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Developing models to predicting the effect of crises on construction projects using MLR technique

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ABSTRACT

Most construction projects are exposed to multiple external and internal problems and obstacles that lead to a crisis within the construction project, which may lead to the failure of the construction project. It is also a source of concern for owners, stakeholders, and contractors alike due to its difficulty. As a result, a new approach to dealing with crises prior to their occurrence is required. Accurate construction project prediction concerns at the early stages of a construction project are critical factors in the success of a project. This study develops anticipatory models for construction project crises by identifying and categorizing the major different variables that affect construction project objectives and indicate time overrun, cost overrun, and poor quality for construction projects before crises occur. The most influential factors on the failure of construction projects in Iraq were identified in this study; some of these factors affect project implementation time, others affect project cost, and the remaining factors affect construction project quality. The independent variables measurement model is designed to collect accurate raw data from the site. This model is based on 53 data samples collected from various multi-story building projects, which were used to construct and test the model. From MLR multiple linear regression results, three equations were derived from calculating the percentage of overrun (**time, cost and quality**) because of the construction project being affected by crises. Found that the correlation coefficient of the above models is (99.8%, 98.6%, 96.5%), respectively.

Keywords: Multi Linear Regression MLR, Construction Projects, Crises, Predicting, Iraq

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1. Introduction

A crisis is defined as an unanticipated event that confronts the organization and poses a significant threat to its high priority values, necessitating an immediate response [1]. There is a scarcity of studies and research on crises and their negative effects on the construction sector in Iraq. In any case, the researcher could go over a few of these papers [2]. Although crises share characteristics such as threat, suddenness, high uncertainty, urgency, stress and emotions, a scarcity of information resources, and destructiveness, they also contain opportunities if addressed properly [3][4]. Crisis management is a process that includes activities such as prediction, prevention, and preparation, property determination and control, recovery, and[5], as illustrated in Figure (1).

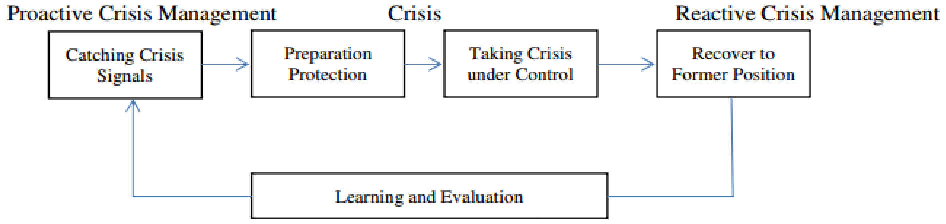

Figure 1. Crisis management processes

Crisis management is a process that entails detecting and evaluating crisis signals, as well as taking and implementing the necessary precautions to overcome a crisis with minimal damage[6]. As a result, early detection of crises can help to avoid crises and their associated harm. Every country has a history of various crises and the negative effects they have on all aspects of the state's life. Iraq, for example, has experienced numerous crises, including economic, political, health, and environmental crises, particularly from 1991 to the present. It has had an impact on a wide range of important industries. When the economic, political, and health situations are tumultuous, all sectors are affected. These various crises usually result in economic disaster. To lessen the impact of a crisis, we should create a system that predicts how severe the impact will be. The research aims to investigate, analyze, and evaluate the various factors of crises and their impact on construction projects in Iraq, as well as to develop a system for predicting the impact of multiple crises on the final construction project's objectives. The scheme aims to accurately predict when a crisis will occur so that the government, construction companies, and engineers have enough time to prepare. Previous studies have succeeded in establishing a system to predict the impact of the economic crisis. Reflections are used to predict the impact based on each origin crisis causing without any internal correlation between them, due to the growth of many affected sectors through the economy [7]. Through this study, the researcher aims to answer a set of questions related to the research topic and its problem: 1. What is the role of using information technology and artificial intelligence to manage various crises in Iraq's construction projects? 2. What are the main factors that help deal with crises and disasters efficiently through information technology? 3. How can MLR technology be used to develop a proposed model to predict the impact of crises on construction projects?

1.1. Research motivation

The following are the motivations for the study:

1. There has been no prior research on crisis factors and their impact on project goals.
2. The use of (MLR) as an advanced technology in the Iraqi construction industry has become a key necessity for project success.
3. A scarcity of international research on predicting future construction project crises.
4. There is a clear weak point in forecasting construction project crises because old methods are incorrect, slow, and untrustworthy.

1.2. Research hypotheses

The research hypotheses were advanced: "The methods used it to forecast building crises in Iraq have a flaw, likely to result in imprecision, speed, and reliability. As a result, modern processes and approaches for forecasting crisis situations in construction industry that are based on models for different accuracy, simplicity, and easiness of use are required."

2. Research methodology

The methodology of this research is represented in the following Figure 2.

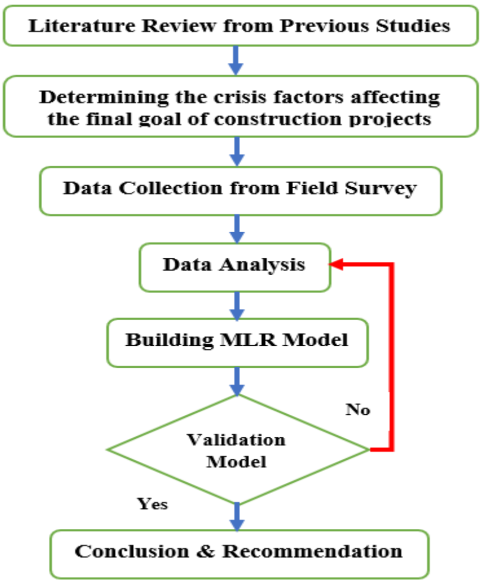

Figure 2. Methodology of the research

2.1. Identification of multiple linear regression (MLR) model variables

"Linear regression is a statistical procedure for determining the value of a dependent variable based on the value of an independent variable. Linear regression assesses the relationship between two variables" [8]. "It is a modeling technique that predicts a dependent variable based on independent variables" [8]. This paper describes the development of multiple linear regression models for (cost overrun, time overrun, and poor quality) construction projects. The methodology in this chapter is primarily based on identifying the various crisis factors that affect the final construction project objectives. Furthermore, seventeen independent variables (time, cost, and quality) of the construction projects were chosen. Each construction project's data is carefully selected. Table 1 depicts the categorization of crisis factors (independent variables) into one sort and reflects qualitative variables as follows: (V1, V2, V3....Vn). The final project objectives (cost, time, and quality) were also used as a dependent variable (**TOP, COP, FPQ**). The crisis factors or independent variables were arranged in the researcher's preferred order of importance.

Table 1. Describe the independent and dependent variables of crisis factors

Kinds of Variables	Code	Variables	Effect on	Unit	Category of data
Independent Variables	V1	Delayed the disbursement financial payments to executing companies	Time Cost Quality	Most likely not= 1 Sometimes= 2 Almost always = 3	Subjective (Quality data)
	V2	Shortage financial allocation for project	Time Cost Quality	Most likely not= 1 Sometimes= 2 Almost always = 3	Subjective (Quality data)
	V3	Serious Infectious Deseases "Covid 19"	Time Cost Quality	Ineffective= 1 Moderate intensity= 2 Intense = 3	Subjective (Quality data)
	V4	Corruption and bribery in government tenders	Time Cost Quality	Most likely not= 1 Sometimes= 2 Almost always = 3	Subjective (Quality data)
	V5	Intervention of political parties in construction	Time Cost Quality	Most likely not= 1 Sometimes= 2 Almost always = 3	Subjective (Quality data)
	V6	Useless of preliminary feasibility studies for projects	Time Cost Quality	Inadequate monitoring=1 Monitoring level medium=2 Monitoring is intense=3	Subjective
	V7	Design errors and inaccuracy of drawings	Time Cost Quality	Most likely not= 1 Sometimes= 2 Almost always = 3	Subjective (Quality data)
	V8	Design changes by the owner	Time Cost	Most likely not= 1 Sometimes= 2 Almost always = 3	Subjective (Quality data)
	V9	Delayed approval for the federal budget	Time Cost	There is no delay= 1 little delay= 2 high delay= 3	Subjective (Quality data)
	V10	Bad weather "high temperatures, low temperatures, heavy rain	Time Quality	Moderate=1 Average=2 Sever=3	Subjective (Quality data)
	V11	Inefficiency of financial and technical of the executing companies	Time Quality	High efficiency=1 Medium efficiency=2 Low efficiency=3	Subjective (Quality data)
	V12	Lack of liquidity for the executing companies or the bankruptcy of the contractor	Time	High Liquidity=1 Moderate=2 Low Liquidity=3	Subjective (Quality data)

	V13	Religious occasions and sudden holidays	Time	Low occurrence=1 Medium occurrence =2 High occurrence =3	Subjective
	V14	Change in the rate of a currency or fluctuation in currency exchange rates	Cost	Most likely not= 1 Sometimes= 2 Almost always = 3	Subjective (Quality data)
	V15	Inaccuracy bills of quantities	Cost	High accuracy= 1 Medium accuracy= 2 Low accuracy = 3	Subjective (Quality data)
	V16	Inadequate technical staff supervising on projects or Weak efficiency of supervising engineering staff	Quality	High efficiency=1 Medium efficiency=2 Low efficiency=3	Subjective (Quality data)
	V17	Inefficiency of executing company cadres	Quality	High efficiency=1 Medium efficiency=2 Low efficiency=3	Subjective (Quality data)
Dependent Variables		Time Overrun Percentage (TOP)	Initial Time=IT Final Time=FT	$TOP = \frac{IT - FT}{IT}$	Objective (Quantity data)
		Cost Overrun Percentage (COP)	Initial Cost=IC Final Cost=FC	$COP = \frac{IC - FC}{IC}$	
		Final Project Quality (FPQ)	Poor Quality=1 (Low) Satisfy Quality=2 (Medium) Good Quality=3 (High)		Subjective (Quality data)

2.2. Data collection from field survey

The engineering questionnaire sampling technique is used for data collection because it is simple to use, frequently used by researchers, certified, and takes little time. The data for this study was gathered through direct data collection from project documents and candid interviews with relevant engineers and project managers. The data was collected from the site using a field survey form that was designed based on the most influential factors on construction project objectives. As shown in , the researcher created a work measurement form for the strength of the columns in order to collect data from construction sites (1). The model included the crisis factors affecting the construction project's objectives, which are independent variables, while the project objectives (time, cost, and quality) are dependent variables. As a result, 53 samples were collected from construction sites and statistically analyzed using the statistical analysis laws outlined .

Table 2. Descriptive Statistics for Data (**TOP, COP, FPQ**)

Statistical Parameter	Actual Input Variables — Time Overrun : (No =53 Sample)													Output TOP
	V1	**V2**	**V3**	**V4**	**V5**	**V6**	**V7**	**V8**	**V9**	**V10**	**V11**	**V12**	**V13**	
Max	3	3	3	3	3	3	3	3	3	3	3	3	3	
Min	1	1	1	1	1	1	1	1	1	1	1	1	1	
Range	2	2	2	2	2	2	2	2	2	2	2	2	2	
Mean	1.887	1.811	1.736	1.943	1.642	1.981	1.698	1.698	1.962	1.830	1.566	1.811	2.000	
S.D	0.776	0.761	0.788	0.770	0.736	0.820	0.845	0.822	0.831	0.778	0.694	0.735	0.832	

Statistical Parameter	Actual Input Variables — Cost Overrun : (No =53 Sample)											Output COP
	V1	**V2**	**V3**	**V4**	**V5**	**V6**	**V7**	**V8**	**V9**	**V14**	**V15**	
Max	3	3	3	3	3	3	3	3	3	3	3	
Min	1	1	1	1	1	1	1	1	1	1	1	
Range	2	2	2	2	2	2	2	2	2	2	2	
Mean	1.887	1.811	1.736	1.943	1.642	1.981	1.698	1.698	1.962	1.283	1.509	
S.D	0.776	0.771	0.788	0.770	0.736	0.820	0.845	0.822	0.831	0.495	0.639	

Statistical Parameter	Actual Input Variables — Final Quality Project : (No =53 Sample)											Output FPQ
	V1	**V2**	**V3**	**V4**	**V5**	**V6**	**V7**	**V10**	**V11**	**V16**	**V17**	
Max	3	3	3	3	3	3	3	3	3	3	3	**3**
Min	1	1	1	1	1	1	1	1	1	1	1	**1**
Range	2	2	2	2	2	2	2	2	2	2	2	**2**
Mean	1.887	1.811	1.736	1.943	1.642	1.981	1.698	1.830	1.566	2.019	2.000	**1.830**
S.D	0.776	0.761	0.788	0.770	0.736	0.820	0.845	0.778	0.694	0.747	0.707	**0.509**

2.3. Multi variables linear regression "MLR"

Regression analysis is a useful tool that enables the researcher to learn a lot more about the relationships in the data under consideration. In this case, MLR describes how much the basic necessary of the set of criteria variables changes when some of the independent variables is changed. The other independent variable, on the other hand, is held constant[9]. A few hypotheses must be developed in order again for linear regression model to function. It has the following physical characteristics:
"Yi = B0 + β1 Vi1 + β2 Vi2+… + βp Vip + εi" ……………….. (1)
Where: i= 1,2,3……,n. Furthermore, assumes the following:
- Yi: is the response at the observation that relates to the levels of the independent variable V1, V2... Vp inputs. The variables in the linear relationship are 0, 1... p. For a singular event (p = 1), the intercept is 0 and the slope of the defined straight line is 1. 1, 2... n are mistakes that scatter all around linear relation at each of i =1 to n findings.

2.4. Developing of predicting models using MLR technique

MLR is used to construct three statistical formulas in this chapter. used It was chosen since it is one of the most commonly used form in this area of study. (Statistical Solutions and Service Products): (SPSS) employs 23 editions as a tool to construct the three models, which are as follows:

- First model (**TOP**): Time Overrun Percentage.
- Second model (**COP**): Cost Overrun Percentage.
- Third Model (**FPQ**): Final Project Quality.

2.4.1. Summary of statistical analysis of MLR models

In this study, the "SPSS) software" (Science version) version was used (23). It has been used to analysis data and develop a productivity rate predictive model. This project's task is to find the linear coefficient of determination of Equation (1). Table 3 depicted a "summary of" the models.

Table 3. A description of the statistics with all models

No. of	Model	R (%)	(R^2)%	Adj. (R^2)%	Std. Error
First	**TOP**	99.8	99.6	0.994	0.029
Second	**COP**	98.6	97.2	0.965	0.018
Third	**FPQ**	96.5	93.1	0.913	0.150

2.4.2. Summary ANOVA for regression analysis of MLR models

As shown in Desk 5", which includes analysis of variance values" "ANOVA" "that can be defined through the explanatory model" as a "whole force by numerical F, as evidenced by the" contrasting colors of the moral analyzation of the F test table (P=Sig 0.0001) "highly significant effect." Which statistical evidence confirms the model MLR's high explanatory power? This model provides a reasonable forecasting when used in this manner.

Table **4.** ANOVA summary Models for regression analysis

No. of Models	Models	Sum of Squares	df	Mean Square	F	Sig
Model.1	Regression	7.325	13	0.563	677.23	0.00
	Residual	0.032	39	0.001		
	Total	7.358	52			
Model.2	Regression	0.464	11	0.042	129.612	0.00
	Residual	0.013	41	0.00		
	Total	0.478	52			
Model.3	Regression	12.549	11	1.141	50.685	0.00
	Residual	0.923	41	0.023		
	Total	13.472	52			

2.4.3. MLR for (TOP) model equation

Table 5 displays the values of the constants, regression coefficients, and statistical significance of independent variables on the dependent variable. The table's summary is as follows:

Table 5. **TOP** Model regression analysis results.

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	Std. Error	Beta		
(Constant)	**0.853**	0.017		50.198	**0.00**
V1, CF23	**-0.034**	0.008	-0.071	-4.317	**0.00**
V2, CF25	**-0.020**	0.009	-0.041	-2.309	**0.026**
V3, CF63	**-0.026**	0.007	-0.054	-3.470	**0.001**
V4, CF29	**-0.124**	0.007	-0.254	-18.44	**0.00**
V5, CF31	**-0.025**	0.007	-0.049	-3.582	**0.001**
V6, CF42	**0.040**	0.009	0.086	4.602	**0.00**
V7, CF47	**-0.025**	0.006	-0.057	-3.955	**0.00**
V8, CF44	**-0.184**	0.007	-0.403	-25.55	**0.00**
V9, CF22	**0.011**	0.007	0.025	1.583	**0.121**
V10, CF61	**-0.151**	-0.151	-0.312	-21.31	**0.00**
V11, CF51	**-0.036**	0.007	-0.066	-5.269	**0.00**
V12, CF24	**-0.074**	0.009	-0.145	-8.637	**0.00**
V13, CF58	**-0.072**	0.006	-0.160	-11.53	**0.00**
Dependent Variable: Time Overtime Percentage (TOP).					

Table (5) shows the regression results of the first model TOP, that can be expressed as the equation (2) below:

TOP= 0.853-0.034(V1)-0.02(V2)-0.026(V3)-0.124(V4)-0.025(V5) +0.04(V6)-0.025(V7)-0.184(V8+0.011(V9)-0.15(V10)-0.036(V11)-0.074(V12)-0.072(V13)……… (2)

Where **TOP** denotes the first model's predicted Time Overrun Percentage. To explain how the solution was tested against by the data utilized in the **MLR** model, a numerical example is given (**TOP**). The following information is provided: "V1=2, V2=2, V3=2, V4=3, V5=3, V6=1, V7=2, V8=1, V9=3, V10=2, V11=3, V12=2, V13=1". Using equation (**2**), the (predicted value) equal (**TOP=-0.593**), which measures up to the calculated values (**TOP=-0.6**) (Case no. 53 in the Appendix: **2**).

2.4.4. MLR for (COP) model equation

The results of the MLR prediction are shown in Table (6), which show that (v1, v2, v3, v5, v9, v14, v15) is the only variable with a noticeably significant effect at $P<0.01$, while the main independent factors have no significant effect at $P>0.01$.

Table 6. **COP** Model regression analysis results.

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	**Std. Error**	**Beta**		
(Constant)	**0.279**	0.011	---	26.432	**0.00**
V1	**-0.034**	0.004	-0.178	-5.124	**0.00**
V2	**-0.020**	0.006	-0.164	-3.576	**0.001**
V3	**-0.023**	0.004	-0.193	-5.389	**0.00**
V4	**-0.011**	0.004	-0.091	-2.413	**0.02**
V5	**-0.023**	0.004	-0.178	-5.614	**0.00**
V6	**-0.003**	0.005	-0.027	-0.604	**0.549**
V7	**0.001**	0.004	0.009	0.252	**0.802**

V8	**0.001**	0.004	0.013	0.338	**0.737**
V9	**-0.021**	0.004	-0.178	-5.124	**0.00**
V14	**-0.038**	0.009	-0.189	-4.381	**0.00**
V15	**-0.045**	0.007	-0.300	-6.207	**0.00**
Dependent Variable: Cost Overrun Percentage (COP)					

Table (6) shows the multiple regression analysis of model COP, which can be symbolized as equation (**3**) below:

COP= 0.279 **-0.034(V1) -0.020(V2) -0.023(V3) -0.011(V4) -0.023(V5) -0.003(V6) +0.001(V7) +0.001(V8) -0.021(V9) -0.038(V14) -0.045(V15) ……… (3)**

Where **COP** denotes the second model's expected Cost Overrun Proportion. A sample calculation is provided to demonstrate how well the formula was assessed against the data used in the Logistic regression (COP). The very next information is provided: V1 = 3, V2 = 2, V4 = 1, V5 = 20, V6 = 2, V7 = 42, V8 = 0, V9 = 2, V10 = 0, V11 = 2. V1 = 3, V2 = 2, V4 = 1, V5 = 20, V6 = 2, V7 = 42, V8 = 0, V9 = 2, V10 = 0, V11 = 2. Using equation (5.3), the (predicted value) corresponds (**COP=-0.2249**), which is consistent with the calculated (real worth), (**COP=-0.22**) (Case no. 53 in the Appendix: 2).

2.4.5. MLR for (FPQ) model equation

Table (7) displays the MLR prediction results, with (v4, V16, V17) being the only variable with a strongly significant effect at P<0.01, whilst residual independent variables had no strong influence at P>0.01.

Table 7. **FPQ** Model regression analysis results.

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	Std. Error	Beta		
(Constant)	**3.704**	0.105	---	35.324	**0.00**
V1	**-0.017**	0.044	0.026	-0.389	**0.699**
V2	**-0.056**	0.046	-0.084	-1.222	**0.229**
V3	**-0.048**	0.037	-0.075	-1.297	**0.202**
V4	**-0.108**	0.033	-0.163	-3.232	**0.002**
V5	**0.29**	0.035	.0.041	0.826	**0.414**
V6	**-0.109**	0.042	-0.175	-2.606	**0.013**
V7	**0.079**	0.033	0.131	2.359	**0.023**
V10	**-0.013**	0.036	-0.020	-0.371	**0.712**
V11	**0.026**	0.073	.095	.893	**0.379**
V16	**-0.261**	0.032	-0.382	-8.108	**0.00**
V17	**-0.451**	0.038	-0.627	-12.03	**0.00**
Dependent Variable: Final Project Quality.					

The regression model of model **FPQ** is shown in Table (7) that can be authored as the formula (4) below:

FPQ=3.704-0.017(V1)-0.056(V2)-0.048(V3)-0.108(V4) +0.29(V5)-0.109(V6)+0.079(V7)-0.013(V10)+0.0261(V11)-0.261(V16)-0.451(V17)…..(4)

The predicted Final Project Quality for the model is denoted by FPQ. A numerical example is provided to aid comprehension. The equation was validated using the data from the Logistic regression (FPQ). "V1=2, V2=3, V3=1, V4=3, V5=1, V6=2, V7=3, V10=2, V11=2, V16=1, V17=2" is the information provided. The (predicted value) calculated by equation (**4**) equals (**FPQ=2.041**), which measures up to the measured value (**FPQ=2**) (Case no. 53 in the Appendix: **2**).

2.5. MLR verification of all models

To make sure that the model matches the requirements and assumptions about the model concept, various technics are used. Model verification seeks to ensure that the model's application is correct [10][11].

2.5.1. Verification of MLR model (TOP model: no. 1)

As shown in Table (5) and Figureure (3), the model (TOP) verification performs well because it has a high correlation (R) (**99.78** percent) between actual and predicted rates. As a result, this model agrees perfectly with the exact measurements.

Table 8. Validation of (**TOP** Model)

No	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	A.CFE*	P.CFE*	Error
1	2	3	2	3	1	3	2	3	3	3	1	2	2	-1	**-0.954**	**-0.046**
2	2	1	2	2	2	2	3	3	3	2	2	3	3	-0.9	**-0.911**	**0.011**
3	3	2	3	3	1	2	3	2	3	3	1	3	3	-1	**-1.021**	**0.021**
4	3	3	3	2	3	2	3	3	3	2	3	3	3	-1.1	**-1.072**	**-0.028**
5	3	3	1	3	3	2	2	3	3	2	1	2	3	-0.95	**-0.973**	**0.023**
6	2	3	1	3	1	3	3	3	2	3	1	3	2	-1	**-1.038**	**0.038**
7	1	2	2	3	3	3	1	2	2	3	2	3	1	-0.75	**-0.79**	**0.04**
8	2	1	2	2	2	2	1	3	1	2	2	2	3	-0.85	**-0.809**	**-0.041**
9	3	2	3	2	1	2	3	2	2	3	1	2	2	-0.8	**-0.762**	**-0.038**
10	2	3	1	3	1	2	3	1	2	2	2	2	3	-0.6	**-0.593**	**-0.007**
Correlation (R): between Actual & Predict of the **Crises Factors Effect on Project Time**														*99.78%*		

A.CFE*= **Actual** Crises Factors Effect, P.CFE*= **Predict** Crises Factors Effect

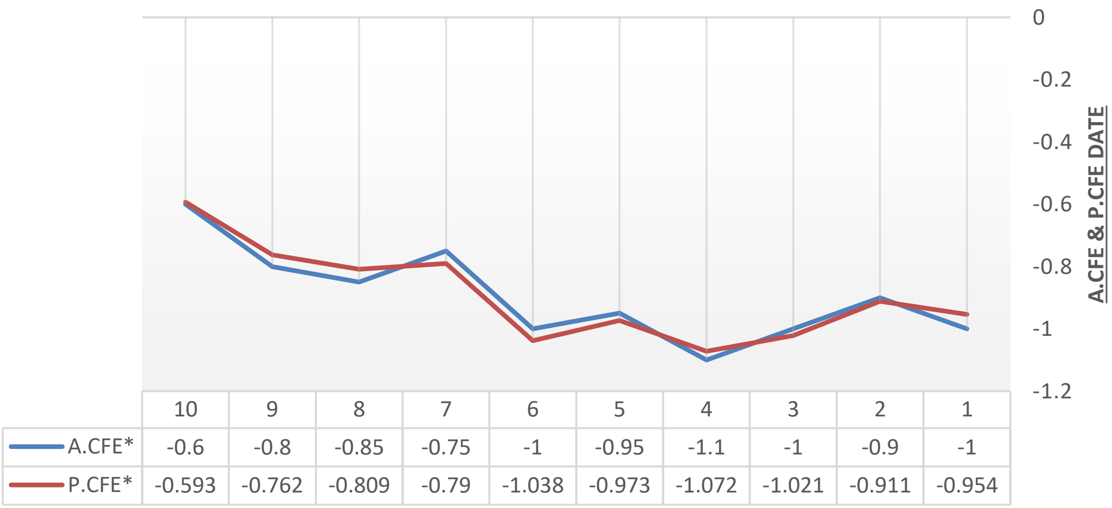

Figure 3. Contrast of actual and predicted **TOP** for validation data

2.5.2. Verification of MLR model (COP model: no. 2)

The model (**COP**) verification has good performance, as shown in table (9), because it has a high correlation (R) of (98.68 percent) between actual Crises Factors Effect on Project Cost and predicted Crises Factors Effect on Project Cost.

Table 9. Validation (**COP** Model)

No	V1	V2	V3	V4	V4	V6	V7	V8	V9	V14	V15	A. CFE*	P. CFE*	Error
1	2	3	2	3	1	3	2	3	3	2	1	**-0.15**	**-0.151**	**0.001**
2	2	1	2	2	2	2	3	3	3	3	2	**-0.19**	**-0.203**	**0.013**
3	3	2	3	3	1	2	3	2	3	1	1	**-0.12**	**-0.140**	**0.020**
4	3	3	3	2	3	2	3	3	3	2	1	**-0.24**	**-0.240**	**0.000**
5	3	3	1	3	3	2	2	3	3	2	2	**-0.23**	**-0.243**	**0.013**
6	2	3	1	3	1	3	3	3	2	2	2	**-0.14**	**-0.145**	**0.005**
7	1	2	2	3	3	3	1	2	2	2	1	**-0.125**	**-0.122**	**-0.003**
8	2	1	2	2	2	2	1	3	1	3	2	**-0.15**	**-0.161**	**0.011**
9	3	2	3	2	1	2	3	2	2	2	2	**-0.18**	**-0.191**	**0.011**
10	2	3	1	3	1	2	3	1	2	3	3	**-0.22**	**-0.225**	**0.005**
Correlation (R): between Actual & Predict of the **Crises Factors Effect on Project Cost**												**98.68%**		

A.CFE*= **Actual** Crises Factors Effect, P.CFE*= **Predict** Crises Factors Effect

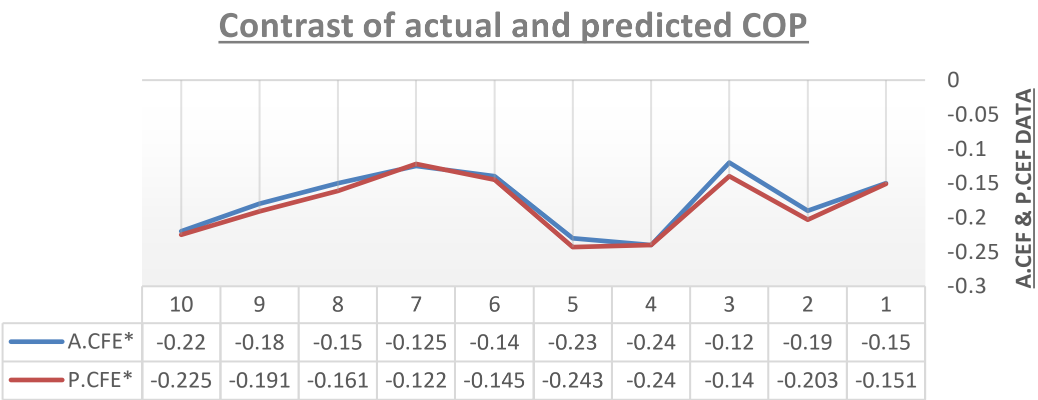

Figure 4. Contrast of actual and predicted COP for validation data

2.5.3. Verification of MLR model (FPQ model: no. 3)

The model (FPQ) verifying performs well, as shown in table (10), since it has a strong correlation (R) (99.7 percent) between actual and predicted Crises Factors Effect on Project Quality.

Table 10. Validation of (**FPQ** Model)

No	V1	V2	V3	V4	V5	V6	V7	V10	V11	V16	V17	A.CFE*	P.CFE*	Error
1	2	3	2	3	1	3	2	3	1	2	3	1	**1.054**	**-0.054**
2	2	1	2	2	2	2	3	2	2	2	2	2	**1.981**	**0.019**
3	3	2	3	3	1	2	3	3	1	3	3	1	**0.972**	**0.028**
4	3	3	3	2	3	2	3	2	3	3	1	2	**2.049**	**-0.049**
5	3	3	1	3	3	2	2	2	1	3	3	1	**1.004**	**-**

No	V1	V2	V3	V4	V5	V6	V7	V10	V11	V16	V17	A.CFE*	P.CFE*	Error
														0.004
6	2	3	1	3	1	3	3	3	1	3	3	1	**0.92**	**0.080**
7	1	2	2	3	3	3	1	3	2	2	1	2	**2.034**	**-0.034**
8	2	1	2	2	2	2	1	2	2	1	2	2	**2.084**	**-0.084**
9	3	2	3	2	1	2	3	3	1	1	2	2	**2.053**	**-0.053**
10	2	3	1	3	1	2	3	2	2	1	2	2	**2.041**	**-0.041**
Correlation (R): between Actual & Predict of the **Crises Factors Effect on Project Quality**												*96.50%*		

A.CFE*= **Actual** Crises Factors Effect, P.CFE*= **Predict** Crises Factors Effect

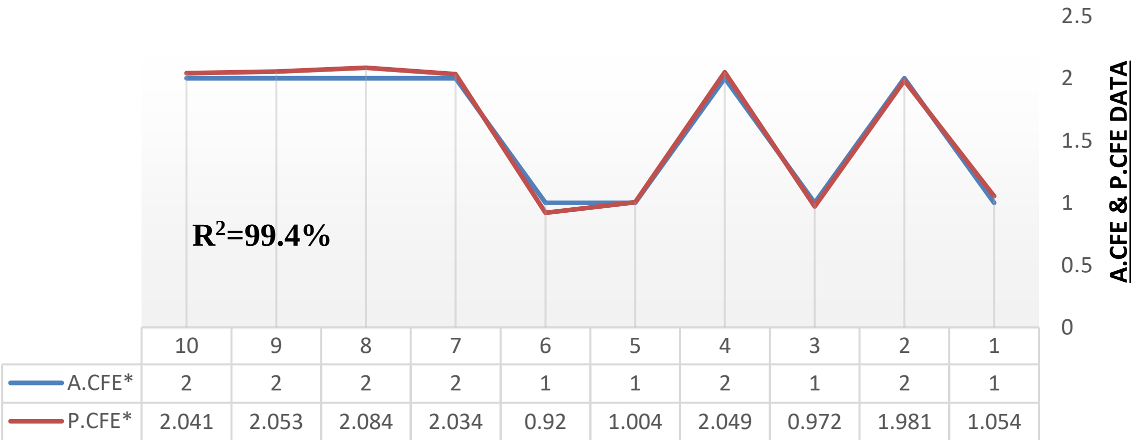

Figure 5. Contrast of actual and predicted **FPQ** for validation data

2.6. Model MLR evaluation

The verification's goal is to confirm the efficacy and accomplishment of whole-system portrayal models. Six statistical equations will be run to check the validity of MLR for models (1, 2, 3, 4) [12]. The performance of the models was evaluated using the following measured variables:

1. Mean Percentage Error (MPE) …$MPE = (\sum \frac{A-E}{A} / n) * 100\%$ .... (1)

Where:

A: actual value
E: estimated value or predicted value
n: total number of cases

The MPE is used to determine the degree of agreement between predicted and actual measured data.

2. Root Mean Squared Error (RMSE) $RMSE = \sqrt{\frac{\sum_{i=1}^{n}(E-A)^2}{n}}$ …….(2)

3. "Mean Absolute Percentage Error" (MAPE)

$MAPE = (\sum \frac{|A-E|}{A} * 100\%)/n$ ……... (3)

The MAPE and proportion RMSE are average error measures.

4. "Average, Accuracy, Percentage" (AA %)… AA %= 100%-MAPE ……….. (4)

AA is calculated to obtain the degree of accuracy.

5. "The Coefficient of Determination" (R^2)

6. The Coefficient of Correlation (R)

The determination coefficient expresses how well the model output data match the desired value. The MAPE and % RMSE are measures of average error. Table 1 shows the findings of the comparative study (11). The MAPE and AAP generated by the MLR model were 4.5 percent and 95.50 percent for the first model, 0.22 percent and 99.78 percent for the second model, and 0.10 percent and 99.90 percent for the third model, respectively. As a result, we can conclude that the MLR has an excellent agreement with measurements taken.

Table 11**.** Comparative Study's Findings

Description	**MLR for model 1 (Data Field No= 53)**	**MLR for model 2 (Data Field 53)**	**MLR for model 3 (Data Field 53)**
MPE	***0.014%***	***0.096%***	***0.001%***
RMSE	***0.025%***	***0.015%***	***0.140%***
MAPE	***4.50%***	***0.22%***	***0.10%***
AA%	***95.50%***	***99.78%***	***99.90***
R	***99.78%***	***98.68%***	***96.50%***
R^2	***99.55%***	***98.68%***	***93.00%***

Numerous trials were carried out in order to arrive at these solutions. During these trials, an error category for conceptual estimation was created[13]. proposed that the error in predicting productivity is approximately + 25%. In this study, error categorization was based on MAPE, as shown in Table (12). According to this table, the model's MAPE is satisfactory.

Table 12. Error Categorization (%)

MAPE		
Good	Fair	Poor
Less than 25	25-50	More than 50

3. Conclusions

Through the results presented in this paper, the following conclusions can be reached:

1. MLR can be used to check different variables simultaneously and their interrelationships. It was noted that MLR models have a "high degree of accuracy (AA %)" of (95.50%, 78%, 99%, 99%), and the correlation coefficients (R) for the built models are (99.78%, 98.68%, 96.50%) respectively.
2. In the first model, it was found that nine factors had a negative impact on the time of the final project: They are Beta values in Table (5) such as: (v1, v3, v4, v5, v6, v7, v8, v10, v11) respectively, are more important to the regression equation. While the others is the lower impact on the regression equation such as residual independents variables such as: (v2, v9).
3. It was also found in the second model (COP) that seven factors negatively affected the cost of the project, the final project, as follows: (v1, v2, v3, v5, v9, v14, v15).
4. Finally, it was found in the third model (FPQ) that three factors negatively affected the quality of the project, the final project, as follows: (v4, v16, v17).

Based on conclusion the following recommendations can be made:

1. It is recommended that all engineering departments in Iraq use the MLR equation developed in this study to estimate the impact of crisis factors on construction projects.
2. Encouraging government projects and contracting firms to collect and store historical data on crisis factors for future research purposes.
3. In order to achieve a better result, another algorithm optimization is required to find the optimal prediction coefficient.

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Declaration of competing interest

The authors declare that they have no any known financial or non-financial competing interests in any material discussed in this paper.

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