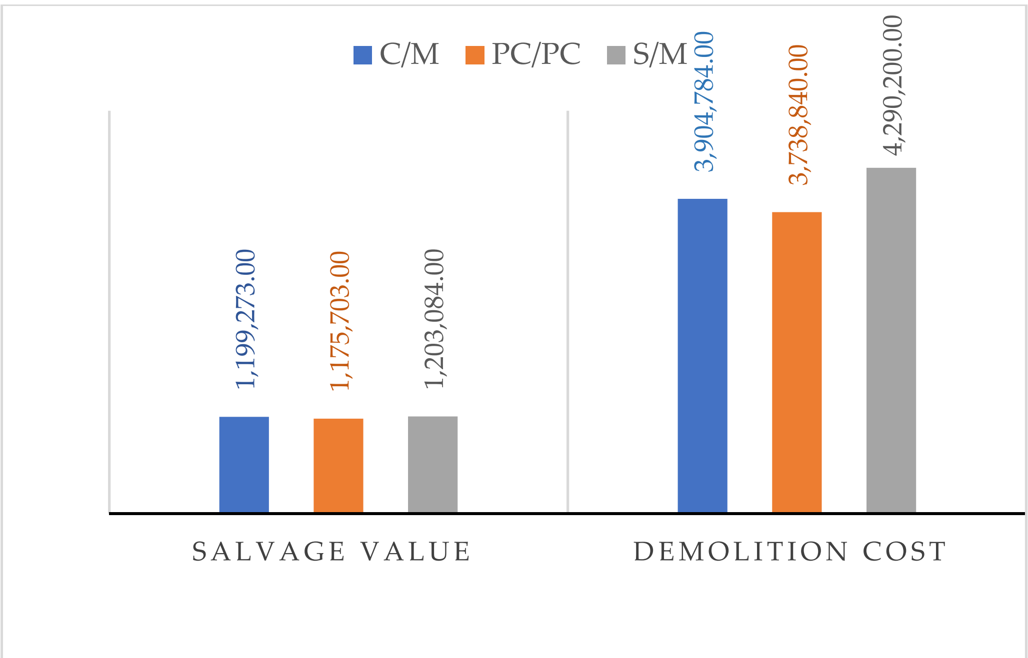
Scheme 2. Shows the operating and maintenance component values of the various alternatives for the case study.

Among the environmental impact costs related to our case study, structure and envelope material waste cost 3.91 million EGP in C/M, 3.68 million EGP in PC/PS, and 4.273 million EGP in S/M, whereas the market price of resulting CO^2 in PC/PS was the lowest compared to C/M and S/M, as shown in Scheme 3.



Scheme 3. The environmental impact cost component values of the various alternatives for the case study.

Precast/pre-stressed concrete construction allows for the possibility of removing existing sections during the demolition of one project, and their reuse in a new project, so PC/PS provides the most savings in demolition costs, followed by C/M and S/M. Thus, it was natural to achieve the highest residual value in PC/PS, as shown in Scheme 4.



Scheme 4. Shows the end-of-life cost component values of the various alternatives for the case study.

6. Discussion

To improve the economic sustainability throughout the lifespan of industrial buildings, an LCC deep learning prediction model framework can be applied. The model published by Reisinger et al. [49] increases the flexibility and economic advantages of industrial building structures, whereas the developed deep learning tool described in this research can be used to model historical costs and forecast the life cycle costs of industrial buildings in Egypt in a fast manner. The proposed framework of this study enables us to predict and compare between three different structures and envelope types of industrial buildings—a reinforced concrete frame, a precast/pre-stressed concrete frame, and a steel frame—and to make decisions as to the most suitable structure.

A few studies have provided feedback on the economic performance of industrial buildings [46–48]. This is why in this study we created a new forecasting tool that can estimate the life cycle costs of the different structural framework alternatives in industrial buildings. The findings of the industrial case study show that the deep learning LCC prediction model framework is effective in selecting the optimal structural frame from among the three alternatives, with an extremely low error ratio of roughly 5%. The LCC of the precast concrete frame with precast concrete walls alternative (PC/PS) achieved the best scores, compared with the reinforced concrete frame with masonry wall alternative (C/M) and the steel frame with masonry wall alternative (S/M), which are increased the LCC by 3.2% and 8.9%, respectively.

According to previous research on the evaluation of the sustainability performance of industrial buildings [13,47,68–70], as an alternative to cast-in-place and steel construction, pre-stressed/precast concrete construction can increase a building's overall sustainability in terms of economic aspects. This can be seen clearly in terms of energy costs, catering and services, cleaning, major repairs, and periodic maintenance costs, as all of these values had the least cost in PC/PS, increasing in C/M by approximately 4% and in S/M by 11%. As such, PC/PS provides the opportunity to investigate the reuse of existing materials from a previous project several times in order to reduce operating and maintenance costs.

The literature on precast concrete buildings [70–73] indicates that this is the most sustainable structure type. The results of this research indicate that a precast concrete frame is the most economically sustainable structural alternative for industrial buildings, as it achieved the lowest cost of all LCC variables. This research presents a quick and easy method to forecast the LCC of buildings without resorting to long and complicated calculations, by using a deep learning network model based on a DBN with RBM hidden layers. Moreover the developed deep learning prediction model allows users to predict the cost closer to the real cost, because it gives a minimal error rate.

Future research directions abound for this model, which is not only useful for the LCC prediction of industrial buildings, as presented here, but also has broader implications for LCC modeling in the modeling of competing options for other buildings. If the prediction model is uploaded with a historical dataset file document (.txt) of any type of building—such as schools, residential, infrastructure, or commercial buildings—the model can learn these data and predict the LCC of a new building of the same type after n years.

7. Conclusions

A new approach is presented in this study for modelling historical costs and forecasting the life cycle costs of industrial buildings in Egypt in a fast manner. This method is based on a deep learning network, which combines a deep belief network and restricted Boltzmann machine. The dataset was composed of 312 values, with 6 input and 11 output criteria, in an Excel sheet, and converted into a document file (.txt) to prepare it for uploading to the model. The LCC prediction model inputs were building area, floor height, number of floors, structure and envelope type, building age, and year of construction. The outputs of the model were initial cost, operating and maintenance (energy cost, catering and services, cleaning, major repairs, periodic maintenance, and rent and insurance), environmental impact cost (structure and envelope material waste costs, and market price of resulting CO_2), and end-of-life cost (salvage value and demolition cost). All costs of buildings were converted to the "present values" in 1991, according to the rate of inflation. During the training phase of seven case studies in the deep belief network, three hidden layers of restricted Boltzmann machines, with six hidden neurons in each hidden layer, achieved the minimal errors of the model outputs.

The prediction model was experimentally validated by seven case studies of precast industrial buildings over a study period of 30 years, from 1991 to 2021. The prediction model calculated the error ratio between 3.20 and 3.82 for the seven case studies. This model provides a much more accurate forecast of construction costs in the long run.

Statistical methodology was utilized to validate the outputs of the network by using some descriptive statistics, regression, mean square error, and autocorrelation, with the assistance of SPSS Statistics v22. The fit was reasonably good for all cases of regressions between the outputs of the network and the actual costs, with R values 0.995 or above. In the deep learning prediction model, the outputs were strongly correlated.

This model is not only useful for forecasting the LCC of precast industrial buildings, but also has wider implications for modelling LCC in competing option modelling in three types of structural frames: reinforced concrete frames, precast/pre-stressed concrete frames, and steel frames. This modeling was applied in an industrial case study to compare and make a decision as to the most suitable structure and envelope type of buildings in terms of economic sustainability, at an extremely constant error ratio of about 5%. The results show that the precast concrete frame is the most economically sustainable of the structural alternatives for industrial buildings, as it achieved the lowest LCC after 30 years compared with the reinforced concrete frame and the steel frame, which increased the LCC by 3.2% and 8.9%, respectively.

There is a future opportunity to apply this prediction model to all manner of buildings, such as schools, economic buildings, infrastructure, or residential buildings; if a historical dataset file document (.txt) of the same type of building is uploaded, the model can learn these data and predict the LCC of a new building of the same type after n years.

Future research should study the environmental impact cost criteria related to a wide range of industrial buildings in more detail, as this was not covered clearly in this study.

Future studies may assess other types of building using sustainability measures and life cycle costing techniques, such as offshore structures.

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