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Construction Claims Prediction and Decision Awareness Framework using Artificial Neural Networks and Backward Optimization

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Abstract:* *This paper presents optimized artificial neural networks (ANNs) claims prediction and decision awareness framework that guides owner organizations in their pre-bid construction project decisions to minimize claims. The framework is composed of two genetic optimization ANNs models: a Claims Impact Prediction Model (CIPM), and a Decision Awareness Model (DAM). The CIPM is composed of three separate ANNs that predict the cost and time impacts of the possible claims that may arise in a project. The models also predict the expected types of relationship between the owner and the contractor based on their behavioral and technical decisions during the bidding phase of the project. The framework is implemented using actual data from international projects in the Middle East and Egypt (projects owned by either public or private local organizations who hired international prime contractors to deliver the projects). Literature review, interviews with pertinent experts in the Middle East, and lessons learned from several international construction projects in Egypt determined the input decision variables of the CIPM. The ANNs training, which has been implemented in a spreadsheet environment, was optimized using genetic algorithm (GA). Different weights were assigned as variables to the different layers of each ANN and the total square error was used as the objective function to be minimized. Data was collected from thirty-two international construction projects in order to train and test the ANNs of the CIPM, which predicted cost overruns, schedule delays, and relationships between contracting parties. A genetic optimization backward analysis technique was then applied to develop the Decision Awareness Model (DAM). The DAM combined the three artificial neural networks of the CIPM to assist project owners in setting optimum values for their behavioral and technical decision variables. It implements an intelligent user-friendly input interface which helps project owners in visualizing the impact of their decisions on the project's total cost, original duration, and expected owner-contractor relationship. The framework presents a unique and transparent hybrid genetic algorithm-ANNs training and testing method. It has been implemented in a spreadsheet environment using MS Excel® and EVOLVERTM V.5.5. It provides projects' owners of a decision-support tool that raises their awareness regarding their pre-bid decisions for a construction project.

Keywords: Claims, Artificial Neural Networks, GA Optimization, Awareness

I. INTRODUCTION

Construction projects are characterized by being highly dynamic, globally competitive, and increasingly challenging. The subtle aspects relevant to the political, economical, and cultural differences of the contract parties of an international construction project in Middle Eastern countries (projects owned by either public or private local organizations who hire international prime contractors to deliver the projects), coupled with their diverse expectations may eventually lead to claims that would impact both the time and cost of the project. Consequently, once decision to bid for an international construction project has been made, specific project studies and additional contract analysis must be undertaken to predict the factors that may lead to claims in each project, as well as their related cost and time impacts.

Although international forms of construction contracts have been prepared to identify the rights and obligations of the contract parties and to address the risks that may be encountered in projects; it is almost impossible that the contract will cover every simple matter related to the project. According to Levin (1998), a claim is an unavoidable consequence of the construction processes. Thus some gaps, ambiguities and conflicts may exist in the contract that may result in disagreements and disputes regarding the contractual obligations of its parties (Fisk, 2005). As such, when any of the parties to a contract feels that his or her rights have not been met by the other party, according to contract conditions; he or she will file a claim against the other party, which will probably have an impact on both parties.

In Egypt, international contractors handling construction project are faced with several challenges that may lead to claims, such as (1) use of unfamiliar contract specifications, local materials, local labor laws, and regulations (e.g., the legal requirement to undergo a partnership with a local contractor); (2) utilization of non-standard contract forms and (3) lack of adequate time, local market data, and expertise to analyze the impact of these challenges during the bidding stage. The latter may hinder international contractors from conducting a proper risk management strategy prior to bid submission that may

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subject them to potential risks, leading to damages and loss of profit. On the other hand, due to the scarcity of market data and inadequate level of experience of local owners with international contracts, a project owner may not be entirely aware of the results of his or her key project decisions nor the consequences of his or her behavior prior to or during the contract negotiation stage.

These problems prompt developing an intelligent framework that can aid local/international contractors, working in Egypt, in predicting the impact of expected claims, based on the project decision variables. The framework also advises local owners on the optimum settings of the project variables that would minimize the negative impacts of claims during the construction stage. The major difficulties and challenges that are addressed by this research are:

1. Handling behavioral and technical decisions of subjective nature during the bidding phase of the project and showing their consequences on the project outcomes.
2. Selecting a suitable artificial intelligent technique that can best address the problem.
3. Finding proper number of data cases that can provide reliable model outputs.
4. Applying a transparent model that clearly demonstrates its various computational steps.
5. Creating a robust tool that can help the users predict the outcomes of their decisions, using a simple interface (spread sheet environment).

II. LITERATURE REVIEW

Since the 1980s, researchers have demonstrated that there has been a significant potential for applying artificial intelligence (AI) tools to claims prediction and analysis (Diekmann and Kruppenbacher 1984). They recommended conducting further research work to develop viable claims analysis tools for construction professionals. Some examples of these AI techniques are case-based reasoning (CBR), rule-based expert systems, and artificial neural networks (ANNs). Case-based reasoning (CBR) is an artificial intelligence (AI) problem solving paradigm that has been previously applied to predict claims, analyze bids, and resolve litigation cases (Arditi and Tokdemir 1999, Allen et al. 2000, Ashley 1990, Ashley and Rissland 1988, Chua and Chan 2001, Ren et al. 2001). It simply means using old experiences from previous claims or litigation cases to reach a conclusion about new situations or cases. It has many advantages such as its ability to propose prompt solutions to problems, as well as its excellence in proposing solutions in domains that a decision-maker may have not experienced before. Moreover, CBR is unique in evaluating solutions when no algorithmic method is available for evaluation. It is also superior in interpreting open-ended and ill-defined concepts which can provide early warning of potential future problems (Kolodner 1992). However, CBR is more applicable to situation classification, argumentation, solution evaluation, justification and case interpretation, than situations where conducting quantitative analysis of claims' impacts is a necessity.

Expert systems are rule-based techniques that have been historically applied in the area of claims management, owing to their capability of representing "factual knowledge" in specific areas of expertise and providing the problem-solving results that "simulates experts' decisions" (Kim and Adams 1989). Not only have expert systems been capable of processing data, but they have also been capable of processing experts' knowledge (Kim and Adams 1989). Thus, expert systems offer means of storing and sharing knowledge that allow more people to have access to expertise, when no expert is available for consultation (Hosny et al. 1994, and Elbarkouky and Fayek 2011). However, expert systems are deficient in a major aspect compared to other artificial intelligence tools, as they do not support the self-learning function.

Artificial neural networks (ANNs) are AI techniques that provide a "self-organizing" and "self-learning" forecasting tool that have been inspired by the structure of the "human biological system" (Caudill and Butler 1990). Artificial neural networks technique can be successfully applied to resolve complex and imprecise information processing problems, as one of its hallmarks is its ability to learn from past experiences (Sun and Xu 2011). Chau (2007), who adopted a particle swarm optimization (PSO) model to train perceptrons in predicting the outcome of construction claims in Hong Kong, concluded that ANN has resolved the modeling problem in a cost effective manner. This technique provides an "adaptive" forecasting method that performs well when the environment or the system being modeled varies with time (Boussabaine 1996), and it does not require an assumption of a specific data distribution (Elhag and Wang 2007). The previous characteristics of ANNs suit the dynamic and multifaceted problem of time and cost prediction of construction claims than those of the traditional approaches such as statistical and mathematical models. For example, statistical prediction models including regression analysis may require predicting the relationship between project cost and time in advance using regression functions. This is, sometimes, impossible because the relation between time and cost is non-linear and may vary based on the project situation (Sun and Xu 2011). Moreover, unlike expert systems, the ANNs technique does not require setting predestined rules between its inputs and outputs. This is an advantage of the ANNs because projects, especially those of global contexts, are dynamic and unique in nature, whose specific circumstances may vary or develop over time. Finally, ANNs technique has been successfully applied to similar construction prediction problems because it is capable of dealing with numerical input data (Moselhi et al. 1991; Gaber et al. 1992; Williams 1994; Chua et al. 1997; Hegazy and Ayed 1998; Emsley 2002; Attalla and Hegazy 2003; Hosny et al. 2011; Taormina et al. 2012).

In this paper, ANNs are integrated with genetic algorithms to develop a claims' impact prediction and decision awareness framework for international construction projects in Egypt. The application of a hybrid

ANNs-genetic optimization method in an integrated spreadsheet environment clarifies the relationship between the input and output parameters of the model. It also enables conducting a backward optimization technique to help setting optimum decisions (e.g., a suggested contract type) to achieve a given output (e.g., specific minimum cost impact or better owner-contractor relationship). This feature provides an improvement over other non-transparent traditional ANNs training and testing techniques, such as the back propagation method (Hegazy and Ayad 1998). Also, the use of a simple user-friendly interface for data input and analysis enhances the robustness of the models used in this framework.

This paper is a continuation effort for previous research done by Hosny (2006). In the previous publication (i.e., Hosny 2006), the paper was oriented to investigate the ability to predict the claims (related to cost and time) from a set of historical project. The effective factors were selected and an appropriate ANN architecture was determined to be able to predict increase in cost and time given these set of factors. In addition, a statistical analysis of the data was performed to determine causes of claims.

In the current paper, the following contributions are accomplished:

- Developing a more reliable ANN prediction model to predict the potential relationship between owner and contractor
- Investigating how to support owners' strategic contractual decisions (e.g., best contract type, the general condition to use, project duration, etc) to reduce the severity of potential claims
- Classifying the input factors to determine the controllable factors that can be monitored by the owner to reduce claims. These factors act as decision variables during optimization
- Developing a simple what-if-analysis tool to enable the owner to track the impact of his or her project decisions on project success
- Implementing backward genetic optimization to determine the proper values of the controllable variables that may result in minimizing project claims
- Developing a customizable optimization tool that enables the selection of variables and facilitates deciding whether to consider, cost, time and owner/contractor relationship as objectives and/or constraints. The tool ensures the smooth transition between being an objective or a constraint with the ability to specify relative weights in case of multi objectives.

The next section describes the different components of the optimization framework.

III. COMPONENTS OF THE CLAIMS IMPACT PREDICTION AND DECISION AWARENESS FRAMEWORK

This section defines the components of the optimized artificial neural networks claims' impacts prediction and decision awareness framework (Fig.1). The framework is mainly composed of two ANNs genetic optimization models: a Claims Impacts Prediction Model (CIPM), and a Decision Awareness Model (DAM).

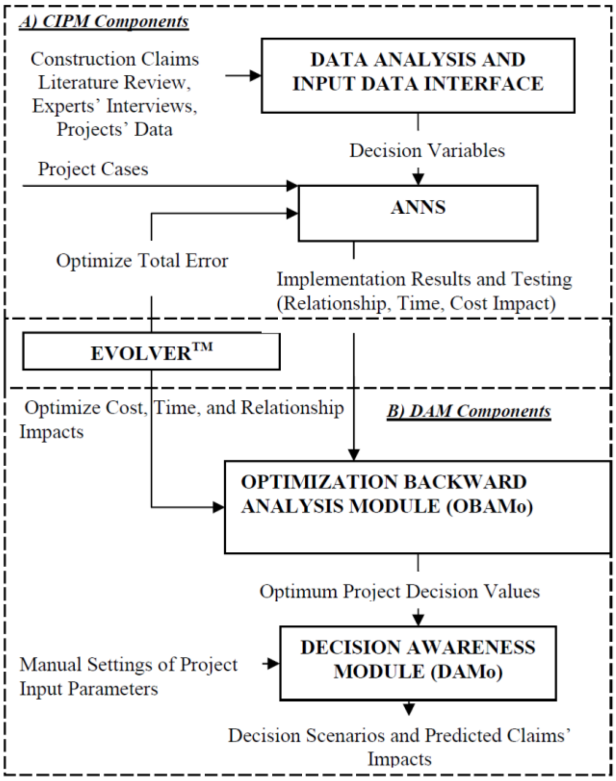


FIGURE I
Claims Impact Prediction and Decision Awareness Framework.

The Claims Impact Prediction Model (CIPM) predicts the cost and time impacts of projects' possible claims as well as the type of relationship between the owner and contractor. It is based on specific project decision variables that may trigger claims such as project type, project duration, project cost, contract type, project selection criteria, design status, and owner's and contractor's behaviors. Those variables were set as the input parameters to the CIPM and they were determined by conducting literature review of construction claims, interviews with construction claims experts in the Middle East, and analysis of lessons learned of fifty-four international construction projects in Egypt. The CIPM provides early warning to owners and contractors by predicting the possible delays and cost overruns that may impact the project due to claims, which can help contractors in making the decision whether to bid for an international construction project in Egypt or not.

The Decision Awareness Model (DAM) includes a genetic algorithm Optimization Backward Analysis Module (OBAMo) to determine the optimum settings of the owner's controllable decision variables (i.e., contract type, design status, and owner-contractor behavior) by minimizing the values of the predicted claims' impacts—outputs of CIPM. The model also includes a Decision Awareness Module (DAMo) which implements a user-friendly interface that allows project owners to set project decision variables that are within his or her control to certain preferred values and visually analyze their relative impacts on the project cost, time, and type of relationship with the contractor.

The next section describes the data collection and analysis phase that determined the input parameters of the Claims Impact Prediction Model (CIPM) and explains its network training and testing process, using EVOLVERTM V.5.5 add-in for MS Excel®.

IV. DEVELOPMENT OF THE CLAIMS IMPACT PREDICTION MODEL (CIPM)

A. Input Data Collection and Analysis Phase

Literature review, experts' interviews, and analysis of Egyptian international construction projects (projects owned by either public or private local organizations who hired international prime contractors to deliver the projects) were conducted to determine the input parameters of the Claims Impact Prediction Model (CIPM). Those parameters comprised the project decision variables that can be controlled by the owner, such as: contract type and owner's behavior towards changes as well as other input variables that are not within the control of the project owner, such as project type and inflation possibility (Hosny 2006).

Several research studies in the area of construction claims were reviewed, particularly those concerned with the analysis of the effect of different project characteristics on the occurrence of claims and those relevant to identifying the sources of construction claims in both developing and developed countries (Diekmann and Girard 1995, Shapiro 2004, 198 Hosny 2006, Bramble and Callahan 2010, Mohamed et al. 2011). Then, interviews with construction industry experts who had more than twenty years of experience in managing construction projects in the Middle East were conducted to screen the identified variables and determine their possible values. Finally, fifty-four international projects in Egypt were analyzed to determine the major claims that caused delays and cost overruns in these projects.

Table 1 illustrates the information gathered from these projects, such as project category, owner type, contractor type, contract condition, payment method, contract value in Egyptian Pounds (EGP), percentage increase in the original contract value and duration of these projects. The projects' counts of each category are illustrated between brackets in Table 1.

Based on previous observations that were made by Hosny (2006), the increase in the duration and cost due to claims in the projects that utilized lump sum contracts was significantly less than those of unit price contracts. For those projects that used International Federation of Consulting Engineers (FIDIC) contracts, the cost and duration increase was significantly less than the projects that utilized custom-made contracts, which can be referred to the difference in the nature between both types. The relative increase in the cost and duration of the projects that applied custom-made contracts over those that used FIDIC contracts can be referred to the fact that owners who use FIDIC are expected to be familiar with international standards. Also, the international contractors are more familiar with FIDIC contracts than custom-made contracts.

Based on the data collection and analysis phase, the major causes of claims resulting in cost overruns and schedule delays of international projects in Egypt, are illustrated in Fig. 2. This phase resulted in determining fourteen input parameters to the CIPM that instigated project claims in international construction projects in Egypt.

TABLE I
Data of Fifty-Four Egyptian International Construction Projects

#	Project Category	Owner Type	Contractor Type	Contract Condition	Contract Type	Original Value Ranges (M-EGPs)	% Increase in Cost	% Increase in Duration
22	Industrial	Private (17), Public (5)	Prime (18), Sub (3), Consortium (1)	Law 89 (8), Custom (11), FIDIC (3)	LS (2), U/P (20)	< 10M (13), 10 to 100M (8), >100M (1)	< 10% (10) 10 to 20% (2), 20 to 100% (8), > 100% (2)	<10.00% (6), 10 to 20% (1) 20% to 100% (12), >100% (3)
12	Touristic	Private	Prime	Custom (11), FIDIC (1)	U/P	< 10 M (4), 10 to 100M (8)	< 10% (5), 10 to 20% (2), 20 to 100% (3), > 100% (2)	<10% (1), 10 to 20% (2), 20% to 100% (4), >100% (5)
2	Heavy Project	Public	Prime	Custom	LS (1), U/P (1)	< 10 M (1), 10 to 100M (1)	< 10% (1) 20 to 100% (1)	20% to 100% (1), >100% (1)
5	Infrastructure	Public	Prime (4), Sub (1)	Custom (3), Law 89 (2)	LS (2), U/P (3)	< 10M (3), 10 to 100M (2)	< 10% (3) 10 to 20% (2)	<10.00% (2), 20% to 100% (3)
9	Building	Public (2), Private (7)	Prime (8), Sub (1),	Law 89 (2), Custom (5), FIDIC (2)	LS (4), UP (5)	< 10M (5), 10 to 100M (4)	< 10% (3) 10 to 20% (2) 20 to 100% (4),	10 to 20% (2), 20% to 100% (5), >100% (2)
1	Commercial	Private	Prime	Law 89	LS	< 10M	< 10%	< 10%
3	Residential	Private	Prime	Law 89	UP	< 10M (2), 10 to 100M (1)	10 to 20% (3)	10 to 20% (1), 20% to 100% (2)

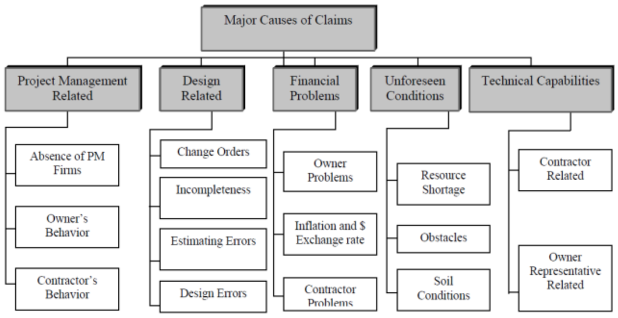


FIGURE II
Major Factors Causing Schedule Delays and Cost overruns in International Construction Projects in Egypt (adapted, Hosny 2006)

Table 2 illustrates the project decision input variables as well as their possible attribute values. It also shows whether those variables could be controlled by the owner prior to the bidding stage or not.

B. CIPM Model Training and Testing Phase

The Claims Impact Prediction Model (CIPM) is composed of three stand-alone ANNs, as suggested by Hosny (2006). Each has a different prediction purpose based on the training and testing results of the fourteen parameters (input nodes) and the output node of each ANN. The first artificial neural network (ANN1) predicts the percentage category of project cost increase due to possible claims. The values of its output parameter are classified into four categories: (1) 0-10%, (2) 10-20%), (3) 20-30% and (4) >30%. The second artificial neural network (ANN2) predicts the percentage category of duration increase due to possible claims. The values of its output parameter are also classified into four categories: (1)

0-10%, (2) 10-20%, (3) 20-40% and (4) >40%. The third artificial neural network (ANN_3) predicts the resultant owner-contractor relationship in terms of whether it is going to be (1) friendly, (2) neutral or (3) adverse. Three-layers were created for each of the three ANNs: one input layer, one hidden layer, and one output layer that can be outlined as follows:

TABLE II
Input and Output Variables of the ANNs of the CIPM

Input Variables	Description	Values	Controllable?
1. Owner's General Behavior	Approach adopted by owner in dealing with contractor in project issues.	(1) Partner, (2) Helpful, (3) Mild, (4) Bad	Yes
2. Owner Behavior (Price Negotiation)	No. of rounds that the owner passes through in negotiation with contractors until reaching a decision	(1), (2), (3), (4), or (5) rounds of cost negotiations	Yes
3. Owner Behavior (Time Negotiation)	Owner willingness to accept changes in project milestones	(1) Lenient, (2) Moderate, (3) Tough	Yes
4. Project Type	Type of project	(1) Touristic /Commercial, (2) Residential, (3) Educational/Admin., (4) Infrastructure, (5) Industrial	No
5. Owner Type	Type of owner Organization	(1) Private, (2) Public	No
6. Project Selection Criteria	The approach followed in selecting the winning bidder whether based on least cost, min relative score (financial over technical, …)	(1) Minimum Cost, (2) Minimum Relative Score, (3) Technical Pass	Yes
7. Contract condition	Type of general condition used whether FIDIC, Egyptian law, …	(1) Customized, (2) Law 89 (Public contract), (3) FIDIC or International	Yes
8. Project Cost to Duration Ratio	Total cost divided by project duration which reflects the monthly volume of work expected	Divides total project cost by its duration	Duration only
9. PM Involvement Stage	In which stage in the project the project manager was assigned.	(1) Design Stage, (2) Construction Stage, (3) No PM	Yes
10. Owner's Behavior Towards Change	Owner trend in making changes after signing the contract	(1) Mild, (2) Moderate, (3) Major	Yes
11. Design status prior to construction	The status of the design when letting the bid. Was it complete or it still under progress?	(1) Complete, (2) Incomplete	Yes
12. Financial Problems	Whether the finance for the project was available before construction or the owner still has to find some sources for financing his project.	(1) Non, (2) Owner, (3) Both, (4) Contractor	No
13. Inflation Possibility	The economic situation of the country and the purchasing power of the currency from one year to the other.	(1) No, (2) Yes	No
14. Contractor's Technical Quality	Contractor technical capabilities and his history in providing quality products.	(1) Average, (2) Excellent	Yes
Output Variables		**Values**	**ANN Number**
1. Percentage Category of Cost Increase	The expected percentage increase in project cost	(1) 0-10%, (2) 10%-20%, (3) 20%-30%, (4) >30%	ANN1
2. Percentage Category of Duration Inc.	The expected percentage increase in project duration	(1) 0-10%, (2) 10%-20%, (3) 20%-40%, (4) >40%	ANN2
3. Owner/Contractor Relationship	The expected relationship between owner and contractor during project execution.	(1) Friendly, (2) Neutral, (3) Adverse	ANN3

1. The input layer had 14 neurons that represented the fourteen input parameters illustrated in Table 2.
2. The hidden layer had 7 neurons which is half the number of neurons of the input layer as recommended by Hegazy and Ayed (1998).
3. The output layer of each ANN included one neuron which represents the percentage impact category of the project cost, duration and owner-contractor relationship in ANN1, ANN2 and ANN3 respectively.

The external and internal structure of the three ANNs of the CIPM and their components are illustrated in Fig. 3. The three ANNs have been implemented in a spreadsheet environment (MS Excel®) that provides an excellent environment for solving several construction management problems (Moore and Weatherford 2001, and Elhakeem and Hegazy 2005). Data was collected from thirty-two international construction projects in Egypt to implement and test the CIPM.

The thirty-two projects were selected from the fifty-four projects illustrated in Table 1 for training and testing purposes, based on the available data of the fourteen input parameters of each project. Note that the data of the fifty-four projects were collected prior to determining the final parameters used to create the ANNs, which was the reason why twenty two industrial projects with missing parameters' data were excluded. Twenty-six randomly selected projects were chosen for training and six for testing the model. Figure 4 illustrates an example of ANN1 where the number of training cases is 26 cases, the number of input neurons equals to 14 inputs (project decision and input variables) and the number of output neurons equals to one neuron (percentage category of project cost increase).

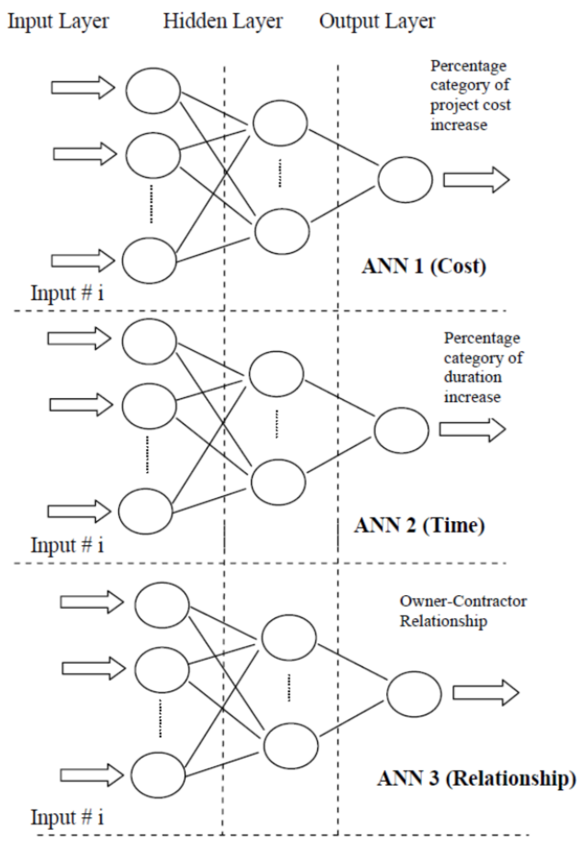


FIGURE III
The external and internal structure of the three ANNs and their components

Designing the ANN structure by determining the appropriate number of hidden layers and the number of neurons in each layer is an important issue for multilayer feed-forward networks. To determine the best structure, an iterative (trial and error) process is used that relies on increasing the number of nodes in one and two hidden layers till the network reaches a desired performance for both training and testing sets. This process is guided by recommendations from previous research work. Based on heuristics, Hegazy et al. (1994) suggested that the number of hidden nodes may be set as one-half of the total input and output nodes. Accordingly, six, seven and eight hidden nodes were examined with three activation functions: hyperbolic tangent (tanh), exponential, and linear for hidden and output neurons. The best ANN structure (minimum error) was achieved when using: one hidden layer with seven neurons and hyperbolic tangent as the activation function for all hidden nodes and the output node.

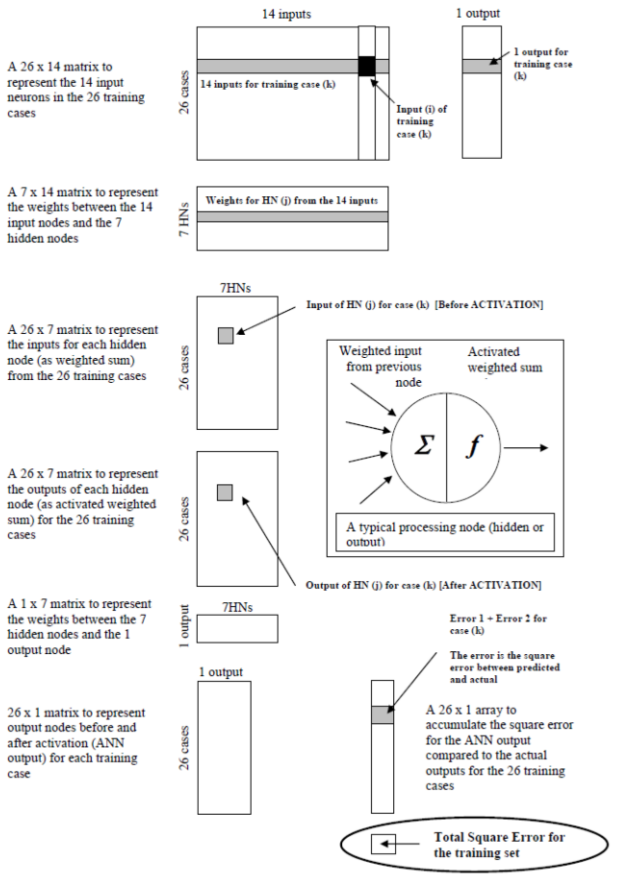


FIGURE IV
Implementation of ANN1 in a Spreadsheet Environment

The training was carried out as an optimization problem where the weights of the different layers were set as variables and the total square error (difference between ANNs outputs and actual outputs of the 26 cases) was set as the objective function to be minimized. The optimization was conducted using EVOLVERTM V.5.5 add-in for MS Excel® that applies Genetic Algorithms (GAs) for non-linear optimization problems. Over-fitting during training was handled in the proposed approach by continually monitoring the error resulting from the testing set. If the error of the testing set decreases with the minimization of error of the training set, the optimization process continues minimizing the training set error, else the optimization algorithm retrieves the values of best variables reached. The GAs settings, however, was set to use a population size of 100 with automatic random number generator seed. The crossover rate was selected to be 0.8 and mutation rate as 0.1. During the training process when there is no improvement, the mutation rate is increased to reduce falling in local minima.

Figure 5 sorts and allocates both the training and testing results within their relevant output categories (1, 2, 3, or 4) in each of the three ANNs. The percentage error in the training cases of ANN1 was equal to approximately 11.5% due to two under predicted cases and one overly predicted case out of the 26 training cases. No error took place in the six testing cases of ANN1. The percentage error in the training cases of ANN2 was equal to approximately 7.6%, resulting from two cases that were overly predicted. The error in prediction in the two cases was within the limit of one category of percentage duration increase. The percentage error in the six testing cases of ANN2 was 16.6% (one actual case out of six was in category 3, yet it was predicted in category 4). No errors did exist in both the training and testing cases of ANN3.

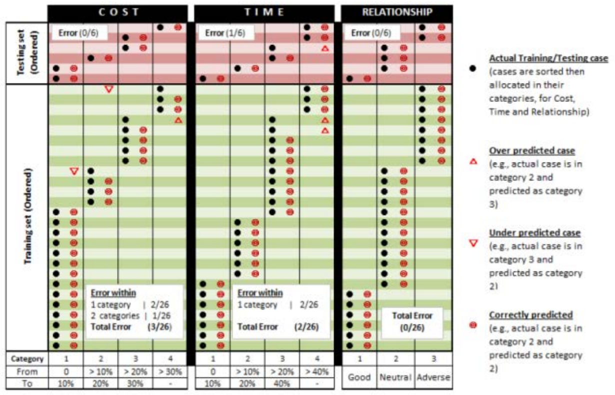


FIGURE V
CIPM Network Training and Testing Results

Although the performance of the CIPM was satisfactory, training needs to incorporate more recent cases in order to be able to predict the expected project performance more accurately. Alternatively, the effect of each individual input variable on project performance has to be investigated to be able to decide on the variables to be eliminated or modified to improve the model. Ongoing research efforts are currently being implemented to measure the effect of each input variable on total project cost and duration. Moreover, the study of the cases revealed that some factors may have to be further detailed or amended to reduce claims' impacts in international projects in Egypt, such as:

1. Major change orders should be carefully analyzed before execution to measure their time and cost impacts.
2. Specifications and drawings should be revised for completeness, consistency and coordination.
3. Prequalification of contractors should be conducted prior to actual bidding phase with special emphasis on contractor work experience in the region, current workloads and personnel allocated to the project.
4. Local owner's behavior usually lead to adverse relationship between the project parties, which may result in cost overrun and schedule delays, and, consequently, to contract termination and project failure. Therefore, project parties should reduce their indifferences and think of adopting a partnering or a consensus approach (Elbarkouky and Fayek 2011) in

initiating their projects to achieve a win/win situation for all parties.

Note that the above factors were already covered in higher level factors in this research study, yet they may need to be further detailed in future research work. For example, the factor "contractor technical quality" covers the contractor work experience in the region, current workloads and project personnel. Also, the factor "Design status prior to construction" would consider the completeness of specification and drawings. In addition, the model also incorporates four factors that reflect the owner behavior in this study, yet there is always more room to further investigate additional subjective variables that may affect the owner's behavior in different projects' settings.

C. DECISION AWARENESS MODEL (DAM)

The Decision Awareness Model (DAM) assists project owners in deciding on the optimum values of their controllable project decisions and behavioral characteristics (Table 2), prior to the bidding phase of the project. The DAM is composed of two modules: an Optimization Backward Analysis Module (OBAMo) and a Decision Awareness Module (DAMo). The former module applies an optimization backward analysis technique. It enables the owner to decide on the optimum settings of the project's controllable decision variables and his behavioral characteristics by minimizing the individual outputs of the CIPM model. In a reverse manner, the DAMo permits a project owner to visualize the instant variations in the project cost increase, duration increase and owner-contractor relationship. This can be achieved by modifying the settings of the project's controllable decision variables and owner's behavioral characteristics using a user-friendly input interface that has been implemented on MS Excel®.

Figure 6 illustrates the user input interface of the OBAMo. This module categorizes the project variables into: uncontrollable (fixed) input variables, controllable owner behavioral decision variables and controllable project related decision variables. Using an optimization backward analysis technique, the OBAMo empowers the owner to decide upon the optimum settings of the project's controllable decision variables and owner's behavioral characteristics, by minimizing the individual outputs of the CIPM model or any combination thereof.

Fig. 6a displays the predicted outputs of the CIPM model. The initial values are computed by running a base case scenario in the CIPM based on the preferences of the owner in setting both controllable and uncontrollable variables. Figure 6b illustrates the optimization parameters of the OBAMo. The model includes an interactive "optimization builder" (Fig. 6c) that facilitates the setting of any of the optimization parameters as either objective functions to be minimized or constraints to be respected. The optimization builder allows combining any of the parameters in one objective function to be minimized. This can be done by using relative importance values that can be either integers or decimals based on the preference of the project owner using the "optional" relative importance textbox (Fig. 6c). For example, the owner may prefer the project cost to be three times more significant than the project duration by entering the value "3" in the relative importance textbox of the percentage category of project cost increase and the value "1" in the relative importance textbox of the percentage category of project duration increase. The optimization builder also allows setting any of those parameters as constraints whose attributes are entered using a dropdown box (Fig 6c). The values of those attributes are selected from the available ranges of the three output variables of the CIPM (Table 2).

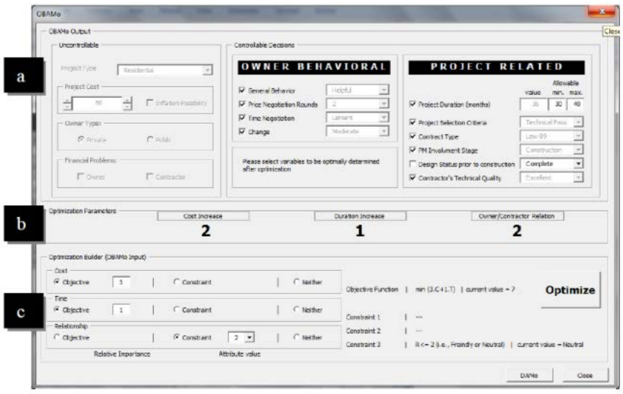


FIGURE VI
Screenshot of the Optimization Backward Analysis Module (OBAMo)

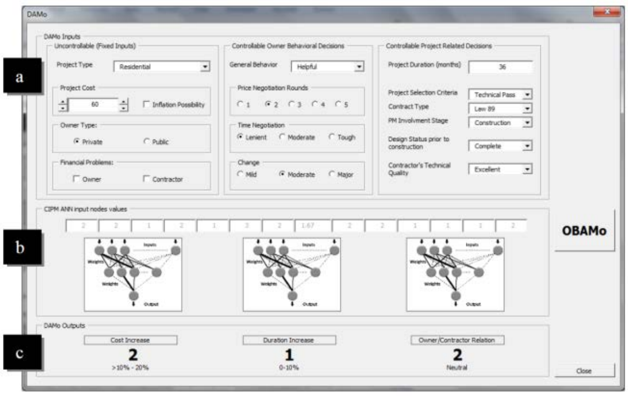
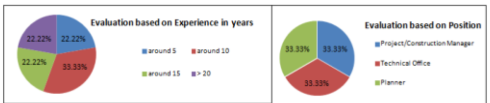


FIGURE VII
Screenshot of the Decision Awareness Module (DAMo)

Similar to the Optimization Backward Analysis Module (OBAMo), the Decision Awareness Module (DAMo) assists a project owner to visualize the different controllable and uncontrollable project variables, yet, unlike the OBAMo, it enables the owner to manually enter the preferred values of the controllable variables using an intelligent user-friendly interface (Fig. 7a). It displays the values of those variables (Fig. 7b) based on the attributes entered by the user. Then, it predicts the outcomes of every scenario in terms of the percentage category of project cost increase, project duration increase and owner-contractor relationship (Fig 7c). This module is an effective decision support tool that enables project owners to envision the impact of their behavior and project controllable variables and come up with best combination of project and behavioral decisions.

D. SYSTEM VALIDATION

The learning paradigm of artificial neural networks includes a testing procedure, which represents the first verification and validation of the suitability of the approach and the correctness of its results. An additional face validation strategy has been conducted by distributing a questionnaire to experts and owner organizations to evaluate the whole system performance, and determine potential benefits to the industry and asses model credibility. Interviews were conducted with nine experts to introduce the system to them and illustrate its functions and main features. Experts were then allowed to experiment with the developed model and its application and compare to their projects. Next, each expert was asked to evaluate the system based on two sets of criteria related to the novelty/expected benefits to the construction industry of the two main functions of the proposed model: (1) the Claims Impact Prediction and (2) the Decision Awareness with its the backward optimization feature to support decision makers in their contractual decisions. The respondents were asked to evaluate each criterion using a score from 1 to 5, where 1 indicates ‘poor’ and 5 indicates ‘excellent’. Information related to experts’ positions and years of expertise with a detailed summary of their opinions as criteria average and deviation is then presented as shown in Figure 8. The overall average score was 4.28 out of 5, which is considered acceptable.



					Average				Average
DAMo Average	4.50	4.22	3.83	4.08	4.17	4.22	4.06	4.22	4.17
DAMo Standard Deviation	0.62	0.09	0.41	0.80	0.60	0.62	0.63	0.62	
Beneficial to Industry	4.50	4.17	4.00	4.50	4.28	4.33	4.33	4.17	4.28
Simple Interface	5.00	4.33	4.00	4.50	4.44	4.33	4.33	4.67	4.44
Sufficient of Outputs	4.00	4.17	3.50	3.25	3.78	4.00	3.50	3.83	3.78
OBAMo Average	4.69	4.38	3.75	4.38	4.31	4.58	4.17	4.17	4.31
OBAMo Standard Deviation	0.37	0.61	0.53	0.58	0.61	0.60	0.65	0.54	
Benefit	4.75	4.67	3.25	4.25	4.28	4.83	4.00	4.00	4.28
Facilitating What-if-Analysis	4.75	4.50	4.25	4.50	4.50	4.83	4.50	4.17	4.50
Flexibility	4.25	4.33	3.50	3.75	4.00	4.33	3.50	4.17	4.00
Output Comprehensive	5.00	4.00	4.00	5.00	4.44	4.33	4.67	4.33	4.44
General opinion Average	4.75	4.67	4.25	4.25	4.50	4.67	4.17	4.67	4.50
General opinion Standard Deviation	0.35	0.29	0.35	0.35	0.35	0.29	0.29	0.29	
Overall Average	4.63	4.35	3.84	4.25	4.28	4.46	4.13	4.25	4.28
Overall Standard Deviation	0.39	0.58	0.47	0.63	0.59	0.59	0.59	0.55	0.59

FIGURE VIII
System Validation - Questionnaire Results

The respondents addressed some constructive comments to be added to future versions:

1. Add help screens and notes
2. Add sensitivity analysis
3. Include effect of market
4. Differentiate between PM whether internal or exterior a project
5. Flexibility to add more cases to database
6. Consider another factor related to soil type

V. CONCLUSIONS

This paper presents an intelligent claims prediction and decision awareness framework that is composed of two models: a Claims Impact Prediction Model (CIPM) and a Decision Awareness Model (DAM). The framework is capable of (1) identifying the possible input decisions for international construction projects in Egypt (mainly Building and Touristic projects) that may lead to claims as well as defining the causes that may contribute to the initiation of such claims; (2) Integrating Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs) in one model (the CIPM) to predict the cost and time impacts of possible claims, as well as the type of relationship between the projects parties, based on the owner’s key decisions in setting the project variables; (3) suggesting the optimum project decisions that can help minimizing the impact of claims using the genetic Optimization Backward Analysis Module (OBAMo); and (4) enabling project owners to predict and visualize the impact of their key decisions on the project using the Decision Awareness Module (DAMo). The ANNs were trained and tested using a genetic optimization technique applied through EVOLVERTM V.5.5 which was implemented in a user-friendly MS-Excel spread sheet environment that improved on other non-transparent traditional ANNs training and testing methods. The framework provided projects’ owners and international contractors with a robust user-friendly decision-support tool that raises their awareness with regard to their pre-bid decisions using hybrid genetic algorithm-ANNs models. Owner organizations can benefit from the model in running What-If scenarios to realize the effect of the changes in the input variables (e.g., design status, owner behavior toward price, selection criteria, etc.) on the expected output. The developed model allows for backward genetic optimization to determine the values of the controllable variables that results in minimum effect of claims. Although the paper introduces a novel approach to predict claims and support owner organizations to reduce their impacts on cost and time, the developed model is limited only to building and touristic project types. Ongoing research efforts are currently being implemented to include other types of projects (e.g., industrial projects).

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