MODELLING RISK FACTORS IMPACTING CONSTRUCTION PROJECT BUDGET PERFORMANCE IN NIGERIA

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ABSTRACT

Studies have shown that the level of accuracy of construction project budgets is significantly affected by the level of risk information available during budget preparation. The aim of this study is to model the risk factors impacting on construction project budget performance in Nigeria. Data were collected via questionnaire survey of design firms operating in the major cities of Northern Nigeria. The responses obtained were analysed using descriptive analysis, mean scores, standard deviation and Statistical Package for Social Sciences version 21 neural network software for the development of neural network models. Neural networks is a set of non-linear data modeling tools consisting of input and output layers plus one or two hidden layers. The connections between neurons in each layer have associated weights, which are iteratively adjusted by the training algorithm to minimize error and provide accurate predictions. Results showed eleven risk factors with both high likelihood of occurence and sigificant impact on construction project budget required the respondents to estimate the percentage variations between actual and initial “construction project budget” at 30%, 50% and 70% completions of executed projects. The models developed showed that construction project budget prediction vary with the actual expenditure by +25% at 30% completion, +25% at 50% completion and +25% to 40% at the 70% completion stages respectively. Validation of the models showed a 73%, 70%, and 66% accuracy at 30%, 50%, and 70% completion stages respectively. This signifies the need for construction professionals in Nigeria to take into consideration the significant risk factors during the project appraisal so as to ensure optimal budget performance and successful projects delivery. With this model budget variations can be predicted up to 40% of the initial budget estimate. This signals the short comings of the existing models. The model will provide an opportunity for taking pro-active measures, at various stages of construction processes. The model could serve as a basis for keeping the cost of construction projects within the estimated budget and checking the hitherto construction budget escalation.

Keywords: *budget, budget performance, neural network, risk management models, risk.*

INTRODUCTION

Construction project budget is an estimate of probable project target cost which is developed throughout the construction cycle (Odeyinka, 2016). The Association for Project Management (2012) defined budgeting as the process of estimating the cost of a proposed project and setting an agreed target. However, the primary measure of success in preparing the budget estimates is to predict the project capital cost and the whole life cost accurately at project inception.

Jackson (2002) stated that housing and public buildings clients continue to experience cost overruns on set budgets (Jackson, 2002). Potts and Ankrah (2014) revealed that most clients work within tight pre-defined budgets or cost plans, prepared by Cost Consultants during design process. This budget is expected normally not to be exceeded or else the whole scheme may fail. However, there is evidence in the construction management literature indicating that it is difficult to find a project in which cost overrun will not be experienced (Aibinu and Pasco, 2008; Akintoye, 2000; Enshassi, Mohammed & Abdel-Hadi, 2013; Odusami and Onukwube, 2008). This, according to Akintoye & Macleod (1997) and Odeyinka (2000) could be as a result of risk factors inherent in construction projects from the inception to the completion stage.

Augustine et al. (2013), found that the construction industry is exposed to about 53.04% risk, thereby resulting to high failure rate of construction projects. Also Ayegba et al. (2014) found that, in recent years, the industry has been associated with repeated construction cost overrun, time overrun and low quality products. Therefore, the nature, occurrence and impact of risk in construction have become a topic of interest because of the effects on quality, time and cost of construction projects (Ojo, 2010; Windapo & Martins, 2010).

In recent times, a number of models have been suggested by researchers for use as risk management techniques and the results indicated that risk factors impacting on construction budget performance can be successfully assessed, managed and modelled (Baloi & Price, 2003). These techniques include, Monte Carlo Simulation (MCS), Project Evaluation and Review Technique (PERT), Probability and Impact (P&I), Likelihood of Occurrence of Risk (LOR), Analytical Hierarchy Process (AHP) and Fuzzy Logic (Baloi & Price, 2003; Abdelgawad & Fayek, 2010). However, these models have been faulted to require detailed quantitative information that is normally not available at the planning stage and their applicability in real project are also very limited (Thomas, 2006; Abdelgawad & Fayek, 2010; Eybpoosh, Dickmen & Talat-Birgonul, 2011; Tamosaitiene, Zavadskas &Turskis, 2013). MCS has the function of analyzing the using the probability approach. Multiple regression analysis arrives at the result through statistical analysis and easy to analysed, though the results are in linear form. Koo et al. (2010) stated that Artificial Neural Network (ANN) is more accurate than Multiple Regression (MR), MCS, PERT and others. It is therefore, vital to model the observed significant risk factors using ANN in predicting the risks. More so, Jackson (2002) in his study suggested that new integrated models are also required to help cost estimators and other professionals to systematically manage risk during project appraisal.

In the same vein, Wanyona (2005), indicated that, intuition, judgment and experience have been the method of risk analysis currently used as a techniques of dealing with risk impacts during risk management in budget prediction. Despite these techniques, the industry continues to suffer poor performance with many projects failing to meet the time and cost targets due to improper assessment of risk factors in construction budgeting (Ojo, 2010). According to recent researches (Adafin et al., 2016; Odeyinka & Dada, 2016), the variability between the initial budget estimate and the actual cost of project is as a result of non-consideration of risk factors inherent during the budget development. Other researchers are also advocating for identifying and evaluating the impact of risk factors on project budget. The proactive identification of risks and their outcomes is essential for budget prediction and for estimating future risk impacts (Wanyona, 2005).

Several factors that result to the risks mentioned above, have impact on construction project budget at the project development stage. These factors include: market condition; project complexity; quality of information and flow requirements; availability of design information; client's change/changes in owner's requirements; project team's experience of the construction type; method of construction; inadequate tender documentation; expertise of consultants; and site investigation (Adafin and Rotini, 2016). Hence, risk identified at the project development stage can be assessed and managed successfully. If risks are properly dealt with, final cost of the construction project can be expected to be within the budget (Baloi & Price, 2003; Adafin, Rotimi & Wilkinson, 2016).

The aim of this research is to model the risk impact of risk factors impacting on construction project budget performance in Nigeria. The objectives to assess the likelihood of occurrence of the risk factors and their level of impact on construction project budget performance in Nigeria; to develop and validate models for predicting the impact of risk factors on construction project performance.

LITERATURE REVIEW

BUDGET

In Construction project, budget is an estimate of a probable project target cost that is developed throughout the construction life cycle (Odeyinka and Dada, 2016). It is a formal statement of the financial resources set aside for carrying out of specific activities at a given period of time. Putzer (1995) cited in Wanyona (2005) stated that the aim of budget is mainly to aid the planning process, to communicate cost plans to the various cost managers and to control costs. APM (2012) defined budgeting as the process of estimating the cost of a proposed project and setting an agreed target. The budgeting process ensures that managers plan for future operations. Capital budgeting specifically involves a process of allocating the financial resources of a firm in a manner that best attains its overall cost objectives. In addition, the budget process relates to an entire activity or operation and also encourages consultation between building participants so that they can anticipate problems before they arise.

Budgets do not indicate the actual problem areas, but should guide the client on the likely exposures to financial risks (Wanyona, 2005). According to Odeyinka (2016), the primary measure of success in preparing budget estimates is to predict the project capital cost and the whole life cost accurately at the project inception. Anigbogu *et al*. (2007) concurred that the first step toward ensuring that problems are avoided in construction process is the production of accurate cost estimates. The effect of bad budget at the early stage of a construction project includes embarking on an infeasible project and rejecting feasible project (Lowe *et al*., 2006).

Budget is therefore, useful to all parties involved in a project as a planning and control tool. Budget could be employed by the client to get priorities among projects competing for limited resources. It also enables the client to set the machinery in motion for meeting the interim valuations as at when due and also used to justify the elimination of uneconomic project(s) as well as the revision of its objectives to meet the demand of a manageable project. Budget could also be employed by the consultants as cost control tool in managing construction project.

BUDGET PERFORMANCE

During the execution of any construction project, cost is a very important factor for the project to succeed. The initial budget estimated does not actually represent the final cost expected. This has been confirmed by some researchers that many of the construction projects executed experienced several challenges ranging from simple to complex issues.

Morrison (1984) has found lack of budget performance in the UK construction industry where data on educational, commercial and housing projects were collected from seven separate quantity surveying firms and found on average of 12% was obtained by these Quantity Surveyors. Ogunlana (1991) also reported the significant deviations that were observed between design cost estimates and accepted tenders, using the information that were sourced from seven design offices on maintenance projects in the UK.

In Singapore, Cheong (1991) found that the disparity between budget estimates and contract sums is generally between 5% and 10%. Cheong (1991)'s study gathered opinions across a wide range of quantity surveyors. Significantly, Cheong's analysis of 88 projects (i.e. educational, commercial, residential, public and community, etc.) from one quantity surveying consultancy in Singapore found that the deviations between the budget estimates and contract sums ranged from 33.79% (overestimates) to 31.30% (underestimates).

In New Zealand Construction Industry, Adafin et al. (2016) reported that the reliability of the budget varied depending on project types. Whereas a deviation of between -3.67% and +3.95% was obtained for the residential projects; between -3.98% and +12.15% deviation was for educational projects; commercial projects attracted between -14.22% and +16.33% while the refurbishment projects had a deviation of between -10.07% and +30.14%.

In Nigeria, Oke, Ogungbile, Oyewobi, & Tengan (2016) in their study of factors affecting the performance of construction projects by surveying professionals in the Nigerian construction industry, found that the most important factors affecting project performance were: project design cost, unavailability of resources, project complexity, quality of equipment and raw materials, while client satisfaction, on-time completion and productivity were considered to be the main measures of construction project performance. It was concluded that that project owners must work collaboratively with all the professionals involved in carrying out construction project in order to facilitate good performance.

RISK MANAGEMENT MODELS FOR CONSTRUCTION PROJECT PERFORMANCE

A number of researchers have developed models for use as risk management techniques. Baloi and Price (2003) also reported that global risk factors that affect construction cost performance can be modelled using Fuzzy Set Theory and a fuzzy decision support system can be developed. Their process was to determine the most significant risk factors; define the different linguistic variables that correspond to the constructs used by construction professionals to describe risk factors through literature search, questionnaires and interviews with construction industry practitioners.

Dikmen and Birgonul (2006) use AHP within a multi-criteria decision making (MCDM) framework for risk and opportunity assessment of international construction projects. They calculated the overall risk level of each project by multiplying the relative probability with the relative impact for each risk and then adding the score up. Hsueh et al. (2007) to develop a multi-criteria risk assessment model for construction joint-Ventures. It merely proposes that decision makers are able to make- judgments: the higher the expected utility value, the lower the overall project risk. Zayed et al. (2008) use AHP to assign weights to risks before calculating project risk level, which is defined as the sum of the weighted risk effects of risk factors.

Odeyinka (2007) developed a risk/impact assessment model for evaluating the impacts of risk on the budgeted cost of traditionally procured building projects after using the significant risk factors from the analysis of the data received through a questionnaire survey. The developed model shows a very good predictive ability; indicating that the model could assist in pro-actively determining the likely impacts of identified risks on the budgeted cost of traditionally procured building projects.

However, these models have been faulted to require detailed quantitative information that are not available normally at the planning stage and their applicability in real project are also very limited (Thomas, 2006; Abdelgawad et al., 2010; Eybpoosh et al., 2011; Tamosaitiene et al., 2013).

Monte Carlo simulation has the function of analyzing the outlier using the probability approach. Multiple regression analysis arrives at the result through statistical analysis and easy to analysed, though the results are in linear form. Koo, Hong, Hyun & Koo (2010) stated that artificial neural networks (ANN) models are more accurate than most of the models earlier developed. More so, Jackson (2002) opined that new integrated models like neural networks are required to help cost estimators and other professionals to systematically manage risk during project appraisal. It is therefore, vital to develop a model using ANN in predicting the risks at the early phase of projects.

Abdulrazaq (2015) developed models for predicting the impact of risk factors on construction contractors' cash flow forecasts by collecting data via a questionnaire survey of contractors operating in the Nigerian construction industry. The models developed showed that construction contractors' cash-out forecasts vary with the actual expenditure by +20%, +25% and +25% at the 30%, 50%, and 70% completion stages respectively. Validation of the models shows a 77%, 69%, and 67% accuracy at 30%, 50%, and 70% completion stages respectively. However, this can only be used for cash flow managements in Nigerian construction industry.

A neural network approach uses measurable factors and performance sampled from actual projects. It is a predictive modeling approach new to the area of project success. With the complexity of the construction industry, the modeling process can be a difficult task if the functional relationships between the input factors and project outcomes cannot be clearly defined. It possesses the ability to learn relationships based on specific cases of the real world experience, even for data that is highly correlated, multivariate, nonlinearly and then generalize the solutions to other cases. This gives it the flexibility in modeling process that is not available in regression and other existing methods where the relationships have to be guessed and the model is only as good as the relationship it represents. One example of the practicability of the ANNs is the Neuronal Risk Assessment System (NRAS) developed by Maria-Sanchez (2005). This method shows a very practical manner for implementing ANNs for assessing the risks in infrastructures projects. The main goal of the system was to determine the contingency amount based on specific project risks. The results show the capabilities of ANNs to imitate the data, offering a great new approach for performing risk analysis. This input-process-output mechanism is called neural network feed-forward.

METHODOLOGY

For the purpose of identifying the appropriate sample size of this study, stratified sampling method was adopted for the study because the target population was already known with differences in region of residence and profession of the consultants. It was also adopted for the reason of splitting the population into categories and randomly selecting from within each category of the respondents.

Construction professionals on projects were considered as the target respondents for the survey through self-administered questionnaire surveys. These include, Architects, Quantity Surveyors, Structural Engineers, and Electrical & Mechanical Engineers operating in the major cities of Northern Nigeria (Abuja (FCT), Kaduna and Kano). For the purpose of identifying the appropriate sample size of this study, stratified sampling method was adopted for the study because the target population was already know with differences in region of residence and profession of the consultants.

However, considering Abuja (420), Kaduna (291) and Kano (39), where most of the firms are either located or have their head offices and also time frame and resources available for this research, a sample frame of 750 was arrived at. Using Krejcie and Morgan's (1970) formula, a sample size of 254 was determined and used for the study. Krejcie and Morgan (1970) used the following formula to determine sampling size:

$S = X^2NP(1-P)/ d^2(N-1) + X^2P(1-P)$ ……………………..(1)
Where:
S = required sample size
X^2 = the table value of chi-square for one degree of freedom at the desired confidence level

N = the population size
P = the population proportion (assumed to be 0.50 since this would provide the maximum sample size)
d = the degree of accuracy expressed as a proportion (0.05)

Table 1: Population, Sample Frame and Response Rate

S/N	Population (Consultants)	Sample Frame	Response Rate
1	Abuja	420	53
2	Kaduna	291	32
3	Kano	39	18
	Total	**750**	**103**

Empirical data (regarding budget variation between the initial and actual cost of recently completed projects) from the archives of Quantity Surveyors and also their perception regarding the risk factors in terms of occurrence and their impact in case they occur) were sought for through self-administered questionnaire surveys. The questionnaire contains a table that consists of 36 risk factors potentially impacting the construction project budget performance from the literature. The remaining 6 factors were gathered from the pilot survey carried out on the initially proposed questionnaire and included to make it a total of 42 risk factors in the amended questionnaire which was used for collection of data. Respondents were requested to provide opinions regarding the likelihood (i.e. probability) of each factor occurring and their severity (i.e. impact) should the risk factors occur. The respondents were requested to rank on a scale of 0 to 5, the likelihood of occurence as well as the impact (severity) of the risk factors identified from literature. From the first analysis, 11 risk factors that have 3.00 mean score and above for both occurrence and impact were extracted and used for the second survey. Respondents were requested to provide their opinions regarding the likelihood (i.e. probability) of each factor occurring. On the second table, respondents were asked to approximate percentage difference between actual and forecasted expenditure in percentages, at 30%, 50% and 70% completions of executed projects as a result of the risks occurrence as these are the levels the literature reported that variations between the initial and actual cost of construction projects are likely to occur.

The quantitative data were analysed using Statistical Package for Social Sciences software and the results of descriptive statistics obtained include frequency distributions tables, measures of central tendency (means) and standard deviation. The mean analysis was computed and used to rank the likelihood of occurence of the factors in decending order. Since the scale was 0-5, the mean calculate was 3.0 and the factors have scores from 3-5 were ranked significance. The two data sets were used to model the risk factors impacting on the cost of building projects.

RESULTS AND DISCUSSIONS

Table 2: Occurence of Risk Factors Affecting Project Budget Performance

Risk factors	Respondents' Perceptions 1	2	3	4	5	Mean	Std. Deviation	Rank
Unforeseeable changes in materials prices	1	6	15	53	28	3.98	0.863	1
Under-estimation	3	6	25	40	29	3.83	1.001	2
Market condition	0	10	21	51	21	3.81	0.875	3
Lack of skilled labour	3	10	26	45	19	3.65	0.987	4
Client's change/changes in owner's requirements	1	17	21	48	16	3.59	0.975	5
Changes in cost planning data	0	10	38	40	15	3.58	0.858	6
Defective design and specification	2	15	24	48	14	3.55	0.967	7
Little or no information about M&E services	3	8	46	23	23	3.53	1.018	8
Expertise of consultants	0	9	47	32	15	3.51	0.850	9
Project scope	2	18	27	39	17	3.50	1.028	10
Increase in duration of the project	3	7	43	36	14	3.50	0.917	11
Project team's experience of the construction type	3	6	51	32	11	3.41	0.868	12
Quality of information and flow requirements	7	11	42	35	7	3.24	0.977	13
Extent of pre-contract design completion	4	22	35	35	6	3.17	0.966	14
Project complexity	7	31	23	29	13	3.10	1.167	15
Government legislation/policy	2	31	41	19	10	3.04	0.979	16
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Type of structure	2	34	40	19	8	2.97	0.954	17
Sustainability of materials used and quality	7	38	24	20	14	2.96	1.179	18
Quality of work done	8	34	29	19	13	2.95	1.158	19
Availability of design information	6	33	32	26	6	2.93	1.022	20
Availability and supplies of materials	6	30	43	15	9	2.91	1.011	21
Quality of materials	7	34	34	17	11	2.91	1.095	22
Planning requirements or restrictions	3	35	44	12	9	2.89	0.959	23
Lack of expertise in client's organisation	20	25	20	24	14	2.87	1.341	24
Type and quality of cost planning data	14	25	33	26	5	2.83	1.103	25
Legal requirements	12	22	46	17	6	2.83	1.030	26
Procurement system	17	24	33	17	12	2.83	1.230	27
Tender inflation	6	39	30	24	4	2.82	0.988	28
Contract conditions	6	41	32	16	8	2.80	1.032	29
Unforeseeable fluctuation in labour prices	9	38	33	15	8	2.76	1.062	30
Availability and supplies of labour	3	32	44	16	8	2.74	1.084	31
Inadequate cost plan/tender documentation	10	30	47	15	1	2.68	0.877	32
Lack of multi skilled supervisor/consultants	27	23	20	24	9	2.66	1.325	33
Zonal rates Market condition	26	16	39	15	7	2.62	1.206	34
Project location	21	24	39	15	4	2.58	1.089	35

Site constraints	7	50	35	7	4	2.52	0.873	36
Type of client	18	37	28	17	3	2.51	1.056	37
Tender period	11	46	30	14	2	2.51	0.927	38
Client’s brief	15	48	19	16	5	2.50	1.074	39
Type of project	23	27	36	12	4	2.48	1.088	40
Method of construction	26	28	28	18	3	2.46	1.136	41
Type of bidding	27	29	30	15	2	2.38	1.086	42

Source: field survey, 2018.

The table above contained details of the results of the perceptions of the respondents from the survey. The risk factor whith the highest occurence is “Unforeseeable changes in materials prices”. This is followed by “Under-estimation”, “Market condition”, “Lack of skilled labour”, “Client’s change/changes in owner’s requirements”, “Changes in cost planning data“, “Defective design and specification”, “Little or no information about M&E services”, “Expertise of consultants”, “Project scope”, “Increase in duration of the project”, “Project team’s experience of the construction type”, “Quality of information and flow requirements”, “Extent of pre-contract design completion”, “Project complexity” and “Government legislation/policy”. These represent the top sixteen (16) risk factors that occur in construction projects budgets in Nigeria amongst the 42 risk factors. The positions of the 16 factors does not come as a surprise as changes in materials prices that was ranked 1st has become a critical issue and have no control in Nigerian. Under-estimation was ranked 2nd by the respondents as a factor with high occurrence. Under-estimation in technical terms means “forecasting errors”, i.e., in terms of imperfect techniques, honest mistakes, inadequate data, inherent problems in predicting the future, lack of experience on the part of forecasters, etc. (Ascher, 1978; Flyvbjerg et al., in press; Morris & Hough, 1987; Wachs, 1990) cited in (Flyvbjerg et al., 2002).

Table 3: Impact of Risk Factors on Project Budget Performance

	Respondents’ Perceptions							
Risk Factor	1	2	3	4	5	**Mean**	**Std. Deviation**	**Rank**
Unforeseeable changes in materials prices	1	6	39	37	20	3.63	0.897	1
Under-estimation	3	7	38	33	22	3.62	0.991	2
Defective design and specification	2	15	24	48	14	3.55	0.967	3
Market condition	0	10	44	35	14	3.51	0.850	4
Government legislation/policy	7	2	51	23	20	3.46	1.046	5
Lack of skilled labour	3	10	43	33	14	3.44	0.946	6
Changes in cost planning data	0	11	49	31	12	3.43	0.836	7
Project team’s experience of the construction type	3	15	39	27	19	3.43	1.044	8
Increase in duration of the project	4	10	42	36	11	3.39	0.942	9
Availability and supplies of materials	1	14	41	42	5	3.35	0.813	10
Client’s change/changes in owner’s requirements	4	5	47	32	15	3.33	0.933	11
Lack of expertise in client’s organisation	3	23	36	19	22	3.33	1.132	12
Procurement system	3	20	40	30	10	3.23	0.972	13
Tender inflation	10	11	46	22	14	3.18	1.109	14
Contract conditions	4	17	46	29	7	3.17	0.923	15

Expertise of consultants	0	23	47	25	8	3.17	0.868	16
Availability and supplies of labour	8	12	47	31	5	3.13	0.957	17
Inadequate cost plan/tender documentation	2	19	51	26	5	3.11	0.836	18
**								
Project location	21	16	22	31	13	2.99	1.339	19
Project complexity	5	35	33	20	10	2.95	1.061	20
Little or no information about M&E services	5	30	39	23	6	2.95	0.974	21
Zonal rates Market condition	9	20	46	24	4	2.94	0.968	22
Type and quality of cost planning data	10	31	31	19	12	2.92	1.161	23
Type of client	10	11	46	22	14	2.91	1.095	24
Client’s brief	4	17	46	29	7	2.90	1.133	25
Type of bidding	11	16	53	20	3	2.88	0.942	26
Planning requirements or restrictions	5	37	36	16	9	2.87	1.026	27
Method of construction	16	22	33	24	8	2.86	1.172	28
Unforeseeable fluctuation in labour prices	8	31	38	21	5	2.84	0.998	29
Site constraints	3	23	66	10	1	2.83	0.673	30
Quality of work done	9	27	46	18	3	2.80	0.933	31
Extent of pre-contract design completion	15	21	45	17	5	2.77	1.050	32
Project scope	16	23	42	16	6	2.74	1.084	33
Quality of information and flow requirements	13	26	42	19	3	2.74	1.000	34
Legal requirements	3	47	35	10	8	2.74	0.960	35
Type of structure	10	31	42	17	3	2.73	0.952	36
Quality of materials	12	31	39	16	5	2.72	1.023	37
Lack of multi skilled supervisor/consultants	15	30	34	18	6	2.71	1.099	38
Type of project	10	43	26	17	7	2.69	1.076	39
Availability of design information	7	41	37	15	3	2.67	0.912	40
Sustainability of materials used and quality	9	45	28	15	6	2.65	1.026	41
Tender period	28	27	22	24	2	2.47	1.178	42

Source: field survey, 2018.

From the table above, the risk factor with the highest impact is “Unforeseeable changes in materials prices”. This is followed by “Under-estimation”, “Defective design and specification”, “Market condition”, “Government legislation/policy”, “Lack of skilled labour”, “Changes in cost planning data”, “Project team’s experience of the construction type”, “Increase in duration of the project”, “Availability and supplies of materials”, “Client’s change/changes in owner’s requirements”, “Lack of expertise in client’s organisation”, “Procurement system”, “Tender inflation”, “Contract conditions”, “Expertise of consultants”, “Availability and supplies of labour”, and “Inadequate cost plan/tender documentation”. These represent the top 18 risk factors that have impact on construction projects budget performance in Nigeria amongst the 42 risk factors. It is not surprised that Unforeseeable changes in materials prices also has the highest impact as changes in materials prices have no control in Nigerian.

Table 4: Occurrence/Impact of Risk factors on Construction Budget Performance

	likelihood of occurrence		Degree of Impact	
Risk Factors	Mean	Rank	Mean	Rank
Unforeseeable changes in materials prices	3.98	1	3.63	1
Under-estimation	3.83	2	3.62	2
Market condition	3.81	3	3.51	3
Lack of skilled labour	3.65	4	3.44	6
Client's change/changes in owner's requirements	3.59	5	3.33	10
Changes in cost planning data	3.58	6	3.43	7
Defective design and specification	3.55	7	3.55	4
Expertise of consultants	3.51	8	3.17	11
Increase in duration of the project	3.50	9	3.39	9
Project team's experience of the construction type	3.41	10	3.42	8
Government legislation/policy	3.04	11	3.46	5
**				
Tender period	2.51	42	2.47	42

Source: field survey, 2018.

Table 4 shows the critical risk factors with significance occurrence as well as impacts extracted from the analysis of the initial survey. The Eleven risk factors with significant occurrence and impact were used to design a questionnaire to determine the likelihood of their occurrence. Fifty-four firms were conveniently sampled and asked to rank on a scale of 0 to 5 (Where 0= not applicable, 1= very low, 2= low, 3= medium, 4= high and 5= very high), the likelihood of occurence of the identified risk factors. The second table sought for the professionals to indicate, in their experience, the difference in percentages between initial budget and final contract sum as a result of the occurrence of the risk factors. The questionnaires were retrieved fully (i.e 100%). The retrieved questionnaires were used to develop the models. The numerical data were gathered and entered into the Statistical Package for Socials (IBMSPSS version 23) software. The scores obtained from the 54 respondents were entered as independent variables (or "predictors") while the percentage variations between initial and final contract sum at 30%, 50% and 70% completion stages were entered as dependent variables in the "neural network" section of the software. 73% of the questionnaires (40) were used for training the model, twenty-seven percent (14) for testing and the remaining one percent was excluded for having outlier inputs. The IBM/SPSS neural network software does the training and testing automatically.

THE MODEL

Several models have been developed in this study. The models are for different stages of project completion (i.e. 30%, 50% and 70%). Each model comprises three general units: the architecture, data classification matrix and network information. Data classification matrix is the actual model while the other two offer information on data inputs. To illustrate the working and validation of the models, the 3 units at several stages of completion, for federal government projects are shown below. A score of 3 on a 0-5 Likert scale was pre-set as critical. The cut-off point was applied to the risk impact mean score only because some risk variables can be low in occurrence but high in impact.

Table 5: Data Classification for the neural network (at 30% completion)

Sample		Predicted			
		10.00	25.00	30.00	Percent Correct
Training	10.00	4	6	1	36.4%
	25.00	0	14	1	93.3%
	30.00	3	7	1	9.1%
	Overall Percent	**18.9%**	**73.0%**	**8.1%**	**51.4%**
Testing	10.00	2	2	0	50.0%
	25.00	2	4	0	66.7%
	30.00	1	5	1	14.3%
	Overall Percent	**29.4%**	**64.7%**	**5.9%**	**41.2%**

Table 5 shows the practical results of using the network. For each of the sample, Cells on the diagonal of the cross-classification of cases are correct predictions while cells off the diagonal of the cross-classification of cases are incorrect predictions. Hence, form the 37 cases held for training the network, 4 out of 11 cases for 10% were correctly classified, 14 out of the 15 cases for 25% were correctly classified and 1 out of the 11 cases for 30% were correctly classified. Overall, 51.4% of the cases were trained correctly. The testing sample reveals an overall 41.2% correct classification of the cases. This infers that for four (4) out of ten (10) times the variation to the budget will be 25%. This model differ from Abdulrazaq (2015) study, where he had 34 cases held for training the network, and 15 out of 17 cases for 20% were correctly classified, 7 out of the 9 cases for 25% were correctly classified and all the eight cases for 30% were correctly classified. Overall, 88.2% of the cases are trained correctly.

Table 6: Network information for the neural network (at 30% completion)

Description		**Serial No.**	**Factors**
Input Layer		1	Unforeseeable changes in materials prices
		2	Under-estimation
		3	Market condition
		4	Lack of skilled labour
		5	Client's change/changes in owner's requirements
		6	Changes in cost planning data
		7	Defective design and specification
		8	Expertise of consultants
		9	Increase in duration of the project
		10	Project team's experience of the construction type
		11	Government legislation/policy
	Number of Units[a]		55

Hidden Layer(s)	Number of Hidden Layers	1
	Number of Units in Hidden Layer 1[a]	10
	Activation Function	Hyperbolic tangent
Output Layer	Dependent Variables 1	Variation at 30% Completion
	Number of Units	3
	Activation Function	Softmax
	Error Function	Cross-entropy

a. Excluding the bias unit

The output layer comprises the 3 responses on the differences between the actual and predicted budget overrun as suggested by the respondents, in percentages (i.e. 20%, 25% and 30%). Each output unit is some function of the hidden components. The network uses 70% of the data for training and 30% for testing, as shown on table 4.

The figure (as attached in the appendices) is termed "feed forward" architecture because the connections in the network flow forward from the input layer to the output layer without any feedback loops.

Table 7: Data Classification for the neural network (at 50% completion)

Sample		Predicted 10.00	25.00	30.00	40.00	Percent Correct
Training	10.00	5	1	0	0	83.3%
	25.00	1	12	1	0	85.7%
	30.00	2	8	0	0	0.0%
	40.00	2	6	1	0	0.0%
	Overall Percent	**25.6%**	**69.2%**	**5.1%**	**0.0%**	**43.6%**
Testing	10.00	2	1	0	0	66.7%
	25.00	0	4	1	0	80.0%
	30.00	0	2	2	0	50.0%
	40.00	3	0	0	0	0.0%
	Overall Percent	**33.3%**	**46.7%**	**20.0%**	**0.0%**	**53.3%**

From the table 7, the output layer comprises 4 predicted cases in percentages (i.e. 10%, 25%, 30% and 40%). Hence, of the 39 cases held for training the network, out of 6 cases for 10%, 5 were correctly classified, 12 out of the 14 cases for 25% were correctly classified, and none out of the 10 cases and the 9 cases for 30% and 40% respectively were classified correctly. Overall, 43.6% of the cases were trained correctly. The testing sample reveals an overall 53.3% correct classification of the cases. This infers that for five (5) out of ten times the variation to the budget will be 25%. The results of this model have variation with that of the Abdulrazaq (2015), where 34 cases were held for training the network and 1 out of 3 cases for 10% was correctly classified, 13 out of the 14 cases for 25% were correctly classified, 2 out of the 11 cases of 30% were correctly classified, and none of the seven cases for 40% were correctly classified. Overall, 45.7% of the cases are trained correctly.

Table 8: Network information for the neural network (at 50% completion)

Description		Serial No.	Factors
Input Layer		1	Unforeseable changes in materials prices
		2	Under-estimation
		3	Market condition
		4	Lack of skilled labour
		5	Client’s change/changes in owner’s requirements
		6	Changes in cost planning data
		7	Defective design and specification
		8	Expertise of consultants
		9	Increase in duration of the project
		10	Project team’s experience of the construction type
		11	Government legislation/policy
	Number of Units[a]		55
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		11
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Variation at 50% Completion
	Number of Units		4
	Activation Function		Softmax
	Error Function		Cross-entropy
a. Excluding the bias unit			

Table 8 shows that the input layer contains the eleven significant factors, which were recognised by the neural network as the “predictors”. Each predictor is represented by a different colour and the scores entered by the respondents are indicated in boxes. The hidden layer comprises 11 unobservable nodes. The value of each hidden unit is a function of the predictors generated by the network. The hidden nodes determine the relationship between the inputs and the outputs in what is termed a “black box” manner.

Table 9: Data Classification the neural network (at 70% completion)

Sample		Predicted 10.00	25.00	30.00	40.00	Percent Correct
Training	10.00	**0**	3	0	0	0.0%
	25.00	**1**	7	0	3	63.6%
	30.00	**2**	4	3	2	27.3%
	40.00	**0**	5	1	5	45.5%
	Overall Percent	**8.3%**	**52.8%**	**11.1%**	**27.8%**	**41.7%**
Testing	10.00	0	1	0	3	0.0%
	25.00	0	5	1	4	50.0%
	30.00	0	0	0	1	0.0%
	40.00	0	2	1	0	0.0%
	Overall Percent	**0.0%**	**44.4%**	**11.1%**	**44.4%**	**27.8%**

Table 9 shows that the output layer comprises 4 predicted cases; 10%, 25%, 30% and 40%. Hence, from the 36 cases held for training the network, none out of the 3 cases for 10% were classified correctly, 7 out of the 11 cases for 25% were correctly classified, 3 out of the 11 cases for 30% were classified correctly and 5 out of the 11 cases for 40% were classified. Overall, 41.7% of the cases were trained correctly. The testing sample revealed an overall 27.8% correct classification of the cases. This infers that for 5 out of 10 times the variation to the budget will between 25% and 40%. This model has variation with the findings of Abdulrazaq (2015) where 37 cases were held for training the network and all 4 cases for 15% was correctly classified, all 24 cases for 25% were correctly classified, and all 9 cases of 30% were correctly classified. Overall, 100% of the cases are trained correctly.

Table 10: Network information for the neural network (at 70% completion)

Description	**Serial No.**	**Factors**
Input Layer	1	Unforeseeable changes in materials prices
	2	Under-estimation
	3	Market condition
	4	Lack of skilled labour
	5	Client’s change/changes in owner’s requirements
	6	Changes in cost planning data
	7	Defective design and specification
	8	Expertise of consultants
	9	Increase in duration of the project

		10	Project team’s experience of the construction type
		11	Government legislation/policy
Hidden Layer(s)	Number of Units[a]		55
	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		8
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Variation at 50% Completion
	Number of Units		4
	Activation Function		Softmax
	Error Function		Cross-entropy

a. Excluding the bias unit

The input layer comprises the eleven significant risk factors, which were recognised by the neural network as the “predictors”. Each predictor is represented by a different colour and the scores entered by the respondents are indicated in boxes. The hidden layer comprises 8 unobservable nodes. The value of each hidden unit is a function of the predictors generated by the network. The hidden nodes determine the relationship between the inputs and the outputs in what is called a “black box” manner.

VALIDATION OF THE MODELS

The remaining 14 data set were used to test the forecasting ability of the models. Input data regarding the probability of occurrence of the eleven significant risk factors were entered and the network requested to forecast the percentage variation at 30%, 50%, and 70% completion stages. The validation tests conducted on the model are a comparison between the predicted and the actual (the actual being the percentage variations provided by the respondents in the 14 data sets). The relative mean deviation (RMD) was used as a statistical tool to verify the predictability of the models. The highest percentage variations predicted by the model were compared with the percentage variations entered by the respondents. This is because the respondents were asked to enter the highest percentage variations on the table provided in the questionnaire.

Table 11: Performance of the Neural Network Models (at 30%, 50%, and 70% completion stages)

	at 30% completion			at 50% completion			at 70% completion		
Data set No.	Actual variation	Predicted variation	Relative absolute Percentage deviation	Actual variation	Predicted variation	Relative absolute Percentage deviation	Actual variation	Predicted variation	Relative absolute Percentage deviation
1	30.00	25.00	17%	25.00	25.00	0%	40.00	25.00	38%
2	25.00	25.00	0%	25.00	25.00	0%	40.00	25.00	38%
3	25.00	25.00	0%	30.00	25.00	17%	35.00	25.00	29%
4	30.00	25.00	17%	30.00	25.00	17%	35.00	25.00	29%
5	30.00	25.00	17%	40.00	25.00	38%	35.00	25.00	29%
6	25.00	25.00	0%	40.00	25.00	38%	40.00	25.00	38%

7	30.00	25.00	17%	25.00	25.00	0%	45.00	25.00	44%
8	30.00	25.00	17%	25.00	25.00	0%	20.00	25.00	25%
9	30.00	25.00	17%	30.00	25.00	17%	30.00	25.00	17%
10	30.00	25.00	17%	32.00	25.00	0%	30.00	25.00	17%
11	25.00	25.00	17%	40.00	25.00	38%	40.00	25.00	38%
12	25.00	25.00	0%	30.00	25.00	17%	35.00	25.00	29%
13	30.00	25.00	17%	30.00	25.00	17%	35.00	25.00	29%
14	25.00	25.00	0%	25.00	25.00	0%	20.00	25.00	25%
	Mean Percentage Error=		**27%**		**Mean Percentage Error=**	**30%**		**Mean Percentage Error=**	**34%**
	Mean Percentage Accuracy		**73%**		**Mean Percentage Accuracy**	**70%**		**Mean Percentage Accuracy**	**66%**

The relative percentage deviation measures for each of the 14 data sets used in testing the accuracy of the models are shown in table above. It is clear from table 8 that the mean percentage error ranges between 27% and 34%. It is clear that the accuracy levels achieved at the 30% completion stage is highest. This may be connected to the fact that the respondents' experience is more required at the initial stage of construction projects. Entries at the 50% completion are less accurate owing, probably, to the fact that the tendency to forget the actual percentage variation is higher at those stages of projects. Also entries are 70% lesser in accuracy than 50% completion due to the fact that trend to forget actual percentage variations in this stage is also high at this stage of the project. The finding concurs with Abdulrazaq (2015) but differs with Odeyinka *et al.* (2013) model, which was found to be more accurate at the 50% completion.

CONCLUSION AND RECOMMENDATION

Sixteen (16) risk factors were found to have highest occurrence on the construction project budget performance and 18 significant risk factors impacting the construction project budget performance in Nigeria. The average variations predicted between actual and final cost of consrtuction projects in the Nigerian construction industry are 25% above the predicted at 30% completion stage, 25% above the predicted at 50% completion stage, and 25% to 40% above the predicted at 70% completion stage. The results obtained have variations with those obtained from previous studies from UK, Europe, Middle East and the little in Africa (Akintoye, 2000; Odusami & Onukwube,2008; Odeyinka, 2010; Enshassi et al., 2013; Ameyaw et al., 2015; Adafin et al., 2016). However there is a significant difference in the perception of Construction professionals in Nigeria on the likelihood of occurence and impact of risk factors on budget performance.

The study recommends that Construction Professionals in Nigeria should take the sixteen (16) risk factors with the highest occurrence and the eighteen (18) risk factors with the highest impact on "construct project budget performance" into consideration when developing the budget for construction projects in order to have a good budgetary performance at the end of the projects. The study also recommends that future research should be carried out on risk factors affecting budget performance at different phases of project completion than the ones adopted for this study. This will justify the differences at those phases of project completion possible. Further studies should be carried out on civil/heavy engineering projects so as to explore their budgetary performance.

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