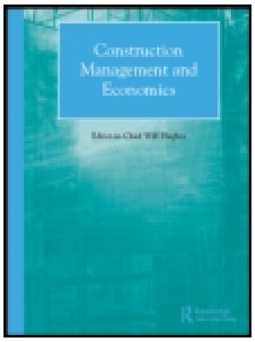

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A neural network bid/no bid model: the case for contractors in Syria

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Despite the crucial importance of the 'bid/no bid' decision in the construction industry, it has been given little attention by researchers. This paper describes the development and testing of a novel bid/no bid model using the artificial neural network (ANN) technique. A back-propagation network consisting of an input buffer with 18 input nodes, two hidden layers and one output node was developed. This model is based on the findings of a formal questionnaire through which key factors that affect the 'bid/no bid' decision were identified and ranked according to their importance to contractors operating in Syria. Data on 157 real-life bidding situations in Syria were used in training. The model was tested on another 20 new projects. The model wrongly predicted the actual bid/no bid decision only in two projects (10%) of the test sample. This demonstrates a high accuracy of the proposed model and the viability of neural network as a powerful tool for modelling the bid/no bid decision-making process. The model offers a simple and easy-to-use tool to help contractors consider the most influential bidding variables and to improve the consistency of the bid/no bid decision-making process. Although the model is based on data from the Syrian construction industry, the methodology would suggest a much broader geographical applicability of the ANN technique on bid/no bid decisions.

Keywords: ANN, ANN bidding model, 'bid/no bid' criteria, construction, Syria

Introduction

Contractors' survival is strongly dependent on being able to successfully deal with different bidding situations usually with limited time space. Bidding on unsuitable projects could result in a large loss or consume time and resources that could be invested in more profitable projects. Not bidding for a project could result in losing a good opportunity to make profit, improve the contractors' strength in the industry and gain a long-term relation with a new client. Bidding for a new project commits the bidder to bid preparation costs. Thus, contractors need to be more selective in bidding to reduce such costs.

The usual practice is to make the 'bid/no bid' decision on the basis of intuition derived from a mixture of gut feelings, experience and guesses (Ahmad, 1990; Fayek, 1998). Numerous factors are involved in this highly unstructured process. Thus, the need for automated systems to assist contractors make their bidding decisions has been a subject of research for a long time. Many bidding models have been developed, mainly for estimating the probability of winning a contact with a certain margin, i.e. mark up. These models have not been popular amongst practitioners due to various reasons including the large amount of data tracking and mathematical calculations required to implement them (Ahmad, 1990; AbouRizk *et al.*, 1993). Ahmad and Minkarah (1988) conducted a questionnaire survey to uncover the factors that characterize the bidding decision-making process in the USA. Subsequently, Ahmad (1990) proposed a methodology based on the decision analyses technique for making the bidding decisions. This model requires many inputs some of which the bidder, especially those with limited experience, might not be able to provide.

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In addition, it assumes that all factors contribute positively to the total worth, i.e. desirability of the 'bid' decision, of the project under consideration. No distinction was made between some factors that count for the bid decision, such as profitability, and others that might count against the bid decision, such as 'degree of hazard'. Shash (1993) identified, through a modified version of the same questionnaire used by Ahmad and Minkarah (1988), 55 factors that characterize the bidding decisions in the UK. The need for work, number of competitors tendering and experience on similar projects were identified as the top three factors that affect the 'bid/no bid' decision.

Ahuja and Arunachalam (1984) proposed a model to aid contractors to systematically evaluate the risk due to the uncertainty of availability of the required resources before bidding on a new project. As argued by Ahuja and Arunachalam, it is vital for contractors to optimally use their own resources by procuring new projects to employ resources that will be released progressively from ongoing projects. A CPM summary network with resource allocation is required for this model. The model tries to help contractors to balance both resources owned, those available from ongoing projects and resources that must be procured. For each alternative, the model produces a duration and cost estimate for the project. In fact, this model is better considered a resource allocation model and not a 'bid/no bid' model. It does not have clear criteria to give a bid or no bid recommendation. Also, resources, and risks related to them, are not the only criteria that affect the 'bid/no bid' decision-making process (Wanous *et al*., 1999).

AbouRizk *et al.* (1993) proposed an expert system called BidExpert. This model was integrated with a database management program, called BidTrak, that retrieved historical information from past bids submitted by the company and its competitors. The user needs to provide information about the project and the company. The information provided by the user and derived from BidTrack is, then, passed to BidExpert that is also linked to two external programs: the 'Fair and Reasonable Mark up Pricing Model' (FaRM) and a program to calculate the accuracy of the cost estimation. BidExpert processes the outcomes using its knowledge base and provides the user with a 'bid/no bid' recommendation. The necessity for historical information limits the applicability of this model. BidExpert has other drawbacks. For instance, the company capacity is evaluated by the number of projects the company has handled in the last five years and the number of the current projects, without any consideration of the projects' sizes.

Wanous *et al.* (1998) conducted a questionnaire survey to uncover the parameters that influence the 'bid/no bid' decision-making process in Syria. The survey has helped to identify 35 factors that are considered by Syrian contractors and to uncover the practice of making bidding decisions by Syrian contractors. Only 3% of the contractors who participated in this survey use some sort of mathematical procedures to make their bidding decisions. The vast majority relies on subjective judgement based on past experience to decide whether to bid or not. This is very much in line with similar studies conducted in other countries as shown in Table 1. All these studies have emphasized the need for qualitative bidding methods. Subsequently, Wanous *et al.* (2000) proposed a parametric 'bid/no bid' strategy. Only the most important bidding factors identified by Wanous *et al.* (1998) were considered in this model. Each factor was assigned a parametric scale to assess its contribution toward the bid decision. Based on the total contribution, i.e. Bidding Index, the model recommends whether to bid or not with a certain degree of confidence. The parametric model was 85% accurate in simulating the actual bidding decisions in 20 real-life projects. However, it has some limitations. For example, it assumes a linear influence of the decision's criteria on the final decision, which might not be the case.

The present paper describes a new ANN application on the bid/no bid decision-making process. Neural networks gain their analogy-based, problem-solving capabilities by learning from a set of data records of inputs associated with the actual (desired) outputs. Neural networks, once trained, are able to predict outcomes from new examples based on analogy with the examples used in training (Anderson and Gaarslev, 1996). An ANN development software called 'NeuralWorks Professional II/ Plus' was used in this study. Data on 182 real-life projects were pre-processed and transformed into series of inputs-output patterns. Twenty cases were randomly selected and reserved for validation. The remaining examples were used in training numerous neural network configurations. It has been demonstrated that the ANN technology is a very reliable tool for modelling the 'bid/no bid' decision. The developed model predicted the actual decisions in 90% of the same real life bidding situations used to validate the parametric model proposed by Wanous *et al.* (2000).

The rest of the paper is organized as follows. In the next section, we explain why the ANN is suggested as a

Table 1 Use of mathematical bidding models in various countries

Country	Contractors using mathematical bidding models (%)	Researcher(s)/date
USA	11.1	Ahmad and Minkarah (1988)
UK	17.6	Shash (1993)
Australia	12.0	Ting and Mills (1996)

new tool for modelling the 'bid/no bid' problem. The third section explains how the required data were collected and pre-processed. The fourth section describes the development process. Then the developed model is tested and validated. Finally, we summarize the findings and make recommendations for future improvement.

Why neural networks?

An artificial neural network is a computational model loosely based on the biological nervous system. ANN models can usually find solutions for very complex problems. The hidden layers give critical computational capabilities to neural networks. Among various structures and paradigms, the back-propagation network developed by Rumelhart *et al.* (1986) is one of the simplest and probably the most prevalent in neural networks studies (Masters, 1993, 1994; Fausett, 1994; Haykin, 1994; Refenes, 1995; Martin and Morris, 1999) and, thus, was adopted in the present study.

ANN models accept a set of inputs and produce a corresponding set of outputs based on internal mapping relationship encoded in their structure and connection weights (Wasserman, 1994). Potential applications of the ANN to various construction decisions have been highlighted by many researchers including Moselhi *et al.* (1991), Flood and Kartam (1994a, b), Boussabaine (1996) and Anderson and Gaarlev (1996). The literature contains many attempts to model the 'mark up selection' process using ANN with reasonable degrees of success (Moselhi and Hegazy, 1991; Li, 1994, 1996; Li and Love, 1999). Those researchers have claimed that the ANN technique is suitable for modelling the 'mark up selection' because it is a highly unstructured decision. Also, the 'bid/no bid' decision-making is an unstructured process (Ahmad, 1990) and it is characterized by several factors the influence of which is difficult to quantify individually and in combination, lending itself to be a potential application of the ANN technique. Therefore, it has been decided to investigate the applicability of this technique to the first part of the bidding process (bid/no bid).

It is commonly recognized that the black-box feature of conventional ANN models is the central drawback that undermines their practical applications. This problem has been addressed by many authors including Masters (1993) and the *Fuzzy*TECH handbook (1997). However, ANN models still have numerous convincing advantages including:

(1) the approximation ability of ANN technique to learn underlying functional relationships from real life bidding situations, which can easily be collected from contractors;
(2) ANN models are not restricted by assumptions of linearity adopted in most traditional methods (Moshiri and Cameron, 2000);
(3) ANN models can provide meaningful answers even when the data to be processed include errors or are incomplete (Lippmann, 1988).

ANN models do not attempt to replace the human experience and judgement. The model proposed in the present study is no exemption. It is an attempt to introduce the possibility of applying new methods for better utilization of past bidding experiences. The model is expected to be of considerable help to contactors in their bidding decisions without the necessity to large amount of data and without the need to perform complicated mathematical calculations, which has limited the practical application of previous bidding strategies.

The proposed model can suggest initial bidding decisions based only subjective assessment of the bidding situation under consideration. It can be applied along other familiar procedures to reinforce and validate the finial decision. It can also prove very useful for training and performing what-if exercises.

Data collection and preparation

The factors that are considered by Syrian contractors when making their bidding decisions were identified through a formal questionnaire survey supported by six semi-structured interviews as explained in Wanous *et al.* (2000). Thirty-five bidding factors were identified and ranked according to their importance to contactors operating in Syria as shown in Table 2.

Seventeen factors with low importance – i.e. their Importance Index was smaller than 50% – were omitted. The remaining 18 factors were considered as potential input variables for the purposed ANN model as indicated by asterisks in Table 2. These variables were considered to prepare another questionnaire to collect data on real life bidding situations. This questionnaire was posted to 250 contractors in Syria. A total of 124 contractors have responded providing data on 182 projects undertaken during the period 1991–1999. These projects include various buildings (55%), pipeline projects (17%), roads (12%) and dams (11%). Only 5% of the examples provided are on special projects such as power stations, airports and seaports.

The collected data needed first to be pre-processed and transformed into pairs of inputs and outputs. This process involved the following tasks:

(1) Discovery of errors in the data. Missing assessments of certain factors were discovered in five projects (3%) of the collected sample. These projects were disregarded.

Table 2 Selection of the most influential bidding factors

Factor	Importance index	Considered factors
1. Fulfilling the to-tender conditions imposed by the client	89.88%	*
2. Financial capability of the client	77.67%	*
3. Relations with and reputation of the client	76.83%	*
4. Project size	73.17%	*
5. Availability of time for tendering	70.83%	*
6. Availability of capital required	68.33%	*
7. Site clearance of obstructions	68.00%	*
8. Public objection	67.83%	*
9. Availability of materials required	66.33%	*
10. Current work load	65.83%	*
11. Experience in similar projects	64.00%	*
12. Availability of equipment required	64.00%	*
13. Proportions that can be constructed mechanically	64.00%	*
14. Availability of skilled labour	58.00%	*
15. Original project duration	55.50%	*
16. Site accessibility	53.83%	*
17. Risks expected	52.17%	*
18. Rigidity of specifications	50.00%	*
19. Expected project cash flow	47.00%	
20. Degree of buildability	47.00%	
21. Availability of other projects	46.17%	
22. Confidence in the cost estimate	45.33%	
23. Project location	31.67%	
24. Original price estimated by the client	28.50%	
25. Past profit in similar projects	26.50%	
26. Expected date of commencing	24.67%	
27. Availability of equipment owned by the contractor	22.17%	
28. Expected number of competitors (degree of competition)	17.83%	
29. Local climate	17.50%	
30. Specific features that provide competitive advantage	16.33%	
31. Fluctuation in labour/materials price	15.00%	
32. Competence of the expected competitors	12.50%	
33. Relations with other contractors and suppliers	10.33%	
34. Proportions to be subcontracted	05.50%	
35. Local customs	04.17%	

Source: Wanous *et al*. (2000).

(2) Twenty cases were randomly selected from the remaining sample and reserved for the validation process (validation or testing sample).
(3) Transformation of the data set into a format that is suitable for the development software, ‘NeuralWorks Professional II/ Plus’. The data were organized as a set of pairs of inputs and the corresponding outputs, i.e. ‘bid’ or ‘no bid’. Each input variable is a score on a continuous scale from 0 to 6, where 0 is extremely low and 6 is extremely high. The output values are 0 for ‘no bid’ and 1 for ‘bid’.

By this stage, potential input factors were identified and the training and testing samples of real life projects were ready in the required format. The following section explains briefly the development of the proposed ANN model.

The development process

The literature contains several approaches and recommendations for the selection of appropriate structures for ANN models. These include the following (Freeman and Skaoura, 1991; Haykin, 1994; Hegazy *et al*., 1994; Masters, 1993, 1994; Refenes, 1995; Boussabaine, 1999):

(1) start with one hidden layer and add more if required;
(2) with a single hidden layer, a suitable initial size is 75% of the size of the input buffer. For more than one hidden layer, reduce the size of each subsequent layer;
(3) continuous-value input/output pairs use a form of sigmoid transfer function;
(4) a network with a continuous-value inputs may required more than one hidden layer;

(5) in continuous-value inputs and outputs, the number of the processing elements, i.e. nods, in the input buffer and the output layer is equal to the number of the input and output attributes respectively;
(6) generally, fully connected adjacent layers within multi-layer network are best; and
(7) the momentum can be set to (0.9).

However, such rules are not yet widely accepted (Moshiri and Cameron, 2000). There is no single configuration that is adequate for all domains. The topology, therefore, must be determined through a process of trial and errors (Adya and Collopy, 1998).

It was decided to start by examining the simplest possible topology for the ANN 'bid/no bid' model. This structure is composed of the input buffer, which contains 18 nodes fully connected to the output layer, which contains only one node. The sigmoid transfer function and the 'normalized cumulative delta' learning rules were used. The other parameters, i.e. learning coefficient, momentum and epoch size were set to their default values adopted by the development software (NeuralWorks Professional II Plus). This initial structure, with no hidden layers, is identical to a simple linear regression model. It does not take into account any possible non-linear relationships between the bidding variables and the final decision.

The network connection weights (W_i) are first automatically set to small random number between −0.5 and +0.5. Using the back propagation (BP) learning algorithm, the initial model was trained on the training sample (157 projects) for a fixed number of iterations (50 000). Two statistical measures of how well the model has captured the principal relationships in the training data were recorded, the Root Mean Square error (RMS_{train}) and the correlation coefficient (R^2_{train}). The generalization capability of the trained model was then examined using the test sample (20 new projects) and similar error indicators were also recorded, RMS_{test} and R^2_{test}. A total of 47 structures were tried considering more hidden layers with different number of hidden nodes, different learning rules, learning rates, transfer functions and learning iterations. For each trial, RMS and R^2 were recorded. The characteristics of the best model found are shown in Table 3.

The ability of this model to explain the variance in the training data is demonstrated by its small RMS_{train} error and high R^2_{train}. The model also has good generalization ability as shown in the next section. The structure of the selected model is shown in Figure 1. Potential users only need to provide their personal assessments of the bidding situation under consideration in terms of eighteen variables on a scale from 0 (extremely low) to 6 (extremely high). Based on provided inputs, the model produces an index called the Neural Bidding Index (NBI) on a scale from 0 to 1. The closer is the index to 0, the higher the confidence in a 'no bid' recommendation and the closer is the index to 1, the higher the confidence in a 'bid' recommendation.

Testing and validation

A procedure based on guidelines suggested by Refense (1995) and Collopy *et al.* (1994) was employed to evaluate the predictive capabilities of the proposed network and examine the effectiveness of its implementation.

To evaluate the predictive performance of the network, the following guidelines were applied:

(1) *Use out-of-sample validations*. This is very much in line with real-world tasks where one must produce predictions about a case the result of which is not available. The model was able to predict the desirable decisions of 20 real-life bidding situations not used in training with only 10% error.
(2) *Comparisons with other models*. It is a well-established tradition in forecasting research to compare techniques based on their empirical results (Adya and Collopy, 1998). Therefore, if the proposed model is to be taken seriously, it must be evaluated in terms of other models that proved some degree of accuracy. This model is more accurate compared to the parametric model proposed by Wanous *et al.* (2000), which failed to predict the actual bid/no bid decisions in 15% of the same test sample. This is expected because the parametric model is based on assumptions of linearity of relationships between bidding variables and the bidding decision whereas the hidden nodes of the proposed network should have modelled any

Table 3 Characteristics of the final model

Model	No. inputs	No. of hidden layers	Nodes in layer 1	Nodes in layer 2	Iterations	LR	TF	Training		Testing	
								RMS	R^2	RMS	R^2
47	18	2	5	2	57340	N-C-D	Seig moid	0.0282	0.9950	0.1744	0.8120

LR: Learning Rule; TF: Transfer Function; RMS: Root Mean Square error; R^2: Correlation coefficient.

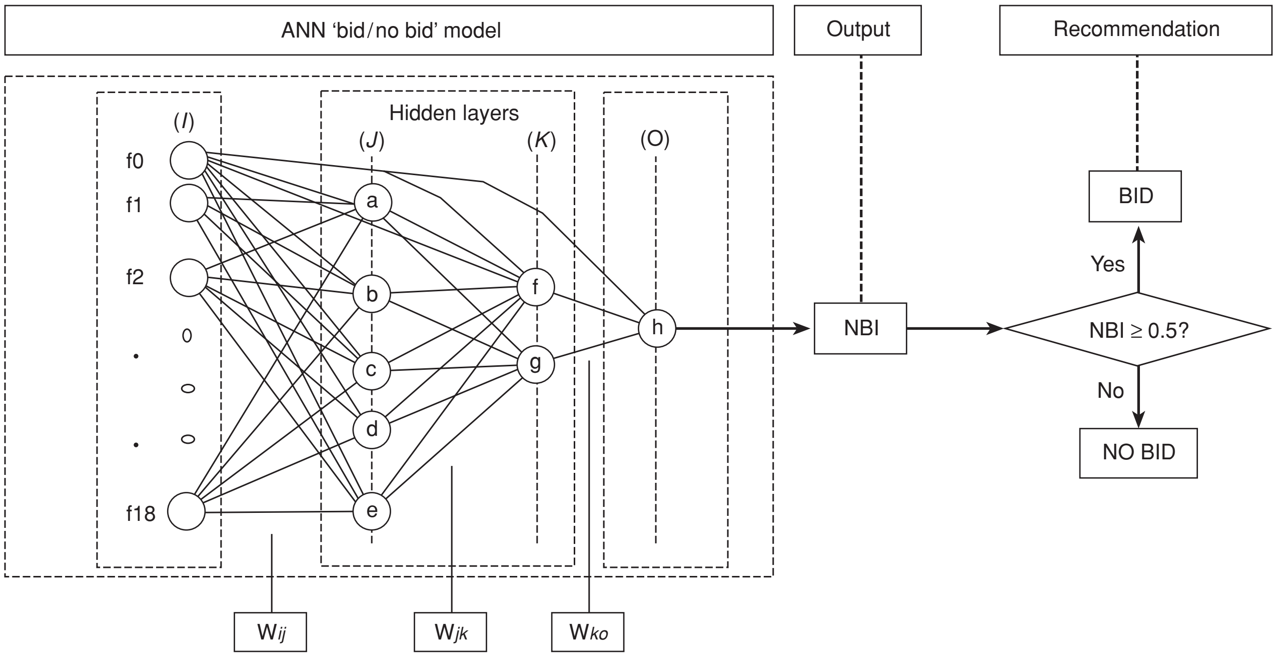

Figure 1 Structure of the final model

non-linear functional relationships imbedded in the bidding cases used for training.

In determining the effectiveness of the development process, guidelines suggested by Refenes (1995) were used:

(1) Convergence, which is to check whether the learning mechanism adopted is capable of modelling the classification defined in the training data. Convergence is concerned only with the in-sample – i.e. training sample – performance. Comparing the network's recommendations with the actual bid/no bid decisions made in the training examples shows a very small prediction error (RMS = 0.0282) and an extremely high correlation between recommended and actual decisions ($R^2 = 0.9950$). This is a clear indication of the effectiveness of using the back propagation leaning method.

(2) Generalization, which examines the ability of the ANN model to recognize patterns outside the learning sample. At this stage, the model was presented with assessments of new unforeseen projects from the test sample. The model's recommendations were very similar to the actual decisions as indicated by a small error (RMS = 0.1744) and a high correlation coefficient ($R^2 = 0.8120$). The model failed to predict the actual bid/no bid decisions only in two cases (10% of the test sample as shown in Table 4. This suggests a good generalization ability of the proposed model.

Furthermore, a user-friendly prototype of the developed model will be sent to contractors who have provided data for this study to further test the model performance and its stability with new real-life projects. In addition, future work will address the black-box problem of the ANN model using neurofuzzy methods so that all subjective bid/no bid decisions can be modelled.

Conclusion

The artificial neural networks technologies have been successfully applied in many areas in construction including mark-up estimation. This paper demonstrates a new application of this powerful modelling tool on the 'bid/no bid' decision-making process. Eighteen of the most influential factors that characterize the bidding decisions in the Syrian construction industry were identified and used as input variables for the developed model. A sample of 182 real-life bidding situations was provided by contractors operating in Syria. Five projects were discarded for incompleteness. Twenty projects were randomly selected and reserved only for validation. The remaining examples were used for training. Although there are some empirical rules suggested in the literature for specifying the optimum structure of ANN models, they have not been widely accepted and the traditional trial and error procedure is still the most popular method to specify the best possible network paradigm. Over 47 network structures were experimented with and the most satisfactory network found consists of an input buffer of 18 nodes for the model input variables, two hidden layers

Table 4 Actual and predicted decisions of test sample

Project No.	Actual decision	NBI	Predicted decision	Notes
1	Bid	0.9120	Bid	
2	Bid	0.8231	Bid	
3	Bid	1.0021	Bid	
4	Bid	0.5325	Bid	
5	Bid	0.9401	Bid	
6	Bid	0.9959	Bid	
7	Bid	1.0155	Bid	
8	No Bid	0.0601	No Bid	
9	No Bid	−0.0015	No Bid	
10	No Bid	0.9862	Bid	Wrong
11	Bid	1.0235	Bid	
12	Bid	0.9988	Bid	
13	No Bid	0.9603	Bid	Wrong
14	Bid	0.9789	Bid	
15	No Bid	0.0486	No Bid	
16	No Bid	0.1824	No Bid	
17	No Bid	−0.0204	No Bid	
18	Bid	0.9879	Bid	
19	Bid	1.0207	Bid	
20	No Bid	0.0028	No Bid	

with five and two hidden nodes respectively and one output node. Potential users need only to provide their personal assessments of a certain bidding situations in terms of 18 variables on a scale from 0 for extremely low to 6 for extremely high. The model then produces an index between (0) to (1). A 'bid' recommendation will be made if this index exceeds (0.5) otherwise the model will recommend not to bid. A standard validation procedure was used to test the accuracy of the proposed model and the effectiveness of its development.

The model proved to have strong learning capability as suggested by a very low prediction error (RMS = 0.0282) and an extremely high correlation ($R^2 = 0.9950$) between the model recommendations and the actual decisions in the learning sample. The generalization capability of the model was also tested on different sample of 20 real-life bidding situations. The recommendations made were very close to the actual decisions as revealed by a high collection ($R^2 = 0.8120$) and a low prediction error (RMS = 0.1744). The model wrongly predicted only 10% of the actual bidding decisions made in real life. This demonstrates a high accuracy of the proposed model and the viability of neural network as a powerful tool for modelling the bid/no bid decision-making process. The major limitation of conventional neural network models is that they can be difficult to interpret. This problem can be addressed through neuro-fuzzy network approaches (Zhang and Morris, 1996). Alternatively, users can use ANN models in conjunction with other methods with which they are familiar. By comparison between the outputs, they could build more confidence in the network. Some further improvements include facilities for database management and dynamic maintenance by training the system on newly completed examples. Although, the proposed model is based on data from the Syrian construction industry, the methodology has much broader geographical applicability.

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