Predicting Construction Materials Prices Using Fuzzy Logic and Neural Networks

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Abstract: Changes in construction materials prices have a great impact on the cost of construction projects. Such changes in prices occur randomly at different rates over time. There is no clear relationship that can be used to provide accurate calculations of materials prices. One of the biggest problems that faces the construction contracts is unbalanced rights and obligations between owners and contractors (the two parties of construction contracts). It is necessary to have a system that is capable of estimating the size and amount of the change in materials prices at reasonable accuracy. There is also a need to predict the change in building materials prices (either increase or decrease) during the execution phase of the project as well as during the preparation of tenders. Thus, determination of the appropriate lead time to order needed building materials to execute various activities could be done. This research presents a system that utilizes fuzzy logic to identify construction materials that are most sensitive to the change in prices. The research proposes a methodology for identification of construction materials that are most sensitive to the change in prices to be used in modifying the contract price with an attempt to predict the amount of future change in materials prices using neural networks technique. To achieve this objective, the research classifies construction cost items into four different components (building materials, equipment, labor, and administrative expenses), which represent the basic cost elements of any cost item. The system is based on the study of the changes in materials prices that occurred in the Egyptian market from 2000 to 2010. It also provides the impact on the prices of cost items in the priced bill of quantities (BOQ), which is determined by the change in prices of cost items' materials and their share percent on forming the cost item. Getting to identify materials' share in the bill of quantities' items has a great influence on the price of the cost item and the priority in ordering these materials according to their impact on the item's price. The developed system aids construction contractors in studying bids during the tendering stage and procurement planning during the project's execution. It can also be used by owners' representatives to estimate the expected total cost of upcoming projects. The system data are obtained from the Central Agency for Public Mobilization and Statistics in Egypt through published periodicals. A numerical example is presented to demonstrate the use of the proposed system. **DOI:** **10.1061/(ASCE)CO.1943-7862.0000707.** *© 2013 American Society of Civil Engineers.*

CE Database subject headings: Construction costs; Construction materials; Fuzzy sets; Neural networks; Predictions; Pricing.

Author keywords: Cost estimating; Construction materials prices; Fuzzy logic; Neural networks; Quantitative methods.

Introduction

Fluctuations in the prices of construction materials have a significant impact on the success of the construction projects. These unforeseen price changes affect project execution rates and even impacts the ability to finish the projects. As a result of the quick and enormous changes that occur all over the world in construction materials prices, the construction market in Egypt is affected. The increases in building materials prices have become huge and rapid to an extent that a contractor who provides a fair offer becomes unable to meet the technical requirements and specifications of the different construction items. Contracts that are affected by the prices' change are those that have a long execution time. These classes of contracts contain a large number of cost items and activities, and surely the idea of studying one cost item and its materials needs a very long time to estimate the change in prices. As such, different elements are required to be estimated including the rate of the material consumption in the cost item, the percentage of change in the original material price, and the value of price change in the most critical materials to the cost item, which in return will affect the item's price. A list of materials that have a change in price during the project's execution must be specified. Also, having a graph that shows the price change in building materials over time would facilitate planning the timely purchasing of raw materials to minimize the amount of effects resulting from price changes on the total value of the project.

Previous work in predictive modeling can be classified into two categories (Taylor and Bowen 1987): the causal method and the time series method. The causal method assumes that the predicted variable is determined by independent explanatory variables. Linear regression models are typically used to structure the relationships between predictors and predicted variable. The causal method has been used to predict tender price indexes (Akintoye and Skitmore 1994; Mccaffer et al. 1984), building price (Runeson 1988), construction cost (Koehn and Navvabi 1989), early cost estimation (Trost and Oberlender 2003), and construction labor cost in Hong Kong (Wong et al. 2005). On the other hand, the time series method determines future trends based on past values and corresponding errors. A time series is an ordered sequence of values of a variable at equally spaced time intervals. Time series analysis comprises methods that attempt to understand the underlying

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Note. This manuscript was submitted on October 8, 2011; approved on February 22, 2013; published online on February 25, 2013. Discussion period open until February 1, 2014; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Construction Engineering and Management***, Vol. 139, No. 9, September 1, 2013. © ASCE, ISSN 0733-9364/(9)/$25.00.

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J. Constr. Eng. Manage. 2013.139:1190-1198.

context of the data points and make systematic forecasts. Time series forecasting is the use of a time series model to predict future data points based on known past data points. The time series method has been used to forecast Taiwan's construction cost indexes (CCIs) (Wang and Mei 1998), property prices (Chin and Mital 1998), building costs (Taylor and Bowen 1987), and tender price index (Fellows 1991; Ng et al. 2000). Utilizing univariate time series analysis requires just one input variable for creating and calibrating models. Historical engineering news record (ENR) CCI data points were used by Ashuri and Lu (2010) to make informed predictions about future trends in construction costs. The advantage of the time series method over other causal predictive methodologies, such as regression analysis and neural networks (NNs), is that these approaches require data for future values of economic-related variables in order to forecast CCI. Most often, future data on economic factors related to construction, such as the prime lending rate or the number of new housing projects, are not readily available for the creation of these forecasting models. Therefore, univariate time series analysis is identified as the most effective way of carrying out the work to develop predictive models for CCI.

Three proposals for price modification are considered in international contracts. The first proposal suits short-term contracts, the increase of value or percentage, or the expected decrease of prices during the contract's period with a reasonable degree of accuracy. According to this, the inadmissibility of any modification to the contract's price as a result of the increase or decrease of the cost of labor or materials or any other issues would affect the cost of the contract's implementing. The second proposal suits modification of the contract's value with each invoice in accordance with the increase or decrease of the costs of labor and materials specified in the contract by calculating the modification value of the contract. This could happen by calculating the difference between the basic prices, which are taken as a reference for modification (the price 28 days before the tender's submission), and the current price of the contract-specified materials, which were received during the period of implementation according to the current price. The third proposal calculates the contract's value adjustment according to the increase or decrease in the cost of labor, materials, or any other issues that could affect the contract's cost for each monthly invoice. None of previous research highlighted the most common cost items in the different construction types and their percentage in the price of the cost items to predict the changes in materials prices. This paper proposes a methodology for identification of construction materials that are most sensitive to the change in prices with an attempt to predict the amount of future change in materials prices. To achieve this objective, the research classifies construction cost items into different components, demonstrating their percentage in each component. Six steps have been followed in order to conduct the proposed methodology: (1) identify the most common cost items in the different construction types, (2) identify the components of each cost item, (3) determine the percentage of each component in the price of the cost item, (4) collect and analyze the historical data of material prices, (5) apply fuzzy logic to know the importance of materials with respect to the change percent in prices within each cost item separately, and (6) apply neural networks to predict future prices.

Research Contribution

This research proposes a methodology for identification of construction materials that are most sensitive to the change in prices to be used in modifying the contract price with an attempt to predict the amount of future change in materials prices. Neural networks technique is used to make the prediction in an effort to end up with a reasonable estimate of future projects costs. To achieve this main objective, the research classifies construction cost items into four different components (building materials, equipment, labor, and administrative expenses) that represent the basic cost elements of any cost item. Although historical data are obtained from the Egyptian market to build and test the proposed methodology, the methodology can be generalized to be applied to any construction market.

Data Analysis

Thirteen cost items represent the most common items in the majority of the construction projects. This research addresses the idea of price analysis for the repeated items by determining the cost elements within each item and studying the share of each element in the total item price. In order to reach a list that contains the substances that have the greatest impact in price changes, some elements are identified for detailed study in order to estimate the amount of compensation required in the prices of items. Four main categories represent the basic cost elements of any cost item, which are building materials, equipment, labor productivity, and administrative expenses. The proportion of the materials within the cost items differs according to the project and its components. Therefore, the importance of any element of the cost elements changes from one cost item to another. It is possible that the importance of the same material differs from one cost item to another. That is why one element may be the subject of study in one of the cost items when it is totally ignored in another cost item. Therefore, it is important to evaluate each element of the basic cost elements independently in each cost item of the project. The basic criteria of cost elements evaluation are (1) the rate of consumption in this item, (2) the percentage of change in the original price, and (3) the amount of price change. Evaluation of many criteria is subjective and ambiguous in meaning. Also, it is not an easy task to determine one common scale of evaluation for all criteria.

Analysis of Common Cost Items

Studying the main cost items that are repeated in construction projects and analyzing the prices for each element independently is important to determine the components of each cost item and find out the rates of participation in the prices of cost items. Analysis of the previous common cost items (13 cost items), the share of all the cost elements in all the cost items, is listed as per Table 1. The common elements in the 13 cost items are equipment, gravel and sand, cement, blocks, reinforcement bars, insulation material, paints material, ceramic, tiles, marble, wood, aluminum, and steel. The components of the common elements sum 90% of the element price in Table 1. The remaining 10% represents site overheads (e.g., mobilization, cost of issuing insurance letters). These elements of cost are not subject to any increase in prices for their implementation because they take place before the start project execution.

In this research, the data records of the considered materials are gathered during the period between January 2000 to December 2010 by collecting data from periodicals published every two months from the Central Agency for Public Mobilization and Statistics—Egypt (CAPMAS). The published periodicals include the prices for construction materials and the change that takes place on the materials prices in two successive years for the same considered month.

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Table 1. Analysis of Common Cost Items Prices

Item	Component	% share
Excavation and backfilling	Equipment	30
	Labor	35
	Sand	25
Plain concrete	Equipment	10
	Labor	29
	Cement	37
	Gravel and sand	14
Reinforced concrete	Equipment	10
	Labor	29
	Reinforcement bars	40
	Cement	9
	Gravel and sand	2
Block works	Blocks	44
	Labor	32
	Cement	12
	Sand	2
Insulation works	Labor	25
	Insulated material	65
Plaster works	Labor	55
	Cement	32
	Sand	3
Paints works	Labor	55
	Paints material	35
Ceramic works	Ceramic	46
	Labor	35
	Cement	7
	Sand	2
Wood works	Equipment	10
	Labor	30
	Wood	50
Aluminum works	Equipment	10
	Labor	30
	Aluminum	50
Tiles works	Tiles	46
	Labor	35
	Cement	7
	Sand	2
Steel works	Equipment	10
	Labor	30
	Steel	50
Marble works	Marble	46
	Labor	35
	Cement	7

Data Processing

The collected data are initially processed by calculating the average, maximum, and minimum values of each item of the cost items. Accordingly, the different percent of share in each cost item is calculated and the change value in the material prices is obtained during the study period. Finally, the proportion of this change for the price to the original is calculated, and different graphs are generated to illustrate the change in the price.

Developed Fuzzy Model

Fuzzy techniques have been increasingly applied to construction management research area (Chan et al. 2009). The Fuzzy Logic Tool was introduced in 1965 by Lotfi Zadeh to provide a technique to deal with imprecision and information granularity. The fuzzy theory provides a mechanism for representing linguistic constructs such as many, low, medium, often, and few. In general, the fuzzy logic provides an inference structure that enables appropriate human reasoning capabilities.

Task Identification

This stage involves the categorization of the materials forming the item in terms of the degree of importance according to its impact on the price change. As a result, the price changes that occurred during the previous 10 years and the impact of this change in the price of the materials on the total price of the item are determined in order to select the materials that are worth studying to predict their future prices.

Data Analysis

This stage involves collecting the data of the materials existing in the study items and calculating the corresponding values for each criterion of the criteria upon which the comparison is made and determining a range for each criterion based on historical data for material prices from year 2000 to year 2010. The data used in fuzzy model for three criteria are as follows:

- For Criterion 1 (percent of element share in the total cost item's price), it ranges from 0 to 70;
- For Criterion 2 (difference in the study price index element during the study period), it ranges from 0 to 2,000; and
- For Criterion 3 (percent of difference in the cost element price), it ranges from 0 to 710.

Fuzzy Model

A fuzzy set is characterized by its membership function, which represents numerically the degree to which an element belongs to a set. Unlike conventional (crisp) sets theory in which objects are either in or out of a set, fuzzy sets theory allows objects to have partial membership in a set. Decision makers can use linguistic variables both for the criteria and for the degree of satisfying them by materials. The proposed model utilizes an interpretation technique of the linguistic variables that has been used in previous studies (Singh and Tiong 2005; Plebankiewicz 2009).

Fuzzy Numbers and Fuzzy Linguistic Variables

A triangular fuzzy number is a particular fuzzy set F, and its membership function $\mu F(x)$ is a continuous piecewise linear function as per Eqs. (1)–(3) (Cakir and Canbolat 2008).

$$F \subseteq \mathfrak{R} \tag{1}$$

$$\mu F(x){:}\mathfrak{R} \rightarrow [0,1] \tag{2}$$

$$\mu F(x) = 0 \quad \text{for all } x \in (-\infty, l] \cup [u, +\infty) \quad \text{and} \quad \mu F(x) = 1 \tag{3}$$

where $l, m, u \in \mathfrak{R}$; l and u = lower and upper bounds, respectively; m = most likely value of F; and $\mu F(x)$ is monotonically increasing when $x \in [l, m]$, and monotonically decreasing when $x \in [m, u]$.

As a logical approximation to crisp comparison ratios a_{ij}, the comparison ratios are fuzzy numbers such as $\sim a_{ij}$, which portrays the judgment "approximately a_{ij}" and hence describe some degree of blurred human perception about the comparison. Particular linguistic assessment terms, so-called fuzzy linguistic variables, are introduced to represent the underlying fuzzy numbers for criteria evaluations. "A fuzzy linguistic variable is an expression in natural or artificial language" (Zadeh 1975) that describes a collection of values. Assume that there are nonnumerical expressions about the weather condition such as cold, chilly, moderate, warm, and hot, each of which is modeled by a fuzzy number representing the approximate weather degree in intervals (i.e., chilly ranging between 0 and 15°C with a most likely value of 10°C). Then these nonnumerical expressions are referred to as fuzzy linguistic variables (Cakir and Canbolat 2008). Linguistic variables (very important, important, average, low importance, very low importance), refer to the evaluation of the importance degree in evaluation of a given criterion, whereas linguistic variables values (very high, high, medium, small, very small) refer to the evaluation of the degree of materials satisfying the criterion. Linguistic variables are converted into fuzzy numbers, which are reported by Singh and Tiong (2005). The proposed model considers three inputs (percent of element share in the total cost item's price, difference in the study price index element during the study period, and percent of difference in the cost element price) and one output (degree of importance), as shown in Tables 2 and 3, respectively. A linguistic variable is represented by fractional values in the range of 0 to 1 to represent degree of importance using a trapezoidal fuzzy number considering five linguistic variables values for degree of importance, which are very important, important, average, low importance, and very low importance. The trapezoidal fuzzy number (TFN) is represented by four real parameters, a, b, c, d ($a \leq b \leq c \leq d$), as per Table 3. For example, fuzzy number for average important is expressed as (0.4, 0.5, 0.5, 0.6).

Inputs Processing

Mamdani Fuzzy Inference System (FIS) is the most known or used in developing fuzzy models. The output of the system is generally defuzzified, resulting in fuzzy sets that are combined using aggregation operator from the consequent of each rule of the input. A single if-then rule is written as shown in Eq. (4).

$$\text{IF } X \text{ is } A, \quad \text{THEN } Y \text{ is } B \tag{4}$$

where A and B = linguistic values defined by fuzzy sets on the ranges X and Y, respectively. The if part of the rule, X is A, is called the antecedent or premise, while the then part of the rule, Y is B, is called the consequent or conclusion.

Depending on the system, it may not be necessary to evaluate every possible input combination because some may rarely or never occur. By making this type of evaluation, which is usually done by an experienced operator, fewer rules can be evaluated, thus simplifying the processing logic and perhaps even improving the fuzzy logic system performance (Sivarao et al. 2009). In this paper, the input membership function is divided into five linguistic values in which each input is denoted as very small, small, medium, high, and very high, respectively. Also, the output membership function is divided into five linguistic values in which each output is denoted as very low importance, low importance, average, important, and very important, respectively.

The determination of the membership function is done using the ANFIS Toolbox in MATLAB. This technique enabled excellent model development for nonlinear process in which the rules were automatically generated under the ANFIS environment. The membership function and set of rules are fed to the system to determine the response. Each rule in the system is considered very important and critical to generate the predictions in numeric form.

Model Rules

A total of 22 rules are created to get degree of importance for each material and to ensure the desired output is reliable and satisfactory. It indicates the behavior of the response over the change in values of all the three material criteria, which are percent of element share in the total cost item's price, difference in the study price index element during the study period, and percent of difference in the cost element price. For example:

- IF percent of element share in the total cost item's price is very high (i.e, from 56 to 70);
- AND the difference in the price index during the study period is very small (i.e., from 0 to 400);
- AND percent of difference in the cost element price is medium (i.e., from 280 to 420); and
- THEN degree of importance is average (i.e., from 0.4 to 0.6).

Analysis of Results

The developed fuzzy model provides a list of materials within each item and their order according to the importance to the change in prices. As such, materials that are worth studying are those that have a high degree of importance. Material degree of importance changes from one item to another, as linguistic number for average importance ranges from 0.4 to 0.6. Materials that have a degree of importance equal to 0.4 or greater should be taken into consideration. Table 4 lists the impact of materials in cost items. Nine cost items have been determined that have at least one material of 0.4 degrees of importance or greater.

Neural Network Prediction Model

The key feature of many neural networks over regression analysis is that neural networks use nonlinear mathematics and therefore can be used to model highly complex and nonlinear functions. This section is concerned with developing an NN model to discover the relations between some chosen attributes that could describe the expected cost of construction. The model is implemented using *Alyuda Forecaster XL 2.13* (http://www.alyuda.com/) for Microsoft

Table 2. Fuzzy Numbers for Model: Inputs

Linguistic variables	Code	% of element share	Difference	% of difference
Very small	vs	(0.0, 0.0, 14)	(0.0, 0.0, 400)	(0.0, 0.0, 140)
Small	s	(14, 21, 28)	(400, 600, 800)	(140, 210, 280)
Medium	m	(28, 35, 42)	(800, 1,000, 1,200)	(280, 350, 420)
High	h	(42, 49, 56)	(1,200, 1,400, 1,600)	(420, 490, 560)
Very high	vh	(56, 70, 70)	(1,600, 2,000, 2,000)	(560, 710, 710)

Table 3. Fuzzy Numbers for Degree of Importance: Outputs

Linguistic variables	Code	Fuzzy numbers
Very low importance	vli	(0.0, 0.0, 0.1, 0.2)
Low importance	li	(0.1, 0.2, 0.3, 0.4)
Average importance	a	(0.4, 0.5, 0.5, 0.6)
Important	i	(0.6, 0.7, 0.8, 0.9)
Very important	vi	(0.8, 0.9, 1.0, 1.0)

Table 4. Materials Impact in Cost Items Price

Item	Component	Degree of importance
Reinforced concrete	Reinforcement bars	0.811
Block works	Blocks	0.484
Insulation works	Insulation material	0.464
Ceramic works	Ceramic	0.440
Wood works	Wood	0.566
Aluminum works	Aluminum	0.512
Tiles works	Tiles	0.405
Steel works	Steel	0.750
Marble works	Marble	0.402

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Table 5. Training and Testing Materials Error Using Neural Networks

Most important materials	Average absolute error (training)	Average absolute error (test)	Average relative error (%)
Equipment	2.66	3.08	0.67
Gravel and sand	6.03	5.00	1.61
Cement	7.42	6.84	1.68
Reinforcement bars	37.07	25.82	4.66
Blocks	6.68	9.31	2.29
Insulation material	2.05	4.18	0.46
Paints material	1.09	1.46	0.27
Ceramic	1.55	3.76	0.71
Wood	6.23	6.63	1.04
Aluminum	13.61	6.44	1.63
Tiles	0.37	0.04	0.26
Steel	26.85	36.12	4.24
Marble	0.56	0.17	0.42

Excel to predict the future price. The *Alyuda Forecaster XL 2.13* utilizes a back-propagation learning algorithm. Neural networks receive a fixed number of inputs, which represent the characteristic of the problem. For estimation of the price index for a given month, two inputs are considered: (1) price index of the last month and (2) average general number of the last year. These inputs enable correct representation of the characteristics of the problem, which affects the final cost of construction. The output from the NN model is the price index for the next month

From January 2000 to December 2010, 132 data sets were collected. For each data set, the two inputs and the output of the NN model are available to train and test the model. The network is trained by 110 data sets and tested using 22 data sets. To minimize the error of estimation, an experimentation approach was used in which many parameters concerning hidden layers processing elements and learning rates were modified by the trial and error method until the training set reaches a certain accepted error. To verify the performance of a trained network, it is fed with new data that are called the testing set of data, which includes 22 previous months' price index, which are selected randomly. For each cost item, the output data of training sets and the testing sets are compared with the desired output given by the actual price index to illustrate the degree of accuracy. The training and testing errors of the different materials are listed in Table 5. Training and test errors that correspond to reinforcement bars and steel are significantly higher than other categories of materials because those two materials have the largest values in price change and percent of change in price during the considered study period.

Numerical Example

This hypothetical numerical example considers one floor in a housing project that contains all the important cost items that have a great impact on the price change. The total area of the floor is 900 m^2 and it was planned to be executed in 6 months. It was planned to execute the floor in one phase from January 2010 to June 2010 as shown in Fig. 1. But due to some uncontrolled events the project was delayed for 1 year. The scope of work includes the execution of cost items such as excavation and backfilling, plain concrete, reinforced concrete, block works, plaster works, insulation works, ceramic works, paints works, tiles works, marble works, wood work, aluminum work, and steel work. The cost elements of the cost items are equipment, gravel, sand, cement, reinforcement bars, blocks, paint materials, insulation materials, ceramic, wood, aluminum, tiles, steel, and marble. These elements are used to calculate the expected price for the cost item after the price change and to predict future price for the cost items. By using the bill of quantity for the project, the total project price in January 2010 is 1,342,500 L.E. and the cost distribution along the period of execution is listed in Table 6.

Example Modeling

In this section, the actual construction of a floor is modeled to show the future price for cost items. To calculate the future price for a cost item, it is required to provide the following input data: (1) the value of the price change of the selected materials, (2) their share in the total price of the cost item, and (3) their degree of importance. The price adjustment equation is used to calculate the percent of increase or decrease in the cost item's price. The elements are divided into categories according to their degree of importance as shown on Table 7. More than one scenario is designed to calculate the future price of the project by dividing the degree of importance into groups so that the future price of the project can be determined by calculating the expected change in materials prices that are included in the calculation process of each scenario individually. As an outcome of the fuzzy model, the degree of importance of the considered elements ranges from 0.0837 to 0.811.

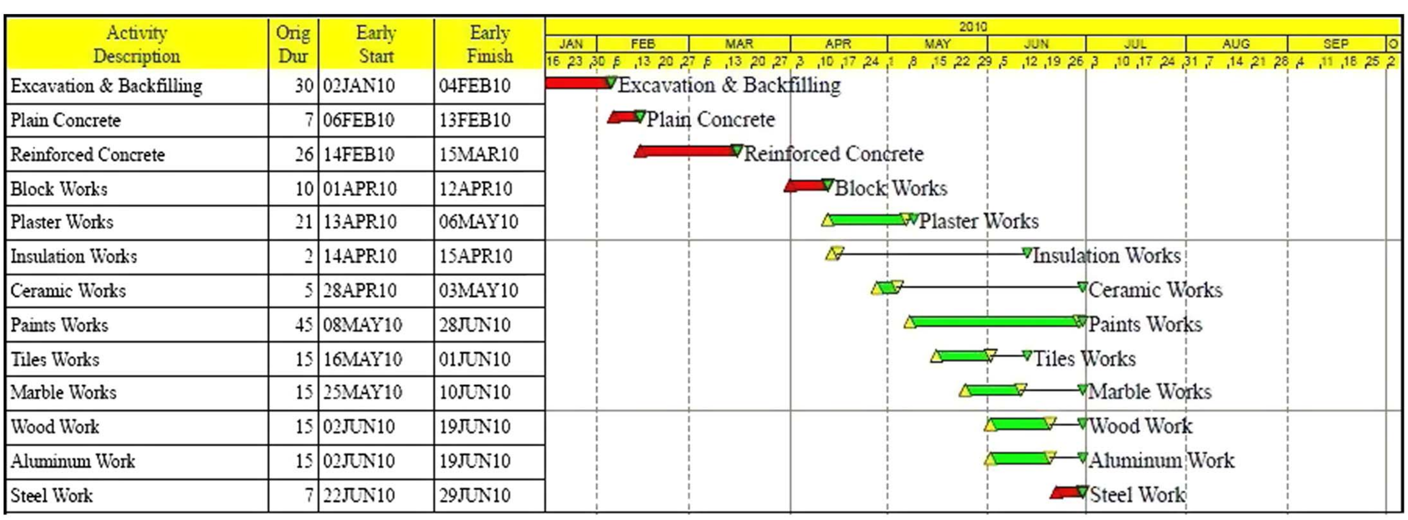

Fig. 1. Project time schedule

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Table 6. Project Cost Distribution along Project Planned Period

Activity	Quantity	Price	Total	Month (2010) January	February	March	April	May	June
Excavation and back filling	2,000	30	60,000	52,000	8,000	—	—	—	—
Plain concrete	200	600	120,000	—	120,000	—	—	—	—
Reinforced concrete	300	1,800	540,000	—	270,000	270,000	—	—	—
Block works	120	500	60,000	—	—	—	60,000	—	—
Plaster works	1,000	30	30,000	—	—	—	21,429	8,571	—
Paints work	1,000	40	40,000	—	—	—	—	18,667	21,333
Insulation works	50	30	1,500	—	—	—	1,500	—	—
Ceramic works	200	90	18,000	—	—	—	—	7,200	10,800
Wood work	20	3,000	60,000	—	—	—	—	—	60,000
Aluminum work	160	500	80,000	—	—	—	—	—	80,000
Tiles works	900	100	90,000	—	—	—	—	84,000	6,000
Steel work	3	1,000	3,000	—	—	—	—	—	3,000
Marble works	800	300	240,000	—	—	—	—	96,000	144,000
				52,000	398,000	270,000	82,929	214,438	325,133
Total project cost						1,342,500			

Table 7. Expected Cost Items Prices for Different Degrees of Importance Using Neural Networks

Activity	Degree of importance	Month (2011) January	February	March	April	May	Jun	Total
Excavation and back filling	>0.0	54,080	8,320	—	—	—	—	62,400
	>0.2	54,080	8,320	—	—	—	—	62,400
	>0.4	52,000	8,000	—	—	—	—	60,000
Plain concrete	>0.0	—	123,600	—	—	—	—	123,600
	>0.2	—	120,000	—	—	—	—	120,000
	>0.4	—	120,000	—	—	—	—	120,000
Reinforced concrete	>0.0	—	326,700	334,800	—	—	—	661,500
	>0.2	—	326,700	334,800	—	—	—	661,500
	>0.4	—	318,600	326,700	—	—	—	645,300
Block works	>0.0	—	—	—	61,800	—	—	61,800
	>0.2	—	—	—	61,800	—	—	61,800
	>0.4	—	—	—	60,000	—	—	60,000
Plaster works	>0.0	—	—	—	22,715	9,085	—	31,800
	>0.2	—	—	—	22,715	9,085	—	31,800
	>0.4	—	—	—	21,429	8,571	—	30,000
Paints	>0.0	—	—	—	—	19,600	22,400	42,000
	>0.2	—	—	—	—	19,600	22,400	42,000
	>0.4	—	—	—	—	18,667	21,333	40,000
Insulation works	>0.0	—	—	—	1,530	—	—	1,530
	>0.2	—	—	—	1,500	—	—	1,500
	>0.4	—	—	—	1,500	—	—	1,500
Ceramic works	>0.0	—	—	—	—	7,416	11,124	18,540
	>0.2	—	—	—	—	7,416	11,124	18,540
	>0.4	—	—	—	—	7,200	10,800	18,000
Wood work	>0.0	—	—	—	—	—	61,200	61,200
	>0.2	—	—	—	—	—	59,400	59,400
	>0.4	—	—	—	—	—	59,400	59,400
Aluminum work	>0.0	—	—	—	—	—	86,400	86,400
	>0.2	—	—	—	—	—	84,000	84,000
	>0.4	—	—	—	—	—	84,000	84,000
Tiles works	>0.0	—	—	—	—	86,520	6,180	92,700
	>0.2	—	—	—	—	86,520	6,180	92,700
	>0.4	—	—	—	—	84,000	6,000	90,000
Steel work	>0.0	—	—	—	—	—	3,060	3,060
	>0.2	—	—	—	—	—	3,060	3,060
	>0.4	—	—	—	—	—	3,060	3,060
Marble works	>0.0	—	—	—	—	99,840	151,200	251,040
	>0.2	—	—	—	—	99,840	151,200	251,040
	>0.4	—	—	—	—	96,960	146,880	243,840

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Table 8. Future Project Cost for Different Degrees of Importance Using Neural Networks

Parameter	Current project cost	Future project cost		
Degree of importance	—	>0.0	>0.2	>0.4
Project cost (L.E.)	1,342,500	1,497,570	1,489,740	1,455,100
Project cost change (%)	—	11.5	11.0	8.4

Table 10. Future Project Cost for Different Degrees of Importance Using Regression Analysis

Parameter	Current project cost	Future project cost		
Degree of importance	—	>0.0	>0.2	>0.4
Project cost (L.E.)	1,342,500	1,480,705	1,457,970	1,434,582
Project cost change (%)	—	10.3	8.6	6.9

The range is divided into three categories: studying all elements (>0.0), studying elements that have degree of importance greater than 0.2 (>0.2), and studying elements that have degree of importance greater than 0.4 (>0.4). These three categories are considered as three scenarios to study future project price from January 2011 to June 2011.

Example Analysis

According to Table 8, in the case of studying all elements (>0.0), the expected increase of the project's cost is approximately 11.5% of the project in January 2010. In the case of studying elements that have degree of importance greater than 0.2 (>0.2), the expected increase of the project's cost is approximately 11% of the project in January 2010, whereas in the case of studying elements that have a degree of importance greater than 0.4 (>0.4), the expected increase of the project's cost is approximately 8.4% of the project in January 2010.

Subsequently, the model has been verified by comparing its results against the results obtained from regression analysis as per Tables 9 and 10. In the case of studying all elements (>0.0), the expected increase in the project's cost predicted by NN technique is 11.5% in January 2010 versus 10.3%, which is obtained from regression analysis. In the case of studying elements that have a degree of importance greater than 0.2 (>0.2), the expected increase in the project's cost predicted by NN technique is

Table 9. Expected Cost Items Prices for Different Degrees of Importance Using Regression Analysis

Activity	Degree of importance	Month (2011)						Total
		January	February	March	April	May	June	
Excavation and back filling	>0.0	54,080	8,320	0	0	0	0	62,400
	>0.2	54,080	8,320	0	0	0	0	62,400
	>0.4	52,000	8,000	0	0	0	0	60,000
Plain concrete	>0.0	0	123,600	0	0	0	0	123,600
	>0.2	0	120,600	0	0	0	0	120,600
	>0.4	0	120,000	0	0	0	0	120,000
Reinforced concrete	>0.0	0	313,200	326,700	0	0	0	639,900
	>0.2	0	305,100	318,600	0	0	0	623,700
	>0.4	0	305,100	318,600	0	0	0	623,700
Block works	>0.0	0	0	0	62,400	0	0	62,400
	>0.2	0	0	0	62,400	0	0	62,400
	>0.4	0	0	0	60,000	0	0	60,000
Plaster works	>0.0	0	0	0	22,929	9,171	0	32,100
	>0.2	0	0	0	22,929	9,171	0	32,100
	>0.4	0	0	0	21,429	8,571	0	30,000
Paints	>0.0	0	0	0	0	19,787	22,613	42,400
	>0.2	0	0	0	0	19,787	22,613	42,400
	>0.4	0	0	0	0	18,667	21,333	40,000
Insulation works	>0.0	0	0	0	1,545	0	0	1,545
	>0.2	0	0	0	1,500	0	0	1,500
	>0.4	0	0	0	1,500	0	0	1,500
Ceramic works	>0.0	0	0	0	0	7,488	11,232	18,720
	>0.2	0	0	0	0	7,488	11,232	18,720
	>0.4	0	0	0	0	7,200	10,800	18,000
Wood work	>0.0	0	0	0	0	0	62,400	62,400
	>0.2	0	0	0	0	0	60,600	60,600
	>0.4	0	0	0	0	0	60,600	60,600
Aluminum work	>0.0	0	0	0	0	0	86,400	86,400
	>0.2	0	0	0	0	0	84,800	84,800
	>0.4	0	0	0	0	0	84,800	84,800
Tiles works	>0.0	0	0	0	0	87,360	6,240	93,600
	>0.2	0	0	0	0	87,360	6,240	93,600
	>0.4	0	0	0	0	84,252	6,180	90,432
Steel work	>0.0	0	0	0	0	0	3,240	3,240
	>0.2	0	0	0	0	0	3,150	3,150
	>0.4	0	0	0	0	0	3,150	3,150
Marble works	>0.0	0	0	0	0	100,800	151,200	252,000
	>0.2	0	0	0	0	100,800	151,200	252,000
	>0.4	0	0	0	0	96,960	145,440	242,400

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Table 11. Standard Error Using Regression Analysis

Most important materials	Standard error
Equipment	7.60
Gravel and sand	10.52
Cement	16.04
Reinforcement bars	79.69
Blocks	19.54
Insulation material	6.79
Paints material	4.40
Ceramic	4.20
Wood	15.25
Aluminum	39.06
Tiles	1.80
Steel	66.41
Marble	2.35

11% in January 2010 versus 8.6%, which is obtained from regression analysis, whereas in the case of studying elements that have degree of importance greater than 0.4 (>0.4), the expected increase in the project's cost predicted by NN technique is 8.4% in January 2010 versus 6.9%, which is obtained from regression analysis. Comparing the errors obtained from neural networks (see Table 5) with the errors obtained from regression analysis (see Table 11), the results reveal that the performance of neural networks outperforms regression analysis.

Conclusions

This research has taken an approach to determine the degree of importance of elements within the components of various construction cost items. According to Egyptian law No. 5 of 2005, which governs the relationship between the owner and the contractor, the contractor provides cost coefficients for cost elements within the technical tender to be used in estimating the amount of compensation in the contract price. This procedure should be applied during the study of tenders to determine the values of cost coefficients in the tender according to the nature and type of the project to be implemented so that an accurate estimate of cost items is obtained, taking into consideration the share of materials within the cost items. The proposed approach is based on the previous studies of the different compensation methods in assessing the price of a contract. The different types of projects and the items that are common in different types of projects have been identified. Three main characteristics have been considered to compare between the materials in terms of impact on prices changes. These characteristics are the rate of participation in the item, the amount of change in the price of materials, and the proportion of this change of the price to the original. Each cost item was studied independently in order to categorize the materials according to their importance within the item in order to select the most important materials to make a correct cost estimate. Fuzzy logic was utilized to calculate the degree of importance of materials by using the MATLAB Tool Box program. In conclusion, this research proposed a methodology to determine the change in items' cost to be used in modifying the contract price. In order to achieve this goal, the following steps were achieved:

- Identification of the construction materials that are important and sensitive to the changes in the market prices of the cost items. A study of different types of projects and the determination of the items most frequent in these projects were carried out. The main factors in the composition of the items are building materials, equipment, labor productivity, and administrative expenses. The most frequent cost elements in all the cost items are equipment, gravel, sand, cement, blocks, reinforcement bars, insulation material, paints material, ceramic, floor tiles, marble, wood, aluminum, and steel. The source of the collected data is the periodicals issued by CAPMAS. The gathered data records of the considered materials were collected during the period that started in January 2000 to December 2010.
- A fuzzy model was formulated to calculate the degree of importance of each material in the item through the three main criteria, namely, the percent of the element's share in the total cost item's price, the difference in the study of the element's price index during the study period, and the difference percentage in the cost element's price. The ranges for all the inputs are divided into five limits: very small, small, medium, high, and very high. The output is divided into five limits: very low importance, low importance, average, important, very important. Twenty-two rules were fed to the MATLAB program to represent the relations between the inputs and output in order to determine the degree of importance of each element within the cost item. The results indicated that the following materials possess the highest impact on cost item prices: reinforced concrete (reinforcement bars), block works (blocks), insulation works (insulation materials), ceramic works (ceramic), wood works (wood), aluminum works (aluminum), tiles works (tiles), steel works (steel), and marble works (marble).
- Formulation of a neural network model to predict future prices of construction materials. These inputs are the price index for the last month and the average general number of all the materials for the last year. By using the price modification equation, the calculation of the percentage of increase or decrease in the cost items prices is possible. As such, the timing decision of purchasing the raw materials during the project's execution can be determined. The training errors obtained from the neural network model range from 0.37 to 37.07 for the different elements, whereas the testing errors range from 0.04 to 36.12.

The research presented a methodology for identification of construction materials that are most sensitive to the change in prices to be used in modifying the contract price with an attempt to predict the amount of future change in materials prices using the neural networks technique. A numerical example of a housing project that consists of one floor was presented in order to demonstrate the capability of the model in predicting the future prices by determining the cost items to be taken into consideration according to their degree of importance. In the case of studying all elements, the expected increase of the project's cost is approximately 13.6% of the cost in January 2010. In the case of studying elements that have a degree of importance greater than 0.2, the expected increase of the project's cost is approximately 13% of the cost in January 2010, whereas in the case of studying elements that have degree of importance greater than 0.4, the expected increase of the project's cost is approximately 10.4% of the cost in January 2010. The performance of neural networks was compared with regression analysis. The results revealed that the neural networks technique outperforms regression analysis with respect to the estimated error in expected increase of the project's elements cost.

References

Akintoye, S. A., and Skitmore, R. M. (1994). "A comparative analysis of three macro price forecasting models." Constr. Manage. Econ., 12(3), 257–270.

Ashuri, B., and Lu, J. (2010). "Time series analysis of ENR construction cost index." J. Constr. Eng. Manage., 136(11), 1227–1237.

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J. Constr. Eng. Manage. 2013.139:1190-1198.

Cakir, O., and Canbolat, M. S. (2008). "A web-based decision support system for multi-criteria inventory classification using fuzzy AHP methodology." *Expert Syst. Appl.*, 35(3), 1367–1378.

Chan, A. P. C., Chan, D. W. M., and Yeung, J. F. Y. (2009). "Overview of the application of fuzzy techniques in construction management research." *J. Constr. Eng. Manage.*, 135(11), 1241–1252.

Chin, T. C., and Mital, D. P. (1998). "Time series modelling and forecasting of Singapore property price: An optimal control approach." *Proc., 2nd Int. Conf. on Knowledge-Based Intelligent Electronic Systems*, IEEE, New York, 370–375.

Fellows, R. F. (1991). "Escalation management: Forecasting the effects of inflation on building projects." *Constr. Manage. Econ.*, 9(2), 187–204.

Koehn, E., and Navvabi, M. H. (1989). "Economics and social factors in construction." *Coastal Eng.*, 31(10), 15–18.

Mccaffer, R., McCaffrey, M. J., and Thorpe, A. (1984). "Predicting the tender price of buildings in the early design stage: Method and validation." *J. Oper. Res. Soc.*, 35(5), 415–424.

Ng, S. T., Cheung, S. O., Skitmore, R. M., Lam, K. C., and Wong, L. Y. (2000). "The prediction of tender price index directional changes." *Constr. Manage. Econ.*, 18(7), 843–852.

Plebankiewicz, E. (2009). "Contractor prequalification model using fuzzy sets." *J. Constr. Eng. Manage.*, 15(4), 377–385.

Runeson, K. G. (1988). "Methodology and method for price-level forecasting in the building industry." *Constr. Manage. Econ.*, 6(1), 49–55.

Singh, D., and Tiong, R. L. K. (2005). "A fuzzy decision framework for contractor selection." *J. Constr. Eng. Manage.*, 131(1), 62–70.

Sivarao, B. P., El-Tayeb, N. S. M., and Vengkatesh, V. C. (2009). "Mamdani fuzzy inference system modeling to predict surface roughness in laser machining." *Int. J. Intell. Inf. Technol. Appl.*, 2(1), 12–18.

Taylor, R. G., and Bowen, P. A. (1987). "Building price-level forecasting: An examination of techniques and applications." *Constr. Manage. Econ.*, 5(1), 21–44.

Trost, S. M., and Oberlender, G. D. (2003). "Predicting accuracy of early cost estimates using factor analysis and multivariate regression." *J. Constr. Eng. Manage.*, 129(2), 98–204.

Wang, C. H., and Mei, Y. H. (1998). "Model for forecasting construction cost indices in Taiwan." *Constr. Manage. Econ.*, 16(2), 147–157.

Wong, M. W., Chan, P. C., and Chiang, Y. H. (2005). "Time series forecasts of construction labor market in Hong Kong: The Box-Jenkins approach." *Constr. Manage. Econ.*, 23(9), 979–991.

Zadeh, L. A. (1975). "The concept of a linguistic variable and its application to approximate reasoning." *Inf. Sci.*, 8(3), 199–249.

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