Late Payments for Contractors Working for Bahrain Government Building Construction Projects: Part II (Modelling Using Artificial Neural Networks and Regression)

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Abstract: The problem of late payment is considered one of the major issues in the construction industry, it is an important issue faced by many countries including Kingdom of Bahrain, and it has many consequences on building construction projects. The main objectives of this research is to create a prediction model to predict the payment delay in days for Interim payments (Model I) and variation payments (Model V) for Ministry of Works (MoW) building construction projects. The main factors of payment delay were identified in Part I of the research and used for the development of models using artificial neural network (ANN) and multi linear regression analysis (MLRA). Finally, the study compared the ANN approach to MLRA and concluded that the estimation accuracy of ANN approach is better than MLRA analysis for payment delay in (days) as it showed more promising results. The best ANN for Model I and Model V were found to be Model I-48 and Model V-60, respectively.

Keywords: Interim payment delay, Variation payment delay, artificial neural network, multi linear regression analysis

1. Background

Late payments have a huge effect on many industries including construction industry. Late payments are also affecting the projects of the Construction Projects Directorate (CPD) in Ministry of Works (MoW) – Bahrain. This study aims to use the factors causing payment delay which were identified in Part I of this research to create prediction models to establish the interim payment delay in (days) and variation payment delay in (days) faced by the contractors working for MoW. This model helps in predicting the delay in payment and ensures smooth completion of work.

In the following sections the literature review will be presented first, where it includes related previous studies, followed by research methodology, and historical data collection and analysis for modelling. Then modelling with neural networks and regression. After that development of interim payment model (Model I) and variation payment model (Model V). Finally, conclusions will be presented and recommendations will be suggested in order to overcome the payment delay issue.

2. Literature Review

2.1 Introduction

Many previous studies discussed the Modeling of ANN and MLRN in Construction Project Management. Börner et al., (2012) stated that a proper description of a model is that it's a structural illustration of a certain object that has critical features to present the actual situation for a set of data in the visual, mathematical or as a computer simulation form. Waziri et al., (2014) stated that the most positive outcomes were found in the analysis done using regression and artificial intelligence for the building construction industry. These two methods showed high understanding of the elements affecting construction durations and their relationships.

2.2 Modeling with ANN and MLRN in Construction Project Management

In 2004 Bordat et al. (2004) analyzed and assessed the extent of cost overruns, time delays, and change orders problem associated with Indiana Department of Transportation construction projects. After identifying influential factors, regression models were developed. The models were created using 2000 randomly selected projects to estimate values of cost overruns, time delay and change orders for future projects. The model provided information about the significant factors affecting cost overruns, time delays, and change orders, which are: bid amount, project type, location by district, weather, and bid comparison variables.

Ayman et al. (2008) study was about risk prediction, which was inducted in Jordan by proposing a probabilistic model to predict the risk effects on time and cost of construction projects. Statistical regression model was developed using real data of 140 projects, it estimated project cost and duration based on historical data. Customized multiple regression models were developed for each project type to obtain statistically reliable results. In conclusion, the proposed model predicted the project cost and

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duration with a precision of $\pm 0.035\%$.Odabaşi (2009) conducted a study on estimating construction duration based on many factors. Simple Linear Regression (SLR) and Multiple Linear Regression (MLR) analyses were conducted by investigating the influencing factors, using previous case study buildings, to predict the construction duration of a project. The confidence in estimation of the regression analyses was investigated, and finally an MLR model was obtained which was based on two parameters: the area of the building, and the area of its front. As a conclusion and contrasting to previous studies, no significant effect was noticed for the cost on project duration.

Yahia et al. (2011) developed an ANN model to predict time contingency in construction projects by identifying the important factors based on a comprehensive survey filled by the Egyptian construction experts. The model was developed in order to have a more reliable prediction for the amount of time contingency that should be added to the scheduled completion time by project planner. **Also** in 2011 an ANN model was developed by Elsawy et al. (2011) for estimating site overhead cost using 52 actual real-life cases of building projects, constructed in Egypt, as training materials. The model presented the site overhead costs as a percentage from the total project cost.

In 2015 ANN model was developed by Naik and Radhika (2015) for the estimation of cost and duration for highway road construction projects. The database was collected from previous projects, normalized and then used as inputs and targets for the ANN models development. The models are trained, tested and validated using MATLAB R2013a Software. The model was trained with feed forward back propagation learning algorithm. The performance evaluation of the ANN was done using MAPE (Mean Absolute Percent Error) by comparing the output values from the ANN with the actual values. The best results were given by the ANN with training function trainlm which is a function that uses Levenberg-Marquardt algorithm and (Nftool approach) with 2 layers and a hidden layer of 10 neurons.

Parminder (2016) developed an ANN model for predicting the time duration of construction projects in India, by first selecting the important factors through extensive literature study. A multi-layers model with back propagation learning algorithm was developed with several cases. The best model obtained was with one hidden layer containing 20 neurons, and with minimum root mean square error of 0.9845. The proposed ANN model was compared with other project planning techniques where it has found to be the most accurate and reliable tool for project duration prediction. In 2016 an ANN was used by Mensah et al. (2016) to predict the duration of prefabricated steel bridge projects in Ghana. Data for 18 completed bridge construction projects were collected to get the independent items to be used as an as input variables and the actual durations as output variables. The model was developed with a feed forward back propagation algorithm and the number of neurons in the hidden layer was obtained by trial and error. The Accurate results of the model was obtained with a coefficient of determination (R2 =0.998) and MAPE of 4.05%. The study has shown that the developed model is suitable for estimating the duration of a bridge project.

In 2017 a model was developed by Renuka et al. (2017) to estimate the expected percentage of the time overrun for a particular construction project during the planning stage. Six major groups causing projects time delay were identified. A questionnaire was answered by project managers by asking them to fill the percentage of delay for each group related issues and the overall delay duration of the construction projects. Thereafter, a regression model was used to analyze the collected data, and the results of the model were used to study the relationship between the percentage of delay and the major group related issues that causes delay.

It was found that most of the previous researches did not include modeling of payment delay and mainly discussed and identified the causes and effect of this issue. Moreover, no research was found to study the payment delay in Kingdom of Bahrain and precisely in governmental building construction projects. Therefore, this study is aimed to identify the causes and effect of payment delay in governmental construction projects in Bahrain and to model the delay in payment based on real case studies in this field.

3. Research Methodology

3.1 Introduction

This section comprises the techniques undertaken to develope a predictive payment model to predict the delay in two type of payments practiced in MoW projects. These payments are: interim payments and variation payments.

3.2 Development of the Model

Development of the model was achieved through the following steps:

- 1-Once the significant factors are identified from the distributed Questionnaire as explained in Part I of this research, the input factors for the models are identified according to the availability of data and compatibility with construction project directorate (CPD) cases.
- 2-The input data for the significant factors are collected from CPD real case studies and is used for the model's development as independent variables (Input) to predict the dependent variable (Output), which is the payment delay (days).
- 3-Model verification is carried out using some of the collected data.

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These models support the study by predicting the payment delay for governmental building construction projects and giving a better understanding for the actual duration needed for a payment to be approved and actually received from the employer. This increases the attention of this issue to overcome the payment delay when encountered without affecting the contractors, consultant or the progress of the project.

4. Historical Data Collection and Analysis for Modeling

4.1 Introduction

This section presents the data collection and analysis to predict the payment delay in days for interim payment delay (Model I) and variation payment delay (Model V) using historical payment cases for building construction projects accomplished in Bahrain during years (2014-2016). The independent and dependent variables used for the design of the models are presented in this chapter along with their relevant data, which are being collected from real case projects.

4.2 Independent and Dependent Variables

The independent variables (input) used in the models design for payment delay prediction are expressed in terms of the payment delay factors collected from the questionnaire results. The payment delay factors considered for Model I and Model V are chosen based on the top twenty factors ranked in Part I of this research by the consultants and contractors as shown in Table (4-1). Eleven of the factors are common in the two rankings of the consultants and contractors, thus, a total of 29 factors are analyzed for inclusion in the models to be developed.

- 1- "Changes in scope of work": This is considered to be the main reason for variation orders and extension of time in governmental projects. It is ranked in first place as per the contractors and consultants perspectives. This factor is affecting and causing many other factors where "change in cope"results in the occurrence of "Incomplete documents for variation claims by the contactor", "Delay in submitting valuation/claim by the contractor", "Delay in extension of time approval by the consultant", "Submission of claims with calculation mistakes by the contractor" and "Slow processing of variations orders" by the consultant". This factor will be expressed indirectly in Model I by the factors: "Occurrence of variations orders" and "Occurrence of extension of time". While will be expressed in Model V by the factor: "Processing of variation orders".
- 2- "Incomplete documents for variation claims by the contactor": Variation orders with incomplete documents are rejected by the consultants and the contractor is requested to resubmit it along with complete attachments. The number of the occurrences of this factor is not available for the used historical cases, thus, it will not be considered for modeling.
- 3- "Delay in submitting valuation/claim by the contractor": This factor will be used in Model I to represent the number of days delayed by the contractor to raise his valuation (request for interim payment). While for Model V no delay occurred in the used historical cases by the contractor in submitting the claim (request for variation order). This is justified by the additional amounts included in each of the variations orders, which can provide an extra profit for the contractor.
- 4- "Delay in extension of time approval by the consultant": The number of delayed days for extension of time approval is not available for the used historical cases; therefore this factor is expressed by the "occurrence of extension of time "in each of the cases by the binary expression.
- 5- "Submission of claims with calculation mistakes by the contractor": Claims with calculation mistakes are rejected by the consultant and sent back to the contractor for rectifying and resubmission; No data are found for this factor, thus, it will not be considered for modelling.
- 6- "Slow processing of variations orders by the consultant": This factor will be used in the development of Model V and is expressed by the number of days required by the consultant to evaluate and approve the variation order submitted by the contractor.
- 7- "Delay in the progress of works and activities" and "In-appropriate implementation of projects program" are both expressed by the "Delay in progress of work "in days. This factor will be used in the development of Model I and Model V.
- 8- "Ministry of finance process" is noticed from the historical case studies to have a major effect on payment delay. Moreover, it is ranked in the 12th position as per the consultants perspective; therefore, this factor will be used in Model I and Model V, and is expressed by the number of days needed for the owner to pay the amounts due to the contractor.
- 9- "Delay in valuation review and evaluation process" and "Delay in issuance of payment certificate process" are ranked in the 4th and 8th position, respectively, from contractors perspective. These factors will be used in Model I and Model V, and are both expressed by the total number of days required for the valuation to be reviewed, approved and issued in the form of payment certificate.
- 10- "Lack of periodical meetings to address payment problem": This factor occurs in all the cases, and it is evidence of occurrence is availability of minutes of meetings of each periodical meeting. It is not included in the models since it is positively occurring in all used historical cases.
- 11- The number of years of experience for each of the contractor and consultant are ranked in 8th and 18th position, respectively, as per the consultants and contractors perspective, respectively. These factors will be used in both Model I and Model V.
- 12- "Long and bureaucratic process in governmental departments", "Inability to follow certain procedures of MoW", "Failure to understand the contract agreement", "Lack of decision making during construction", "Inaccurate bill of quantity" and

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"Accuracy of payment scheduling program" are intangible factors, therefore they will not be included in the models. Although these factors have huge impact on the payment process since they can extend the period of the payment process and makes it longer, more complicated, and less flexible. On the other hand, the positive occurrence of these six factors can hugely improve the payment process and decrease the amount of delay.

- 13- Information on "Delays of documentation required for fulfilling payments", "Inadequate financial resource" and "Slow processing of final accounts" are not available in for the used historical cases, therefore, these factors will not be included in the models.
- 14- "Changes in rules and regulations", "Economic changes "and "Unavailability of funds "do not occur during the used historical cases. All the used historical cases were in years 2014-2016, where no major changes existed with regard to these factor to affect payment processes.
- 15- "Refusal to pay interest on late payment": this factor is not applicable in MoW projects because it is against civil law as discussed earlier in the questionnaire results and literature.
- 16- "Duplication of work": The frequency of work duplication is not available in the historical cases, therefore this factor is eliminated.

| ık | Consultant perspective | | Contractor perspective | |
|-----|--|----------------------|--|------------------------|
| Rar | Factors causing payment delay | Data Remarks | Factors causing payment delay | Data Remarks |
| 1 | Changes in scope | available | Changes in scope | available |
| 2 | Incomplete documents for variation claims. | unavailable | Long and bureaucratic process | Intangible factor |
| 3 | Long and bureaucratic process | Intangible factor | Delay in Extension of time approval | unavailable |
| 4 | Delay in the progress of works. | available | Delay in valuation review and evaluation. | available |
| 5 | Delay in submitting the payment valuation/Claim by the contractor. | available | Slow processing of variations orders. | available |
| 6 | Delay in Extension of time approval | unavailable | Slow processing of final accounts | unavailable |
| 7 | Submission of claims with calculation mistakes. | unavailable | Refusal to pay interest on late payment | inapplicable |
| 8 | Contractor's experience in governmental projects. | available | Delay in issuance of payment certificate Process. | available |
| 9 | Inappropriate implementation of projects program. | available | Lack of decision making during construction | Intangible factor |
| 10 | Delays of documentation required to fulfill payments. | unavailable | Inaccurate bill of quantities | Intangible factor |
| 11 | Inability to follow MoW procedures. | Intangible factor | Inappropriate implementation of projects program. | available |
| 12 | Ministry of Finance processes | available | Changes in rules and regulations | Didn't occur |
| 13 | Failure to understand the contract agreement | Intangible factor | Economic changes | Didn't occur |
| 14 | Accuracy of estimation | Intangible factor | Unavailability of funds | Didn't occur |
| 15 | Slow processing of final accounts | unavailable | Incomplete documents for variation claims. | unavailable |
| 16 | Slow processing of variations orders. | available | Delays of documentation required to fulfill payments. | unavailable |
| 17 | Lack of decision making during construction | Intangible factor | Lack of periodical meetings to address payment problems | Exists in all cases |
| 18 | Accuracy of payment scheduling program | Intangible factor | Consultant's experience | available |
| 19 | Inadequate Financial resource | unavailable | Duplication of work | unavailable |
| 20 | Lack of periodical meetings to address payment problems. | Exists in all cases | Submission of claims with calculation mistakes. | unavailable |

Table 4-1: Factors causing payment delay

The 11 factors shown in Table (4-2) and the 10 factors shown in Table (4-3) are chosen as the input for Model I and Model V, respectively. The rest of the top twenty factors of Table (4-1) are not included in the modelling for reasons like: unavailability of data or non-occurrence of the factor in the real historical cases used to build the model as shown in the remarks column in Table (4-1). Moreover, additional factors are added to the models as per the experts' recommendations, which include the following:

a) "Amount paid in Bahraini Dinar": This factor is used in Model I and Model V for each interim payment certificate or variation payment.

b) "Total available contingency in the contract": This factor reflects the total amount of contingency available at the beginning of each project, and it is usually 10% of the project budget. This factor is used for Model V development because it is concerned with variation orders.

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- c) "Balance of the contingency after each variation payments": This factor is used in Model V, it is shown in the historical data that with the decrease of the contingency amount, approval process for variation orders becomes longer.
- d)"Type of funding resource": There are two types of funding governmental building projects: Local and external, with different payment approval process for each. This factor is used in Model I only because all the historical cases used for Model V development are externally funded.

| | Table 4-2: Internit payment factors used for mod | lei I |
|----|---|-------------------|
| | Factors | Value |
| 1 | Delay in the submission of payment evaluation by the contractor | Days |
| 2 | Valuation review | Days |
| 3 | Payment processed by owner | Days |
| 4 | Variation orders occurrence | Binary expression |
| 5 | Extension of time occurrence | Binary expression |
| 6 | Payment amount | Bahraini Dinar. |
| 7 | Contractor experience | Years |
| 8 | Consultant experience | Years |
| 9 | Externally funded projects | Binary expression |
| 10 | Locally funded projects by government of Bahrain. | Binary expression |
| 11 | Work progress | Days |

| | Factors | Value |
|----|--|-------------------|
| 1 | Variation orders evaluation and approval | Days |
| 2 | Claim review | Days |
| 3 | Payment processed by employer | Days |
| 4 | Allocated contingency in the contract | Bahraini Dinar |
| 5 | Balance of contingency | Bahraini Dinar |
| 6 | Extension of time occurrence | Binary expression |
| 7 | Payment amount | Bahraini Dinar. |
| 8 | Contractor experience | Years |
| 9 | Consultant experience | Years |
| 10 | Work progress | Days |

4.2 Data Collection and Types

The payment delay models are designed using historical data for actual governmental projects. One hundred and fourteen interim payment cases for building projects are used for the development of Model I, while 91 variation payment cases for building projects are used for Model V development. The chosen cases are all for school projects constructed in the years between 2014-2016. The values of the models' factors are extracted from the cases and organized in an Excel sheet for the design purpose. The values of the payment delay factors which are functioning as the input of the models design are defined in two ways. First, as a numerical input, and secondly as binary input (0, 1), where (1) expresses the positive reaction as the availability of the factor in each case and (0) expresses the negative reaction like unavailability of the factor in each of the payment cases. After defining the input factors, the historical data needed for the development of Model I and Model V are expressed as follows:

4.2.1 Factors used in interim payment delay model (Model I)

For interim payment delay model development, eleven factors are chosen and expressed as shown in Table (4-2). They are illustrated below:

- 1. Delay in submitting valuation by the contractor: This factor is expressed by the number of days the submission of payment notice is delayed by the contractor at the end of each month as per payment schedule.
- 2. Claim review by the consultant: This factor is expressed by the total number of days of evaluation and issuance of payment certificate by summing the following: -
- 3. Total number of days from receiving the claim by the project manager until it is forwarded to Cost Engineering Department (CED).
- 4. The total number of days spent by CED for the evaluation and issuance of payment certificate and forwarding it to Finance Resources Directorate (FRD).
- 5. Total number of days for FRD to check and forward payment certificate to Ministry of Finance (MoF) in case of governmental funded projects and to the funding entity in case of externally funded projects.
- 6. Payment processing by owner: This factor is expressed by the number of days spent by the owner to make full payment to the contractor.
- 7. Variations orders occurrence: This factor is expressed by binary expression: 1 in case of the existence of variation within each payment case, and by 0 if there is not.

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- 8. Extension of time occurrence: This factor is expressed by binary expression: 1 in case the payment is affected by extension of time based on expert's opinion and by 0 in case it is not.
- 9. Payment amount: It is expressed by the due amount of payment certificate in Bahraini Dinar.
- 10. Contractor experience: This factor is expressed by the total number of years of experience of the contractor's engineer who process the claim.
- 11. Consultant experience: This factor is expressed by the total number of years of experience of the consultant's (MoW) engineer who process the claim.
- 12. Externally funded projects: This factor is expressed by binary expression: 1 in case it is an externally funded project, and by 0 in case it is not.
- 13. Locally funded projects by government of Bahrain: This factor is expressed by binary expression: 1 in case it is locally funded project, and by 0 in case it is not.
- 14. Work Progress: It is the total number of time delay of the project at the time of each payment.

The actual payment delay in days (dependent variable) for Model I is counted by investigating the following factors:

- 1. The delay in submitting payment valuation by the contractor: This factor is calculated by subtracting the actual date of submitting the payment valuation by the contractor from the planned date of submitting the payment valuation by the contractor.
- 2. Number of day for payment claim to be reviewed and approved by consultant: This factor is calculated by subtracting the date of claim final approval by MoW from the date of claim receival from the contractor.
- 3. Number of days for payment to be paid by owner: This factor is calculated by subtracting the date of payment deposit in contractor bank account from the date of payment final approval is received from MoW.

4.2.2 Factors used in variation payment delay model (Model V)

The variation payments process in MoW as explained in Part I of this research is a long process, and different than the interim payment process especially for externally funded projects, where it involves three stages: prior approval of variation from funding entity, and finally certifying the payment. While for locally funded projects it includes only two stages: variation order approval, and payment certification stage. Table (4-3) shows the factors used in model V and their expressions as illustrated below:

- 1. Variation evaluation and approval: This factor is expressed as follows:
 - a) For locally funded projects, is given by the total number of days for variation orders approval.
 - b) For external funded projects, is given by the total number of days for prior and formal approval of variation.
- 2. Claim review: as defined in Subsection 4.2.1.
- 3. Payment process by owner: as defined in Subsection 4.2.1.
- 4. Allocated contingency in the contract: It reflects the total amount of contingency (Bahraini Dinar) allocated for the project.
- 5. Balance of contingency: This factor is expressed by the amount of contingency (BD) balance in the contract at the time of the variation approval. The collected data has shown the effect of this factor on the approval decision of both the consultant and the client for each variation case, where less number of variations are approved with the decrease of contingency balance during construction, where only the most important variation items are approved.
- 6. Extension of time occurrence: as defined in Subsection 4.2.1.
- 7. Payment Amount: It is expressed by the amount of variation claimed in Bahraini Dinar.
- 8. Contractor Experience: as defined in Subsection 4.2.1.
- 9. Consultant Experience: as defined in Subsection 4.2.1.
- 10. Work Progress: as defined in Subsection 4.2.1.

The actual payment delay in days (dependent variable) for Model V is calculated by investigating the following factors:

- 1. Number of days for Variation order evaluation and approval: This factor is calculated by subtracting the date of variation order final approval by consultant from the date of submission of variation order request by the contractor.
- 2. Number of day for payment claim to be review and approved by consultant: as defined in Subsection 4.2.1.
- 3. Number of days for variation payment to be paid by owner: as defined in Subsection 4.2.1.

5. Modelling with Neural Networks and Regression

5.1 Introduction

In this study two types of models are applied for the prediction of interim and variation payment delay which are: artificial neural network model and regression model. Each of the applied models has different software tools, architecture and features. These differences are explained further in order to get an assumption of the most suitable model for the prediction of interim and variation payments delay. Below is an explanation of the modeling techniques used in this study:

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5.2 Modeling Techniques

The first modeling techniques used is the artificial neural network with multiple layers: are input layer, one or more hidden layers, and one output layer (Goyal and Goyal, 2012). Three learning algorithms are used in this study: Levenberg-Marquardt algorithm, Bayesian regularization algorithm and Scaled Conjugate gradient. The Forecasting of the output is performed through 3 stages which are training, validation and testing. To perform the training; the learning step starts by discovering linear relationships between the inputs and the output data by assigning weight values to the links between the neurons. The second step is feed forward of the network, where the neurons are added to the hidden layer and the input values in the first layer are multiplied by the weights and passed to the second (hidden) layer to create one iteration (Al-Sobiei et al., 2005). At each iteration, the weights are adjustedto minimize the calculated error measure between the output produced and the targeted output. The error minimization process is repeated until an acceptable result is reached (Iranmanesh and Zarezadeh, 2008).In case the predicted results do not meet the desired output and this is measured by the validation stage where the performance (error) is calculated, then the back propagation of error signals takes place in which error is propagated back to all the elements in the prior layer and finally updating of the weights and biases based on the error signal (Amita et.al, 2015). The testing stage is finally performed by measuring the performance of the model using an independent set of data that is not included in the training and validation stage.

The neural models in this study are developed using Neural Networks Toolboxby MATLAB. In MATLAB there are several neural networks tools that help the user to perform any kind of neural networks smoothly and easily such as using the Neural Network Fitting Tool (nftool) and (nntool), as described in "Graphical User Interface "(Demuth et al., 2009).

The second modeling technique used is MRA. Microsoft Excel (Data analysis toolpak) version 2016 is used to develop regression models. Data analysis tool by Excel is used to develop different engineering analyses. The Data Analysis ToolPak is an Excel add-in tool. It contains more widespread functions, including some useful inferential statistical tests for example regression that can provide single and multiple linear regression (Rose et al., 2014).

The models that are used in this study are presented in Figure (5-1) and are tested for both Model I and Model V. Both MATLAB programme and Microsoft Excel are used for the development of the neural network and regression model, respectively.



Figure 5-1: Approaches adopted for models development

5.3 Design of Models

Two models are developed using ANN Toolbox by MATLAB, while the preparation of the input data and statistical computations had been performed by applying Microsoft Excel. The first model is build based on historical data for 114 interim payments data points taken from real governmental building construction projects, while the second model is build based on historical data for 91 variation orders payments taken from other governmental building construction projects. The development of the models includes the steps shown in Figure (5-2) starting from identifying the input factors and collecting historical data as defined previously in Section (4.2), model development, calculation of the performance and finally comparision of different resullts.



Figure 5-2: ANN Models Development

The Payment delay models are developed using the 114 actual interim payment cases for Model I and 91 actual variation payment cases for Model V. The data used in building each of the two models are divided into 3 subsets, (70%) used for training the network and (15%) for validation, and (15%) for testing. The program accepts up to two layers including 1 hidden layer and 1 output layer which are approved to be enough for most engineering problems. Multi-layers ANN models are developed and compared with each other using 2 approaches: 1) nftool (Neural Network Fitting Tool); and 2) nntool (in Network/Data Manager window) from MATLAB software. Hit and trial method is used to test different combinations of training algorithms and hidden neurons to train the models. Three chosen algorithms are used: Bayesian regularization, Levenberg Marquardt algorithm and Scaled conjugate algorithm. These algorithms are all tested along with a tan-sigmoid activation functionto work best with the normalized factors of a range [-1, 1]. In this study the frequently used "backpropagation" network was implemented.

The significant factors used in the development of the regression models for interim payment delay (Model I) and variation payment delay model (Model V) are the same as the factors used in the development of the neural model as defined in Section (4.2). These factors are working as the independent variables for the multiple regression models created by using Microsoft Excel (Data analysis tool).

The performance of the models was recognized through comparing their predicted output over a test sample. The test sample consists of dataset of 18 historical interim payment cases for Model I and 14 historical variation payments cases for Model V. The evaluation approaches that have been used to test the models are as follows: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and Coefficient of Determination (R squared values).

6. Development of Interim Payment Delay Model (Model I)

6.1 Introduction

A total of thirty-three ANN models are trained, validated and tested for model I with different number of hidden neurons and training algorithms using MATLAB nntool. The one hundred and fourteen cases are divided into three sets: the training set consisting of 79 cases; the validation set consisting of 17 cases; and the testing set consisting of 18 cases. The below subsections show the performance of the test samples for multilayer (2 layers) feed-forward network with tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer for predicting interim payment delay. The training algorithms used are Levenberg-Marquardt algorithm, Bayesian Regulation and Scaled Conjugate Gradient. The performance of the training and validation samples for the thirty-three trial models are not involved in the evaluation of models to eliminate the risk of misevaluation, because during the training and learning some models may accomplish good results during the training and validation data set, but very poor on new data which is the test set. Therefore, the evaluation of the models' performance is done by comparing their predicted output over an independent test sample as mentioned in Section 5.3.

6.2 Developing Model I Using MATLAB nntool

A total of thirty-three ANN models are trained, validated and tested for model I with different number of hidden neurons and training algorithms using MATLAB nntool. The performance of the test samples for multilayer (2 layers) feed-forward network with tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer for predicting interim payment delay are compared as shown in Tables (6-1), (6-2) and (6-3). The training algorithms used are Levenberg-Marquardt algorithm, Bayesian Regulation and Scaled Conjugate Gradient. By comparing the computed results for each of the generated

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models using MATLAB (nntool), Model I-12 with 1 neuron in hidden layer based on Bayesian Regulation algorithm and tansigmoid function has been chosen. It has the lowest error values for Interim payment prediction with RMSE of 11.370, MAE of 8.947and MAPE value of 23.266% as shown in Table (6-4). The best performance for the training sample of this model is at 29 epochs with MSE of 0.003, and R value of 0.999. The validation sample performance is not available because the Matlab Programme sets the validation parameter for Bayesian Regulation as zero.

| Table 6-1: | Performance of | f test sample | Model I | using (nntool | and Levenber | g-Marquardt) |
|-------------------|----------------|---------------|---------|---------------|--------------|--------------|
| | | | | | | |

| Target | | | | | | Model no | | | | | |
|---------|---------|--------|--------|----------|---------|----------|---------|--------|---------|--------|--------|
| Output | I-1 | I-2 | I-3 | I-4 | I-5 | I-6 | I-7 | I-8 | I-9 | I-10 | I-11 |
| 24 | 93.926 | 16.347 | 18.564 | 47.799 | 84.902 | 9.000 | 9.587 | 23.127 | 9.290 | 18.129 | 9.030 |
| 64 | 108.677 | 70.601 | 22.939 | 90.319 | 23.740 | 9.000 | 47.781 | 61.102 | 46.180 | 81.232 | 10.813 |
| 115 | 110.088 | 89.622 | 21.427 | 101.665 | 81.242 | 9.000 | 110.794 | 92.930 | 111.864 | 67.441 | 12.330 |
| 26 | 83.865 | 18.498 | 11.685 | 22.032 | 56.276 | 9.000 | 9.787 | 16.891 | 9.234 | 16.818 | 9.083 |
| 9 | 73.282 | 15.401 | 9.351 | 15.665 | 71.975 | 9.000 | 9.427 | 15.090 | 9.040 | 17.718 | 9.021 |
| 62 | 99.628 | 30.891 | 15.924 | 27.368 | 59.572 | 9.000 | 19.359 | 39.711 | 72.656 | 28.263 | 9.298 |
| 23 | 83.656 | 14.148 | 9.662 | 22.776 | 20.156 | 9.000 | 9.843 | 13.769 | 9.657 | 17.860 | 9.171 |
| 30 | 92.402 | 17.910 | 11.388 | 46.329 | 42.942 | 9.002 | 12.262 | 17.058 | 10.964 | 19.864 | 9.162 |
| 21 | 66.304 | 12.149 | 9.095 | 15.370 | 13.162 | 9.000 | 9.304 | 11.876 | 9.143 | 14.054 | 9.100 |
| 67 | 111.414 | 85.159 | 38.883 | 95.597 | 70.507 | 115.000 | 41.300 | 85.708 | 114.942 | 22.385 | 10.651 |
| 19 | 81.262 | 16.529 | 9.486 | 32.908 | 15.742 | 42.112 | 9.037 | 11.526 | 9.469 | 16.128 | 9.072 |
| 60 | 100.861 | 37.379 | 21.576 | 81.598 | 46.593 | 9.000 | 26.135 | 26.630 | 22.316 | 37.781 | 9.846 |
| 19 | 85.120 | 16.330 | 11.005 | 23.567 | 21.826 | 9.000 | 10.057 | 18.099 | 15.728 | 40.426 | 9.185 |
| 90 | 111.703 | 99.130 | 73.742 | 79.411 | 114.824 | 9.000 | 114.522 | 97.386 | 86.420 | 93.317 | 11.746 |
| 27 | 82.551 | 16.895 | 9.884 | 37.069 | 12.130 | 102.353 | 9.081 | 15.074 | 10.148 | 11.927 | 9.100 |
| 40 | 104.370 | 34.955 | 13.028 | 28.716 | 46.556 | 9.011 | 12.229 | 29.401 | 34.874 | 61.210 | 9.277 |
| 25 | 85.087 | 16.934 | 16.915 | 75.928 | 25.854 | 9.703 | 9.063 | 28.015 | 9.511 | 33.411 | 11.083 |
| 30 | 91.991 | 16.283 | 15.627 | 41.114 | 13.617 | 9.044 | 9.016 | 25.425 | 9.300 | 31.308 | 9.503 |
| hidden | 1 | 5 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 100 |
| neurons | 1 | 5 | 10 | 20 | 50 | 40 | 50 | 00 | 70 | 80 | 100 |
| RMSE | 218.027 | 13.810 | 31.130 | 20.4822 | 26.828 | 45.812 | 20.506 | 13.557 | 18.902 | 20.792 | 41.708 |
| MAE | 51.389 | 11.468 | 22.862 | 16.30862 | 18.928 | 36.039 | 17.906 | 10.699 | 14.863 | 15.832 | 31.921 |
| MAPE | 205.458 | 31.410 | 50.304 | 48.51195 | 81.979 | 82.667 | 49.334 | 29.252 | 42.434 | 41.700 | 66.498 |

Table 6-2: Performance of test sample Model I using (nntool and Bayesian Algorithm)

| Target | | | | | Ν | Iodel no | | | | | |
|---------|--------|---------|---------|---------|---------|----------|---------|---------|---------|---------|---------|
| Output | I-12 | I-13 | I-14 | I-15 | I-16 | I-17 | I-18 | I-19 | I-20 | I-21 | I-22 |
| 24 | 25.050 | 17.477 | 17.475 | 22.959 | 21.383 | 20.648 | 22.289 | 16.727 | 22.282 | 23.640 | 22.437 |
| 64 | 76.232 | 71.928 | 72.772 | 85.897 | 79.351 | 107.301 | 74.319 | 93.546 | 81.607 | 74.358 | 78.327 |
| 115 | 89.302 | 102.356 | 100.520 | 104.348 | 99.893 | 98.212 | 99.983 | 102.968 | 100.353 | 98.495 | 100.758 |
| 26 | 19.825 | 15.884 | 14.868 | 17.636 | 18.606 | 13.133 | 20.411 | 14.338 | 18.297 | 19.976 | 19.830 |
| 9 | 15.448 | 12.559 | 12.067 | 11.584 | 14.447 | 10.147 | 14.753 | 11.071 | 14.115 | 15.385 | 15.146 |
| 62 | 42.727 | 50.226 | 35.396 | 52.817 | 39.717 | 58.123 | 52.465 | 47.741 | 38.248 | 40.325 | 42.057 |
| 23 | 19.643 | 17.461 | 15.024 | 15.086 | 19.186 | 17.315 | 19.443 | 14.671 | 16.765 | 19.287 | 20.024 |
| 30 | 24.349 | 27.808 | 18.937 | 20.667 | 25.132 | 19.253 | 24.373 | 19.959 | 20.138 | 23.407 | 27.859 |
| 21 | 14.585 | 12.032 | 11.726 | 10.926 | 14.460 | 12.777 | 12.906 | 10.843 | 12.419 | 14.435 | 14.773 |
| 67 | 89.108 | 110.309 | 103.360 | 113.464 | 99.467 | 111.220 | 111.275 | 109.050 | 97.999 | 97.019 | 100.660 |
| 19 | 16.325 | 12.340 | 13.649 | 12.529 | 18.061 | 11.350 | 13.976 | 11.310 | 13.569 | 16.808 | 18.573 |
| 60 | 45.082 | 49.173 | 41.040 | 58.139 | 45.657 | 55.474 | 57.677 | 52.892 | 42.640 | 42.018 | 48.129 |
| 19 | 20.027 | 15.499 | 15.101 | 15.363 | 20.781 | 16.564 | 18.023 | 14.409 | 16.863 | 20.172 | 21.849 |
| 90 | 93.144 | 110.842 | 110.099 | 111.836 | 106.787 | 113.813 | 113.157 | 111.676 | 109.472 | 104.770 | 108.350 |
| 27 | 18.219 | 16.023 | 15.805 | 15.196 | 19.733 | 15.354 | 17.236 | 13.349 | 15.533 | 19.069 | 20.350 |
| 40 | 50.062 | 52.785 | 35.539 | 59.895 | 42.697 | 65.444 | 62.444 | 45.880 | 41.659 | 43.907 | 44.993 |
| 25 | 19.217 | 14.468 | 17.203 | 17.662 | 24.776 | 19.428 | 14.807 | 14.547 | 17.832 | 20.655 | 26.631 |
| 30 | 23.748 | 15.021 | 18.524 | 19.716 | 26.168 | 14.291 | 18.746 | 16.065 | 21.967 | 24.160 | 26.703 |
| hidden | 1 | 5 | 10 | 20 | 20 | 40 | 50 | 60 | 70 | 80 | 100 |
| neurons | 1 | 5 | 10 | 20 | 50 | 40 | 30 | 00 | 70 | 80 | 100 |
| RMSE | 11.370 | 14.410 | 14.737 | 15.626 | 12.367 | 18.609 | 14.828 | 15.953 | 13.566 | 12.035 | 12.106 |
| MAE | 8.947 | 11.314 | 12.138 | 11.702 | 9.098 | 13.722 | 10.812 | 12.911 | 11.052 | 9.241 | 8.748 |
| MAPE | 23.266 | 30.338 | 31.552 | 30.222 | 21.641 | 33.271 | 28.205 | 34.039 | 28.431 | 23.076 | 20.971 |

| | | | | r | | 9 (| | Je | | 0 | . , |
|---------|--------|--------|---------|--------|--------|----------|--------|--------|---------|--------|---------|
| Target | | | | | | Model no | 1 | | | | |
| Output | I-23 | I-24 | I-25 | I-26 | I-27 | I-28 | I-29 | I-30 | I-31 | I-32 | I-33 |
| 24 | 24.468 | 38.676 | 72.700 | 13.371 | 9.000 | 13.261 | 19.457 | 16.430 | 13.271 | 15.700 | 17.107 |
| 64 | 24.468 | 67.849 | 79.639 | 65.637 | 9.000 | 54.326 | 20.435 | 25.524 | 73.443 | 9.008 | 77.222 |
| 115 | 24.441 | 29.830 | 73.966 | 45.037 | 9.000 | 95.218 | 59.256 | 85.607 | 82.595 | 9.073 | 91.380 |
| 26 | 24.468 | 27.826 | 63.047 | 13.780 | 9.000 | 12.923 | 15.316 | 19.672 | 12.213 | 13.580 | 18.825 |
| 9 | 24.468 | 44.792 | 43.650 | 12.521 | 9.000 | 12.344 | 14.499 | 16.513 | 10.895 | 12.654 | 12.634 |
| 62 | 24.464 | 22.396 | 65.081 | 11.535 | 9.000 | 42.805 | 19.218 | 15.063 | 54.661 | 9.756 | 23.561 |
| 23 | 24.467 | 22.931 | 38.960 | 14.451 | 9.000 | 13.030 | 20.867 | 36.970 | 15.396 | 9.007 | 24.668 |
| 30 | 24.409 | 26.903 | 52.285 | 18.403 | 9.000 | 12.115 | 15.030 | 42.269 | 28.508 | 9.011 | 61.278 |
| 21 | 24.468 | 21.030 | 24.811 | 12.171 | 9.000 | 11.640 | 17.373 | 29.075 | 12.404 | 9.005 | 12.622 |
| 67 | 13.515 | 81.315 | 101.656 | 10.623 | 9.000 | 99.980 | 18.569 | 34.116 | 91.751 | 15.688 | 92.479 |
| 19 | 24.169 | 20.615 | 20.484 | 10.897 | 9.000 | 14.642 | 12.318 | 13.559 | 10.214 | 9.002 | 14.976 |
| 60 | 24.465 | 20.554 | 69.885 | 27.818 | 9.000 | 23.020 | 21.688 | 41.135 | 27.797 | 9.007 | 73.410 |
| 19 | 24.467 | 22.269 | 48.151 | 12.510 | 9.000 | 14.448 | 13.371 | 11.348 | 24.344 | 9.043 | 23.409 |
| 90 | 24.468 | 27.047 | 109.669 | 93.571 | 9.000 | 94.829 | 33.885 | 42.551 | 103.444 | 25.854 | 101.353 |
| 27 | 24.009 | 19.234 | 45.916 | 11.737 | 9.000 | 28.766 | 16.715 | 13.587 | 10.531 | 9.002 | 17.842 |
| 40 | 24.435 | 58.476 | 76.284 | 11.640 | 9.000 | 24.962 | 15.611 | 18.608 | 67.143 | 9.954 | 53.418 |
| 25 | 14.574 | 12.936 | 20.646 | 39.263 | 9.000 | 9.737 | 20.137 | 33.524 | 9.922 | 9.008 | 21.831 |
| 30 | 18.609 | 29.059 | 34.882 | 18.270 | 9.000 | 10.194 | 17.247 | 39.251 | 10.130 | 9.008 | 12.698 |
| hidden | 1 | 5 | 10 | 20 | 20 | 40 | 50 | 60 | 70 | 80 | 100 |
| neurons | 1 | 3 | 10 | 20 | 50 | 40 | 30 | 60 | 70 | 80 | 100 |
| RMSE | 33.685 | 30.397 | 25.716 | 27.606 | 42.865 | 16.717 | 29.029 | 23.196 | 17.000 | 40.456 | 16.568 |
| MAE | 22.288 | 19.164 | 21.194 | 19.653 | 32.722 | 13.811 | 21.723 | 18.633 | 14.243 | 30.886 | 13.113 |
| MAPE | 45.545 | 51.649 | 77.948 | 46.400 | 68.027 | 37.630 | 44.857 | 45.060 | 38.214 | 65.931 | 33.694 |

Table 6-3: Performance of test sample Model I using (nntool and Scaled Conjugate Gradient Algorithm)

Table 6-4: Selected Models for Model I Using Matlab (nntool)

| Model No | MAE | RMSE | MAPE (%) | Training Algorithm | | | | | | |
|------------|--------|--------|----------|--------------------|--|--|--|--|--|--|
| Model I-8 | 13.557 | 10.699 | 29.252 | Levenberg | | | | | | |
| Model I-12 | 11.370 | 8.947 | 23.266 | Bayesian | | | | | | |
| Model I-33 | 16.567 | 13.113 | 33.694 | Scaled | | | | | | |

6.2 Developing Model I Using MATLAB nftool

A total of thirty-six ANN models are trained validated and tested for model I using MATLAB nftool. The performance of the test samples for multilayer (2 layers) feed-forward network with tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer for predicting interim payment delay is compared as shown in Table (6-5), (6-6), and (6-7). The training algorithms used are Levenberg-Marquardt algorithm, Bayesian Regulation and Scaled Conjugate Gradient. By comparing the computed results for each of the selected models using MATLAB (nftool), Model I-48 with 10 neurons in hidden layer based onBayesian regulation algorithm and tan-sigmoid function has been chosen as it has the lowest error values for Interim payment prediction with RMSE of 1.520, MAE of 0.969 and MAPE value of 3.767% as shown in Table (6-8). The best performance for the training sample of this model is at 120 epochs with MSE of 1.457, and R value of 0.999 which is reflecting a good fit of results and high predictive power of the network.

| | | Table 0-5: P | eriormance | e of test samp | le Model | i using (m | tool and Lev | enderg-Ma | arquarut) | | |
|-------------------|---------|--------------|------------|----------------|----------|------------|--------------|-----------|-----------|---------|---------|
| Target | | | | | Μ | lodel no | | | | | |
| Output | I-34 | I-35 | I-36 | I-37 | I-38 | I-39 | I-40 | I-41 | I-42 | I-43 | I-44 |
| 24 | 22.018 | 23.048 | 22.650 | 24.206 | 24.001 | 30.422 | 18.560 | 29.923 | 24.000 | 20.883 | 25.316 |
| 64 | 60.013 | 62.369 | 60.456 | 64.012 | 61.526 | 62.663 | 64.055 | 64.109 | 42.801 | 62.648 | 59.724 |
| 115 | 111.773 | 113.039 | 112.733 | 115.049 | 115.001 | 118.119 | 125.750 | 115.176 | 80.798 | 81.705 | 106.993 |
| 26 | 26.713 | 27.564 | 27.781 | 26.205 | 26.001 | 30.942 | 25.994 | 26.138 | 30.271 | 9.556 | 17.512 |
| 9 | 11.526 | 12.253 | 11.827 | 9.257 | 9.001 | 14.780 | 9.019 | 9.122 | 9.000 | 5.697 | 10.802 |
| 62 | 57.748 | 58.260 | 56.397 | 62.055 | 62.001 | 71.629 | 62.020 | 82.456 | 62.000 | 54.458 | 60.729 |
| 23 | 28.245 | 27.862 | 30.198 | 28.467 | 23.979 | 32.895 | 32.147 | 28.646 | 47.297 | 29.090 | 20.304 |
| 30 | 26.208 | 26.469 | 27.753 | 30.097 | 30.002 | 40.995 | 29.995 | 29.950 | 30.000 | 28.255 | 28.146 |
| 21 | 19.340 | 18.712 | 21.390 | 20.751 | 15.544 | 31.587 | 21.006 | 20.984 | 56.105 | 22.375 | 17.355 |
| 67 | 65.145 | 66.801 | 65.292 | 67.015 | 66.999 | 70.707 | 67.003 | 67.059 | 67.000 | 67.249 | 109.164 |
| 19 | 14.369 | 14.824 | 17.637 | 18.959 | 19.001 | 19.130 | 19.001 | 19.036 | 19.000 | -37.528 | 10.937 |
| 60 | 54.662 | 55.451 | 54.364 | 59.848 | 60.001 | 65.389 | 54.438 | 37.725 | 60.000 | 57.332 | 84.021 |
| 19 | 25.617 | 25.803 | 23.755 | 19.191 | 21.324 | 28.758 | 19.030 | 19.127 | 19.000 | 14.075 | 19.111 |
| 90 | 88.385 | 89.436 | 90.345 | 90.001 | 90.001 | 70.238 | 89.977 | 90.061 | 90.000 | 30.053 | 127.978 |
| 27 | 29.533 | 30.057 | 33.956 | 36.664 | 32.251 | 30.749 | 27.012 | 6.144 | 27.000 | 27.638 | 16.195 |
| 40 | 37.879 | 40.233 | 36.174 | 39.959 | 40.001 | 51.679 | 24.885 | 40.080 | 40.000 | 35.383 | 52.265 |
| 25 | 21.596 | 21.618 | 23.713 | 35.960 | 25.001 | 23.858 | 50.190 | 25.037 | 25.000 | 24.570 | 17.986 |
| 30 | 24.814 | 24.722 | 26.966 | 30.038 | 30.000 | 22.066 | 30.004 | 30.118 | 30.000 | 27.588 | 23.503 |
| hidden neurons | 1 | 5 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 |
| RMSE | 3.719 | 3.410 | 3.744 | 3.679 | 1.970 | 8.424 | 7.898 | 8.872 | 13.865 | 21.536 | 15.645 |
| MAE | 3.371 | 2.890 | 3.118 | 1.539 | 0.916 | 6.998 | 3.966 | 4.238 | 6.615 | 11.482 | 10.126 |
| MAPE | 12.031 | 11.641 | 10.899 | 6.183 | 3.657 | 23.501 | 12.236 | 11.156 | 19.561 | 34.086 | 23.205 |

Table 6-5: Performance of test sample Model I using (nftool and Levenberg-Marquardt)

Table 6-6: Performance of test sample Model I using (nftool and Bayesian Algorithm)

| Target | | | | | | Model no | | | | | |
|---------|---------|---------|---------|---------|---------|----------|---------|---------|---------|---------|---------|
| Output | I-46 | I-47 | I-48 | I-49 | I-50 | I-51 | I-52 | I-53 | I-54 | I-55 | I-56 |
| 24 | 21.998 | 22.997 | 24.308 | 23.997 | 22.428 | 24.644 | 23.532 | 23.446 | 24.247 | 20.883 | 24.430 |
| 64 | 59.487 | 66.006 | 63.592 | 64.568 | 65.084 | 64.206 | 62.675 | 64.476 | 64.106 | 62.648 | 63.472 |
| 115 | 112.003 | 113.070 | 115.238 | 122.962 | 115.408 | 115.128 | 114.020 | 114.699 | 114.847 | 81.705 | 115.300 |
| 26 | 26.956 | 26.231 | 25.258 | 26.186 | 25.901 | 25.857 | 25.179 | 27.197 | 25.384 | 9.556 | 25.216 |
| 9 | 11.273 | 9.953 | 9.386 | 9.639 | 10.269 | 8.706 | 9.825 | 9.892 | 9.350 | 5.697 | 9.085 |
| 62 | 57.501 | 59.505 | 61.349 | 60.860 | 60.992 | 61.966 | 60.352 | 61.129 | 62.307 | 54.458 | 60.882 |
| 23 | 27.490 | 25.875 | 26.534 | 27.994 | 26.766 | 33.938 | 26.163 | 26.204 | 25.150 | 29.090 | 24.518 |
| 30 | 25.365 | 26.615 | 29.170 | 28.321 | 28.628 | 26.150 | 26.936 | 29.143 | 29.488 | 28.255 | 13.309 |
| 21 | 18.501 | 16.032 | 16.505 | 17.814 | 16.547 | 20.710 | 17.537 | 17.519 | 18.470 | 22.375 | 18.298 |
| 67 | 65.008 | 66.694 | 67.269 | 67.113 | 66.817 | 66.969 | 67.231 | 67.175 | 66.928 | 67.249 | 66.954 |
| 19 | 13.712 | 17.217 | 18.840 | 17.184 | 17.508 | 18.921 | 17.434 | 19.659 | 18.858 | -37.528 | 16.152 |
| 60 | 54.372 | 56.285 | 57.974 | 55.221 | 55.207 | 59.405 | 51.776 | 57.507 | 59.115 | 57.332 | 48.144 |
| 19 | 24.800 | 23.558 | 20.108 | 21.449 | 23.154 | 19.438 | 22.881 | 21.312 | 31.688 | 14.075 | 20.904 |
| 90 | 89.389 | 89.251 | 89.674 | 89.407 | 89.365 | 89.881 | 88.971 | 89.218 | 89.556 | 30.053 | 89.389 |
| 27 | 29.313 | 27.910 | 27.672 | 27.376 | 27.898 | 26.999 | 37.567 | 44.904 | 27.188 | 27.638 | 27.040 |
| 40 | 36.977 | 39.274 | 40.054 | 38.758 | 39.528 | 39.775 | 39.108 | 38.824 | 39.625 | 35.383 | 31.259 |
| 25 | 21.032 | 26.471 | 25.576 | 25.596 | 25.312 | 24.942 | 25.314 | 24.977 | 25.039 | 24.570 | 25.098 |
| 30 | 24.145 | 27.264 | 29.338 | 29.532 | 25.167 | 29.952 | 29.644 | 16.375 | 29.917 | 27.588 | 30.003 |
| hidden | 1 | 5 | 10 | 20 | 20 | 40 | 50 | 60 | 70 | 80 | 00 |
| neurons | 1 | 5 | 10 | 20 | 30 | 40 | 50 | 00 | 70 | 80 | 90 |
| RMSE | 3.871 | 2.469 | 1.520 | 2.770 | 2.469 | 2.746 | 3.631 | 5.512 | 3.110 | 21.536 | 5.373 |
| MAE | 3.519 | 2.044 | 0.969 | 1.822 | 1.822 | 1.007 | 2.379 | 2.832 | 1.216 | 11.482 | 2.795 |
| MAPE | 12.442 | 7.388 | 3.767 | 5.535 | 7.078 | 4.089 | 8.221 | 10.460 | 5.714 | 34.086 | 8.426 |

| - | | | | | | <u>N 11</u> | | | 50 | | 0 | |
|---------|---------|---------|---------|---------|---------|-------------|---------|---------|---------|---------|---------|---------|
| Target | | - | | | | Model no | | - | | | | |
| Output | I-58 | I-59 | I-60 | I-61 | I-62 | I-63 | I-64 | I-65 | I-66 | I-67 | I-68 | I-69 |
| 24 | 33.096 | 12.537 | 24.233 | 25.095 | 24.195 | 25.007 | 10.533 | 16.304 | 2.009 | -5.154 | 20.993 | 25.280 |
| 64 | 66.278 | 53.469 | 63.008 | 77.050 | 82.479 | 57.345 | 72.820 | 61.306 | 41.515 | 65.922 | 72.758 | 127.234 |
| 115 | 136.012 | 110.106 | 117.389 | 115.567 | 112.932 | 117.213 | 125.198 | 119.275 | 120.705 | 106.863 | 161.911 | 118.284 |
| 26 | 30.125 | 20.901 | 27.583 | 26.872 | 21.741 | 28.228 | 31.621 | 21.762 | 17.526 | 12.018 | 23.289 | 30.290 |
| 9 | 22.263 | 8.225 | 10.540 | 8.918 | 10.211 | 18.246 | 19.023 | 20.785 | 38.770 | -14.778 | 9.990 | 37.232 |
| 62 | 76.235 | 63.679 | 63.711 | 60.525 | 61.483 | 67.082 | 62.676 | 61.657 | 67.828 | 47.470 | 51.187 | -18.605 |
| 23 | 35.309 | 30.002 | 32.020 | 27.362 | 26.008 | 26.182 | 27.279 | 19.822 | 41.607 | 44.601 | 25.762 | 22.017 |
| 30 | 22.727 | 24.976 | 32.056 | 28.682 | 26.147 | 29.055 | 23.556 | 34.030 | 1.169 | 13.711 | 8.466 | 32.861 |
| 21 | 31.107 | 23.206 | 19.928 | 16.488 | 21.051 | 20.633 | 21.974 | 11.974 | 50.438 | 36.203 | 3.843 | 3.549 |
| 67 | 57.491 | 55.502 | 61.495 | 78.401 | 77.008 | 61.870 | 29.601 | 71.658 | 42.579 | 68.239 | 74.133 | 69.878 |
| 19 | 19.618 | 15.910 | 8.412 | 18.510 | 17.756 | 10.390 | 31.989 | 24.514 | 16.583 | 8.614 | -21.701 | 18.608 |
| 60 | 45.820 | 57.022 | 58.318 | 57.694 | 57.882 | 58.345 | 57.527 | 48.253 | 37.809 | 57.266 | 49.567 | 57.471 |
| 19 | 35.356 | 25.321 | 25.285 | 20.831 | 28.027 | 38.196 | 21.130 | 27.613 | 19.651 | 6.359 | 83.835 | -3.124 |
| 90 | 40.081 | 82.132 | 88.663 | 88.869 | 86.937 | 121.852 | 68.468 | 89.184 | 71.764 | 87.537 | 94.066 | 30.887 |
| 27 | 28.603 | 31.772 | 32.478 | 27.493 | 25.836 | 28.038 | 21.539 | 25.804 | 2.381 | 39.040 | 38.107 | 22.675 |
| 40 | 52.779 | 30.428 | 40.477 | 40.610 | 39.403 | 34.237 | 34.620 | 37.118 | 25.640 | 28.440 | 38.854 | 45.224 |
| 25 | 14.988 | 23.513 | 16.695 | 25.530 | 24.764 | 1.877 | 49.733 | 57.464 | 14.747 | 39.079 | 36.354 | -4.814 |
| 30 | 22.016 | 24.738 | 11.134 | 29.802 | 38.703 | 28.417 | 8.815 | 29.173 | 46.499 | 34.721 | 31.358 | 72.067 |
| hidden | 1 | 5 | 10 | 20 | 20 | 40 | 50 | 60 | 70 | 80 | 00 | 100 |
| neurons | 1 | 5 | 10 | 20 | 30 | 40 | 50 | 00 | 70 | 80 | 90 | 100 |
| RMSE | 16.008 | 6.547 | 6.425 | 4.453 | 6.074 | 11.144 | 14.371 | 9.657 | 19.257 | 14.214 | 22.936 | 31.920 |
| MAE | 12.037 | 5.640 | 4.396 | 2.573 | 3.878 | 7.160 | 10.766 | 6.443 | 16.932 | 12.025 | 14.821 | 20.594 |
| MAPE | 36.611 | 16.810 | 16.702 | 6.522 | 11.112 | 25.718 | 34.679 | 28.003 | 64.145 | 53.859 | 52.962 | 63.630 |

Table 6-7: Performance of test sample Model I using (nftool and Scaled Conjugate Gradient Algorithm

Table 6-8: Selected Models for Model I Using MATLAB (nftool)

| Model No | MAE | RMSE | MAPE (%) | Training Algorithm |
|------------|-------|-------|----------|-----------------------|
| Model I-38 | 1.970 | 0.916 | 3.657 | Levenberg |
| Model I-48 | 0.969 | 1.520 | 3.767 | Bayesian |
| Model I-61 | 2.573 | 4.453 | 6.522 | Scaled |

6.3 Developing of Model I Using Regression Excel Tool

A Linear regression model is used to statistically estimate the relationships among independent and dependent variables. The model is developed using Microsoft Excel (data analysis toolpak) in order to predict the payment delay for interim payment using 114 historical cases. Ninety-six cases are used for development and 18 cases are used for testing the model. Linear regression analysis is used to predict the output of dependent variable Interim payment delay (Y) on the basis of the independent variables which are: Delay in the submission of payment evaluation (X1); Claim review (X2); Payment process by owner (X3); Variation orders occurrence (X4); Extension of time occurrence (X5); Contractor experience (X6); Consultant's experience (X7); Externally funded projects (X8); Locally Funded projects (X9); Work progress (X10); Payment amount (X11). The data for independent and dependent variable are obtained from section (4-2). The linear regression output (Model I-70) is as presented by Equation (6-1), this equation is a result of the outputs shown in Table (6-9).

Y = -48.56 + 1.005*X1 + 1.022*X2 + 1.185*X3 - 0.268*X4 - 0.180*X5 + 0.766*X6 + 0*X7 + 1.484*X8 + 0.002*X9 + 0*X10 (6-1)

The goodness of fit for the Regression Model is shown in Table (6-10) based on 95% confidence intervals. The Multiple R value represents the correlation coefficient of determination with a value of 0.996 showing a strong linear relationship between the predicted output and targets. The calculated R-squared value of 99.2% is representing the goodness of fit for the above equation. This means that 99.2% of the variance in the dependent variable (payment delay) is explained by the model indicating a high predictive power for the model. The adjusted R squared is equal to 0.991 and it represents R squared value in term of the number of variables in the model. As shown both values are very close to each other. The computed standard error is equal to 3.453%, this tells that the average distance for the predicted points falls about 3.453% from the regression line, this result asses a high precision of the prediction for the model. The obtained P-value of 2.054×10^{-103} (considered extremely significant) and reflecting the probability for obtaining an R squared value of 99.2%.

| Code | Variables | Coefficients | Standard Error | Lower 95% | Upper 95% |
|------|---|--------------|-------------------|-----------|-----------|
| С | Constant | -48.56 | 2.791 | -54.1 | -43.0 |
| X1 | Delay in the submission of payment evaluation | 1.005 | 0.036 | 0.93 | 1.08 |
| X2 | Claim review(days) | 1.022 | 0.012 | 0.99 | 1.05 |
| X3 | Payment process by owner (days) | 0.981 | 0.013 | 0.96 | 1.01 |
| X4 | Variation orders occurrence (binary) | 1.185 | 0.709 | -0.22 | 2.59 |
| X5 | Extension of time occurrence (binary) | -0.268 | 1.049 | -2.35 | 1.81 |
| X6 | Contractor Experience (years) | -0.180 | 0.148 | -0.47 | 0.11 |
| X7 | Consultant's experience (years) | 0.766 | 0.350 | 0.07 | 1.46 |
| X8 | Externally funded project (binary) | 0.000 | 0.000 | 0.00 | 0.00 |
| X9 | Locally funded project (binary) | 1.484 | 1.327 | -1.14 | 4.12 |
| X10 | Work progress (delay in days) | 0.002 | 0.007 | -0.01 | 0.02 |
| X11 | Payment amount (BD) | 0.000 | 2.72E-06 | -4.49E-06 | 6.29E-06 |

| Table 6-9: | Regression | Coefficients | for Model | I-70using | equation (6-1 |
|------------|------------|--------------|-----------|-----------|---------------|
| | 0 | | | 0 | |

| Table 6-10 . | Goodness | of Fit | of Mode | 1 I_701 | ising e | austion (| 6-1 | ١ |
|---------------------|----------|---------|---------|---------|---------|-----------|-----|---|
| | Goodiess | 01 I'll | of moue | 11-70t | ising c | quation | 0-1 |) |

| Regression Statistics | Goodness of Fit ≥ 0.80 |
|-----------------------|-----------------------------|
| Multiple R | 0.996 |
| R Square | 0.992 |
| Adjusted R Square | 0.991 |
| Standard Error | 3.453 |
| P-Value | 2.054E-103 |
| Observations | 114 |

Table (6-9) shows the variables coefficients, the standard error along with the lower and upper bound of the confidence interval of each variable. The table shows that seven out of twelve variables (58.3%) has a positive biased coefficient, three out of twelve (25%) has negative biased coefficients and two out of twelve (16.6%) has zero value coefficients. As shown in the table for a 95% confidence prediction interval, about 95% of the observations should fall within Coefficient ± 2 *Standard error from the regression line, these ranges of confidence intervals are expected to comprise the right value of the coefficient for each variable of the regression model.

Table (6-11) shows the P-values of the regression model which examine the effect of each independent variable on the dependent variable and its significance to the model. For a 95% confidence level a P-value of more than or equal to 0.05 is considered not significant, while P-value of less than 0.05 is considered significant. The results show that seven variables are considered as not significant, four out of these seven are binary (0, 1) data variables which are: externally funded projects, locally funded project, Variation orders occurrence (binary), and Extension of time occurrence (binary). This indicates that the model considers all the binary (0, 1) input data as not significant. The other non-significance factors are: Work Progress (Delay in days), Payment Amount (BD), and contractor experience. This is because these three factors do not have a direct effect on the payment delay. The Model consideration of "Extension of time" and "Variation" as non-significant factors may be explained by their non-direct relation with payment delay. Because a delay in the approval of extension of time and variation orders by the consultant causes a delay in issuance of payment certificate and as a result a delay in MoF process which results eventually in a payment delay to contractor. On the other hand, the non-direct relation of work progress to payment delay is expected because the delay in payment evaluation, or 3) cause the occurrence of extension of time. These three might lead to delay in payment to contractor.

 Table 6-11: Significant & Non-Significant Variables Model I-70using equation (6-1)

| Code | Variables | t Stat | P-value | Significance |
|------|---|--------|-----------|-----------------|
| С | Constant | -17.40 | 1.406E-32 | Significant |
| X1 | Delay in the submission of payment evaluation | 27.78 | 6.399E-50 | Significant |
| X2 | Claim review(days) | 83.94 | 2.288E-97 | Significant |
| X3 | Payment process by owner (days) | 75.63 | 9.819E-93 | Significant |
| X4 | Variation orders occurrence (binary) | 1.67 | 0.097 | Not Significant |
| X5 | Extension of time occurrence (binary) | -0.26 | 0.79 | Not Significant |
| X6 | Contractor experience (years) | -1.22 | 0.22 | Not Significant |
| X7 | Consultant's experience (years) | 2.19 | 0.031 | Significant |
| X8 | Externally funded project (binary) | 0 | 1.00 | Not Significant |
| X9 | Locally funded project (binary) | 1.12 | 0.26 | Not Significant |
| X10 | Work progress (delay in days) | 0.28 | 0.78 | Not Significant |
| X11 | Payment amount (BD) | 0.33 | 0.74 | Not Significant |

Accordingly, the model is modified by eliminating the non-significant factors and including only the significant independent factors as per the result of Table (6-11), which are: Delay in the submission of payment evaluation (X1), Claim review (X2), Payment process by owner (X3) and Consultant's Experience (X7), as presented in Equation (6-2).

Y = -48.96 + 0.997 * X1 + 1.023 * X2 + 0.978 * X3 + 0.820 * X7(6-2)

The goodness of fit for the Regression Model is shown in Table (6-12) based on 95% confidence intervals. The Multiple R value is equal to 0.996 showing a very good linear relationship between the predicted output and targets. The calculated R-squared value is equal to 99.1% which is indicating a great predictive power of the model. The adjusted R squared is equal to 0.991. The computed standard error is equal to 3.453%, this result asses a high precision of the prediction by the model. The obtained P-value of 3.699×10^{-112} (considered extremely significant) and reflecting the probability for obtaining an R squared value of 99.1%.

Table 6-12: Goodness of fit of Model I-70 using equation (6-2)

| Regression Statistics | | | | | | |
|-----------------------|------------|--|--|--|--|--|
| Multiple R | 0.996 | | | | | |
| R Square | 0.991 | | | | | |
| Adjusted R Square | 0.991 | | | | | |
| Standard Error | 3.450 | | | | | |
| P-Value | 3.699E-112 | | | | | |
| Observations | 114 | | | | | |

| Table 6-13: Regression | coefficients for Model I-7 | 70 using equation (6-2) |
|------------------------|----------------------------|-------------------------|
|------------------------|----------------------------|-------------------------|

| Code | Variables | Coefficients | Standard Error | Lower 95% | Upper 95% |
|------|---|--------------|----------------|-----------|-----------|
| С | Constant | -48.961 | 1.882 | -52.691 | -45.230 |
| X1 | Delay in the submission of payment evaluation (claim) | 0.997 | 0.035 | 0.927 | 1.067 |
| X2 | Claim review(days) | 1.023 | 0.011 | 1.001 | 1.046 |
| X3 | Payment process by owner (days) | 0.978 | 0.013 | 0.953 | 1.003 |
| X7 | Consultant's experience (years) | 0.820 | 0.252 | 0.321 | 1.319 |

Table (6-13) shows the variables codes, coefficients, the standard error along with the lower and upper bounds of the confidence interval of each variable. The table shows that four out of five variables (80%) have a positive biased coefficient, and one out of five (20%) have negative biased coefficients. As shown in the table for a 95% confidence prediction interval, about 95% of the observations should fall within coefficient value ± 2 *Standard error from the regression line, these ranges of confidence intervals are expected to comprise the right value of the coefficient for each variable of the regression model.

The test sample cases (18 cases) are used to validate the regression models of Equation (6-1) and Equation (6-2) for comparison purpose. The test sample along with the estimated output and the performance errors are shown in Tables (6-14) and (6-15) for Equations (6-1) and (6-2), respectively. As shown in Table (6-14), the performance error values for Equation (6-1) are: RMSE of 15.507, MAE of 3.655, and MAPE% of 12.291%. While Table (6-15) shows the performance error values for Equation (6-2) as follows: RMSE of 3.928, MAE of 3.655 and MAPE of 11.944%. Figure (6-1) shows the targeted and estimated interim payment delays (days) of the regression model for Equation (6-2). It is noticed that there is a remarkable matching between the two curves for Equation (6-2) results, which is reflecting very good performance for the regression model. On the other hand, Equation (6-1) results have slightly less accurate results as shown in Table (6-14). Therefore, it is recommended to choose Equation (6-2) for the regression model (Model I-70).



Figure 6-1: Performance of test sample of regression Model (Model I-70) using equation (6-2)

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 Table 6-14: Performance of test sample of regression model (Model I-70) using equation (6-1)

| Case No. | Target output (days) | Predicted output (days) | Square Error | Absolute error | Percentage error% |
|-------------|----------------------------|-------------------------------|-----------------|-------------------|----------------------|
| 1 | 24 | 22.303 | 0.400 | 0.094 | 0.004 |
| 2 | 64 | 59.595 | 1.038 | 0.245 | 0.004 |
| 3 | 115 | 109.260 | 1.353 | 0.319 | 0.003 |
| 4 | 26 | 27.601 | 0.377 | 0.089 | 0.003 |
| 5 | 9 | 11.058 | 0.485 | 0.114 | 0.013 |
| 6 | 62 | 57.986 | 0.946 | 0.223 | 0.004 |
| 7 | 23 | 28.291 | 1.247 | 0.294 | 0.013 |
| 8 | 30 | 25.844 | 0.979 | 0.231 | 0.008 |
| 9 | 21 | 19.074 | 0.454 | 0.107 | 0.005 |
| 10 | 67 | 64.933 | 0.487 | 0.115 | 0.002 |
| 11 | 19 | 14.359 | 1.094 | 0.258 | 0.014 |
| 12 | 60 | 54.905 | 1.201 | 0.283 | 0.005 |
| 13 | 19 | 25.457 | 1.522 | 0.359 | 0.019 |
| 14 | 90 | 87.311 | 0.634 | 0.149 | 0.002 |
| 15 | 27 | 30.790 | 0.893 | 0.211 | 0.008 |
| 16 | 40 | 37.489 | 0.592 | 0.139 | 0.003 |
| 17 | 25 | 22.044 | 0.697 | 0.164 | 0.007 |
| 18 | 30 | 25.302 | 1.107 | 0.261 | 0.009 |
| Performance | | RMSE 15 507 | MAE | MAPE (%) | |

Table 6-15: Performance of Test Sample of Regression Model (Model I-70) Using Equation (6-2)

| Case No. | Target output (days) | Predicted output (days) | Square Error | Absolute error | Percentage error% |
|-------------|----------------------------|-------------------------------|-----------------|-------------------|----------------------|
| 1 | 24 | 22.338 | 2.763 | 1.662 | 6.926 |
| 2 | 64 | 59.930 | 16.565 | 4.070 | 6.359 |
| 3 | 115 | 109.079 | 35.063 | 5.921 | 5.149 |
| 4 | 26 | 27.515 | 2.295 | 1.515 | 5.827 |
| 5 | 9 | 10.930 | 3.725 | 1.930 | 21.446 |
| 6 | 62 | 56.650 | 28.620 | 5.350 | 8.629 |
| 7 | 23 | 28.149 | 26.512 | 5.149 | 22.387 |
| 8 | 30 | 25.690 | 18.579 | 4.310 | 14.368 |
| 9 | 21 | 18.991 | 4.035 | 2.009 | 9.565 |
| 10 | 67 | 64.142 | 8.169 | 2.858 | 4.266 |
| 11 | 19 | 14.726 | 18.268 | 4.274 | 22.496 |
| 12 | 60 | 54.865 | 26.371 | 5.135 | 8.559 |
| 13 | 19 | 24.295 | 28.032 | 5.295 | 27.866 |
| 14 | 90 | 88.514 | 2.208 | 1.486 | 1.651 |
| 15 | 27 | 30.999 | 15.992 | 3.999 | 14.811 |
| 16 | 40 | 36.234 | 14.180 | 3.766 | 9.414 |
| 17 | 25 | 22.352 | 7.013 | 2.648 | 10.593 |
| 18 | 30 | 25.595 | 19.403 | 4.405 | 14.683 |
| D (| | | RMSE | MAE | MAPE (%) |
| Performance | | | 3.928 | 3.655 | 11.944 |

6.5 Comparison and Discussion of Model I Results

Table (6-16) shows the comparison between the selected models created for interim payment delay using MATLAB (nntool), MATLAB (nftool) and Excel Regression analysis tool. As per the computed results the best performance model is the neural network Model I-48 with 10 neurons in hidden layer based on Bayesian Regulation algorithm and tan-sigmoid function. Model I-48 has error values for RMSE of 1.520, MAE of 0.969, and MAPE of 3.767%. The ANN structure of the model chosen is shown in Figure (6-2). The best performance for the training sample of this model is at 120 epochs with MSE of 1.547 as shown in Figure (6-3), and R value of 0.999 which is reflecting a good fit of results and high predictive power of the network as shown in Figure (6-4). In the second place comes the regression model (Model I-70) with RMSE value of 3.777, MAE of 3.493, and MAPE value of 11.733%. Finally, in the third place the neural network Model I-22 with 100 neurons in hidden layer based on Bayesian Regulation algorithm and tan-sigmoid function. The ANN using MATLAB nftool shows relatively better results than the regression model. Although, on the basis of simplicity and ease of implementation of regression models, it will still give fairly good results for predicting of interim payment delay.

 Table 6-16: Comparison of The selected models for (Model I)

| | | | 1 | | | |
|------------|-------|--------|----------|------------------|------------------|---------------|
| Model No | MAE | RMSE | MAPE (%) | R-squared | Туре | Tool |
| Model I-22 | 8.748 | 12.105 | 20.971 | 0.999 | Neural Network | MATLAB nntool |
| Model I-48 | 0.969 | 1.520 | 3.767 | 0.999 | Neural Network | MATLAB nftool |
| Model I-70 | 3.928 | 3.655 | 11.944 | 0.991 | Regression Model | Excel ATP |

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Figure 6-2: ANN Diagram for Model I-48



Figure 6-3: Training Performance R-Value Result for Model I-48



Figure 6-4: R square value for Model I-48

7. Development of Variation Payment Delay Model (Model V)

7.1 Introduction

The variation payment delay model (Model V) is developed for the prediction of variation payment delay using 91 actual historical cases for MoW building projects. The model is developed as neural network model using MATLAB nntool and MATLAB nftool approaches, and as a multiple linear regression model using Excel data analysis tool pack approach. A total of seventy-six (76) trial Models were created to come out with the best prediction model for variation payments delay.

7.2 Developing Model V Using MATLAB nntool

A total of thirty-six ANN models are trained, validated and tested for model V with different number of hidden neurons and training algorithms using MATLAB nntool. The ninety-one cases are divided into three sets: the training set consisting of 63 cases; the validation set consisting of 14 cases; and the testing set consisting of 14 cases. The performance of the test samples for multilayer (2 layers) feed-forward network with tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer for predicting interim payment delay are compared as shown in Tables (7-1), (7-2) and (7-3). The same training algorithms of Section 6-2 are used. By comparing the computed results for each of the three selected models using MATLAB (nntool), Model V-14 with 5 neurons in hidden layer based on Bayesian Regulation algorithm and tan-sigmoid function has been chosen. It has the lowest error values for interim payment prediction with RMSE of 0.304, MAE of 0.248 and MAPE value of 0.586% as shown in Table (7-4). The performance of the training and validation samples for the thirty-six trial models are not involved in the evaluation of models to eliminate the risk of misevaluation, because during the training and learning some models may accomplish good results with the training and validation data set, but very poor with new data, which

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is the test set. Therefore, the evaluation of the models' performance is done by comparing their predicted output over an independent test sample.

 Table 7-1: Performance of test sample Model V using (nntool and Levenberg-Marquardt)

| Target | | | | | | Moo | iel no | | | | | |
|-------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Output | V-1 | V-2 | V-3 | V-4 | V-5 | V-6 | V-7 | V-8 | V-9 | V-10 | V-11 | V-12 |
| 83 | 79.23 | 82.99 | 82.42 | 80.16 | 85.58 | 79.40 | 73.98 | 87.43 | 79.21 | 89.01 | 67.77 | 80.57 |
| 70 | 64.41 | 70.98 | 68.25 | 54.39 | 69.67 | 64.71 | 66.20 | 70.01 | 70.14 | 72.78 | 56.57 | 69.51 |
| 30 | 31.83 | 29.24 | 33.27 | 26.87 | 29.89 | 24.31 | 41.53 | 27.72 | 28.21 | 30.73 | 31.19 | 30.01 |
| 25 | 28.66 | 25.33 | 30.68 | 24.02 | 26.46 | 21.92 | 38.39 | 24.93 | 25.78 | 27.23 | 28.67 | 26.91 |
| 21 | 24.58 | 19.32 | 24.20 | 19.49 | 21.32 | 26.88 | 25.04 | 21.00 | 22.14 | 21.56 | 20.57 | 21.30 |
| 32 | 31.27 | 32.14 | 30.83 | 24.66 | 37.79 | 25.77 | 33.89 | 32.02 | 85.72 | 32.48 | 28.11 | 31.48 |
| 142 | 154.53 | 142.57 | 155.40 | 208.99 | 142.14 | 135.63 | 134.20 | 142.00 | 142.33 | 146.54 | 131.75 | 141.96 |
| 63 | 59.51 | 62.74 | 58.69 | 57.75 | 63.54 | 47.86 | 68.31 | 63.07 | 56.96 | 62.22 | 57.14 | 62.13 |
| 83 | 81.40 | 84.14 | 79.11 | 90.49 | 82.81 | 67.71 | 85.47 | 82.95 | 82.26 | 86.10 | 74.04 | 83.39 |
| 36 | 35.36 | 35.60 | 36.79 | 32.88 | 34.78 | 28.00 | 46.21 | 35.61 | 36.55 | 36.30 | 33.74 | 36.52 |
| 83 | 81.39 | 82.49 | 85.61 | 88.51 | 86.47 | 81.20 | 82.65 | 96.71 | 83.77 | 85.41 | 74.00 | 81.83 |
| 68 | 64.15 | 64.91 | 69.64 | 64.65 | 64.82 | 61.05 | 63.28 | 68.00 | 68.24 | 69.84 | 59.72 | 68.00 |
| 69 | 65.13 | 66.62 | 71.20 | 65.18 | 67.11 | 62.34 | 65.19 | 70.71 | 68.02 | 71.35 | 61.53 | 67.89 |
| 19 | 24.51 | 20.24 | 35.35 | 19.06 | 21.56 | 19.16 | 20.98 | 18.99 | 39.12 | 31.52 | 28.66 | 35.00 |
| hidden neurons | 1 | 5 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
| RMSE | 4.709 | 1.292 | 6.288 | 18.816 | 2.34 | 7.652 | 6.909 | 3.926 | 15.466 | 4.243 | 8.308 | 4.392 |
| MAE | 3.732 | 0.964 | 4.346 | 9.072 | 1.698 | 6.439 | 5.739 | 1.625 | 6.508 | 2.9 | 7.114 | 1.84 |
| MAPE | 8.062 | 2.295 | 12.405 | 11.49 | 4.217 | 13.05 | 14.432 | 2.402 | 21.997 | 7.9 | 13.477 | 7.492 |

 Table 7-2: Performance of test sample Model V using (nntool and Bayesian Algorithm)

| Target | | | | | | Mod | el no | | | | | |
|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|-------|--------|-------|
| Output | V13 | V14 | V15 | V16 | V17 | V18 | V19 | V20 | V21 | V22 | V23 | V24 |
| 83 | 79.14 | 82.78 | 93.90 | 83.00 | 83.00 | 82.86 | 82.80 | 82.74 | 78.20 | 83.04 | 77.24 | 82.66 |
| 70 | 64.47 | 70.37 | 79.40 | 77.60 | 72.78 | 70.15 | 70.22 | 70.31 | 69.99 | 72.57 | 66.76 | 70.43 |
| 30 | 32.81 | 30.41 | 41.21 | 30.12 | 30.25 | 30.12 | 29.09 | 29.28 | 30.10 | 29.92 | 35.84 | 29.56 |
| 25 | 29.77 | 25.45 | 38.60 | 25.22 | 24.93 | 24.83 | 25.56 | 25.34 | 25.44 | 25.18 | 33.18 | 25.20 |
| 21 | 25.11 | 21.18 | 20.69 | 18.12 | 20.96 | 21.05 | 21.08 | 24.62 | 20.91 | 21.10 | 22.41 | 21.06 |
| 32 | 32.19 | 31.82 | 19.32 | 32.05 | 41.07 | 31.99 | 31.78 | 31.96 | 31.88 | 31.02 | 31.01 | 31.97 |
| 142 | 155.82 | 142.04 | 157.61 | 142.01 | 142.01 | 141.99 | 141.90 | 163.94 | 141.99 | 155.4 | 143.57 | 141.9 |
| 63 | 59.93 | 62.63 | 66.47 | 63.08 | 63.14 | 63.00 | 62.58 | 62.99 | 62.70 | 62.98 | 59.15 | 63.19 |
| 83 | 81.53 | 83.06 | 82.04 | 81.54 | 82.89 | 78.80 | 83.30 | 84.34 | 83.26 | 82.91 | 77.26 | 81.63 |
| 36 | 36.32 | 35.91 | 41.85 | 35.56 | 36.00 | 35.56 | 36.44 | 35.81 | 35.80 | 36.69 | 39.01 | 36.07 |
| 83 | 80.21 | 82.64 | 53.29 | 82.79 | 83.01 | 83.04 | 83.48 | 82.82 | 83.17 | 83.01 | 84.62 | 82.81 |
| 68 | 63.15 | 68.63 | 44.38 | 68.04 | 68.26 | 68.00 | 67.55 | 68.40 | 67.95 | 68.21 | 66.00 | 68.19 |
| 69 | 64.18 | 68.97 | 45.16 | 69.21 | 68.74 | 68.97 | 68.72 | 68.87 | 68.82 | 68.84 | 66.31 | 69.01 |
| 19 | 25.09 | 19.10 | 28.98 | 18.89 | 19.02 | 18.89 | 19.61 | 23.93 | 19.21 | 18.84 | 26.73 | 19.03 |
| No of | | | | | | | | | | | | |
| hidden | 1 | 5 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
| neuron | | | | | | | | | | | | |
| RMSE | 5.260 | 0.304 | 14.828 | 2.213 | 2.539 | 1.132 | 0.433 | 6.101 | 1.298 | 3.659 | 4.475 | 0.424 |
| MAE | 4.178 | 0.248 | 12.225 | 0.960 | 0.930 | 0.390 | 0.372 | 2.457 | 0.498 | 1.335 | 3.829 | 0.255 |
| MAPE | 9.138 | 0.586 | 25.067 | 2.165 | 2.491 | 0.620 | 0.999 | 4.747 | 0.839 | 1.512 | 10.392 | 0.464 |

Table 7-3: Performance of test sample Model V using (nntool and Scaled Conjugate Gradient Algorithm)

| Target | | | | | | Mod | lel no | | | | | |
|---------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Output | V25 | V26 | V27 | V28 | V29 | V30 | V31 | V32 | V33 | V34 | V35 | V36 |
| 83 | 77.271 | 93.902 | 84.097 | 82.85 | 93.087 | 81.469 | 80.542 | 68.294 | 82.159 | 87.273 | 68.39 | 63.807 |
| 70 | 63.529 | 79.404 | 71.313 | 72.801 | 79.377 | 73.986 | 69.256 | 57.219 | 67.455 | 76.851 | 59.808 | 54.192 |
| 30 | 36.318 | 41.211 | 34.296 | 34.866 | 34.153 | 39.395 | 34.566 | 36.067 | 38.293 | 29.819 | 40.222 | 46.096 |
| 25 | 33.693 | 38.596 | 31.604 | 32.752 | 31.149 | 37.145 | 32.27 | 33.034 | 35.071 | 27.315 | 37.421 | 42.819 |
| 21 | 30.025 | 20.688 | 15.4 | 17.094 | 41.732 | 18.354 | 31.522 | 28.809 | 32.454 | 22.225 | 27.242 | 16.415 |
| 32 | 37.283 | 19.315 | 20.766 | 24.054 | 39.342 | 19.591 | 21.585 | 44.873 | 45.904 | 38.47 | 43.084 | 25.37 |
| 142 | 155.89 | 157.61 | 132.81 | 150.89 | 143.19 | 145.64 | 137.12 | 143.4 | 146.71 | 168.82 | 149.84 | 128.42 |
| 63 | 60.164 | 66.466 | 57.98 | 51.917 | 55.924 | 60.915 | 55.969 | 61.163 | 61.324 | 52.357 | 69.733 | 75.911 |
| 83 | 80.739 | 82.037 | 70.353 | 67.155 | 78.405 | 76.718 | 73.711 | 84.675 | 82.709 | 74.528 | 88.949 | 87.668 |
| 36 | 39.237 | 41.854 | 33.995 | 33.562 | 38.439 | 38.983 | 32.48 | 40.482 | 40.623 | 33.032 | 48.125 | 46.24 |
| 83 | 71.98 | 53.288 | 88.054 | 73.427 | 78.533 | 79.387 | 73.822 | 87.817 | 73.748 | 90.965 | 63.734 | 82.72 |
| 68 | 57.249 | 44.384 | 67.493 | 62.116 | 63.006 | 61.943 | 58.562 | 70.013 | 61.753 | 68.579 | 52.564 | 69.679 |
| 69 | 58.034 | 45.161 | 69.785 | 64.197 | 64.243 | 63.326 | 59.182 | 71.11 | 62.271 | 70.851 | 54.714 | 71.17 |
| 19 | 27.135 | 28.975 | 25.709 | 35.587 | 25.422 | 25.73 | 26.669 | 27.381 | 33.412 | 24.222 | 29.185 | 39.292 |
| No of | | | | | | | | | | | | |
| hidden | 1 | 5 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
| neurons | | | | | | | | | | | | |
| RMSE | 8.192 | 14.828 | 6.367 | 8.675 | 8.088 | 6.591 | 7.559 | 7.736 | 8.133 | 8.952 | 11.785 | 12.413 |
| MAE | 7.472 | 12.225 | 5.147 | 7.324 | 6.699 | 5.656 | 6.914 | 6.357 | 6.790 | 6.132 | 11.185 | 10.425 |
| MAPE | 17.518 | 25.067 | 13.160 | 18.501 | 18.819 | 15.532 | 17.576 | 17.147 | 21.120 | 10.407 | 25.540 | 27.862 |

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| Table | Table 7-4: Selected models for Model V using Matlab (nntool) | | | | | | | | | | | |
|------------|--|-----------|----------|--------------------|--|--|--|--|--|--|--|--|
| Model No | RMSE | MAE | MAPE (%) | Training Algorithm | | | | | | | | |
| Model V-2 | 1.292 | Levenberg | | | | | | | | | | |
| Model V-14 | 0.304 | 0.248 | 0.586 | Bayesian | | | | | | | | |
| Model V-27 | 6.367 | 5.147 | 13.160 | Scaled | | | | | | | | |

7.3 Developing Model V Using MATLAB nftool

A total of thirty-nine ANN models are trained, validated and tested for model V using MATLAB nftool. The performance of the test samples for multilayer (2 layers) feed-forward network with different number of hidden neurons, tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer for predicting variation payment delay is compared as shown in Tables (7-5), (7-6), and (7-7). The training algorithms used are Levenberg-Marquardt algorithm, Bayesian Regulation and Scaled Conjugate Gradient. By comparing the computed results for each of the selected models using MATLAB (nftool), Model V-60 structure with 80 neurons in the hidden layer, based on Bayesian Regulation algorithm and tan-sigmoid function has been chosen as it has the lowest error values for variation payment prediction with RMSE of 0.066, MAE of 0.018 and MAPE value of 0.058% as shown in Table (7-8). The best performance for the training sample of this model is at 378 epochs with MSE of 1.287×10^{-11} , and R value of 1 which is reflecting a perfect of results and very high predictive power of the network as shown in Figure (9-8). The performance of the training and validation samples for the thirty-nine trial models are not involved in the evaluation of models to eliminate the risk of misevaluation, because during the training and learning some models may accomplish good results with the training and validation data set, but very poor with new data, which is the test set. Therefore, the evaluation of the models' performance is done by comparing their predicted output over an independent test sample as mentioned in Section 5.3.

Table 7-5: Performance of test sample Model V using (nftool and Levenberg-Marquardt)

| Predicted | | | | | | | Model no | | | | | | |
|----------------------------|--------|--------|--------|--------|--------|--------|----------|--------|--------|--------|--------|--------|--------|
| output | V-37 | V-38 | V-39 | V-40 | V-41 | V-42 | V-43 | V-44 | V-45 | V-46 | V-47 | V-48 | V-49 |
| 83.00 | 83.39 | 82.28 | 83.34 | 83.27 | 83.00 | 83.00 | 91.23 | 83.08 | 83.00 | 85.93 | 83.00 | 83.01 | 83.00 |
| 70.00 | 70.01 | 69.52 | 69.50 | 68.35 | 70.00 | 70.00 | 85.72 | 60.98 | 72.83 | 67.50 | 70.00 | 70.01 | 77.79 |
| 30.00 | 29.31 | 30.97 | 29.61 | 30.59 | 31.96 | 24.54 | 28.73 | 30.06 | 29.40 | 15.76 | 30.00 | 28.07 | 29.99 |
| 25.00 | 24.50 | 26.67 | 24.89 | 25.61 | 26.97 | 20.16 | 24.96 | 25.06 | 25.00 | 10.77 | 25.00 | 25.02 | 24.99 |
| 21.00 | 21.01 | 23.22 | 25.11 | 21.15 | 21.00 | 21.00 | 20.83 | 21.07 | 21.00 | 17.84 | 21.00 | 21.02 | 21.00 |
| 32.00 | 32.02 | 32.21 | 35.72 | 29.56 | 27.00 | 32.00 | 31.83 | 32.09 | 32.00 | 59.09 | 10.37 | 32.01 | 32.00 |
| 142.00 | 141.97 | 144.72 | 142.35 | 142.31 | 142.60 | 167.31 | 141.86 | 207.65 | 142.00 | 190.96 | 142.00 | 142.01 | 142.00 |
| 63.00 | 63.03 | 62.86 | 62.15 | 63.47 | 67.18 | 63.00 | 59.96 | 75.87 | 63.00 | 60.66 | 63.00 | 63.02 | 62.99 |
| 83.00 | 83.02 | 83.15 | 82.63 | 84.67 | 83.00 | 83.00 | 76.00 | 100.02 | 83.00 | 81.02 | 83.00 | 83.01 | 83.00 |
| 36.00 | 36.00 | 36.49 | 36.07 | 36.48 | 36.00 | 40.67 | 35.99 | 50.51 | 36.00 | 33.58 | 35.45 | 36.02 | 22.81 |
| 83.00 | 83.64 | 82.88 | 85.39 | 83.23 | 84.40 | 83.00 | 82.78 | 83.04 | 137.97 | 81.29 | 83.00 | 83.04 | 83.00 |
| 68.00 | 67.80 | 68.20 | 68.49 | 66.64 | 68.00 | 68.00 | 67.79 | 68.03 | 108.63 | 66.32 | 68.13 | 68.04 | 68.00 |
| 69.00 | 69.02 | 69.21 | 69.62 | 67.43 | 68.96 | 69.21 | 68.79 | 68.43 | 110.95 | 67.29 | 69.00 | 65.73 | 69.33 |
| 19.00 | 19.01 | 19.61 | 18.85 | 19.34 | 19.00 | 19.00 | 18.86 | 22.92 | 19.00 | 17.50 | 19.00 | 19.04 | 19.00 |
| No of hidden neurons | 1.00 | 5.00 | 10.00 | 15.00 | 20.00 | 30.00 | 40.00 | 50.00 | 60.00 | 70.00 | 80.00 | 90.00 | 100.00 |
| RMSE | 0.31 | 1.12 | 1.66 | 1.11 | 1.94 | 7.15 | 5.18 | 19.04 | 21.45 | 16.01 | 5.78 | 1.02 | 4.10 |
| MAE | 0.18 | 0.78 | 1.03 | 0.87 | 1.08 | 2.89 | 2.61 | 8.86 | 10.07 | 9.03 | 1.59 | 0.39 | 1.53 |
| MAPE | 0.44 | 2.16 | 2.97 | 1.86 | 2.78 | 4.91 | 3.80 | 11.65 | 13.77 | 19.53 | 4.95 | 0.84 | 3.46 |

 Table 7-6: Performance of test sample Model V using (nftool and Bayesian Algorithm)

| Predicted | | | | | | | Model No. | | | | | | |
|-------------------|--------|--------|--------|--------|--------|--------|-----------|--------|--------|--------|--------|--------|--------|
| output | V-50 | V-51 | V-52 | V-53 | V-54 | V-55 | V-56 | V-57 | V-58 | V-59 | V-60 | V-61 | V-62 |
| 83.00 | 81.18 | 82.56 | 83.00 | 83.00 | 83.00 | 83.00 | 83.73 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 |
| 70.00 | 68.16 | 70.03 | 70.00 | 70.00 | 70.00 | 70.00 | 70.00 | 70.00 | 69.58 | 73.27 | 70.00 | 67.32 | 70.00 |
| 30.00 | 31.33 | 30.22 | 30.00 | 30.00 | 30.00 | 30.00 | 30.00 | 30.00 | 30.00 | 30.00 | 29.76 | 30.00 | 30.00 |
| 25.00 | 26.82 | 25.47 | 25.02 | 25.00 | 25.00 | 25.75 | 25.00 | 25.00 | 25.00 | 25.00 | 25.00 | 25.00 | 25.00 |
| 21.00 | 21.85 | 20.63 | 21.00 | 21.00 | 21.00 | 21.00 | 21.00 | 21.00 | 5.52 | 35.37 | 21.00 | 21.00 | 21.00 |
| 32.00 | 32.36 | 32.20 | 32.00 | 32.00 | 32.00 | 32.00 | 32.00 | 32.00 | 48.39 | 32.00 | 32.00 | 32.00 | 32.00 |
| 142.00 | 143.38 | 142.35 | 144.98 | 146.38 | 142.00 | 142.00 | 142.00 | 140.90 | 146.88 | 129.74 | 142.00 | 142.00 | 142.00 |
| 63.00 | 62.71 | 62.73 | 63.00 | 63.00 | 63.00 | 63.00 | 63.00 | 63.00 | 63.00 | 63.00 | 63.00 | 63.00 | 61.72 |
| 83.00 | 82.44 | 82.83 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 |
| 36.00 | 36.76 | 35.83 | 36.00 | 36.00 | 36.00 | 36.00 | 36.00 | 36.00 | 36.00 | 40.10 | 36.00 | 36.00 | 36.00 |
| 83.00 | 81.77 | 83.57 | 84.78 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 | 83.00 |
| 68.00 | 66.68 | 67.93 | 68.00 | 68.00 | 68.00 | 68.00 | 68.00 | 68.00 | 68.00 | 68.00 | 68.00 | 68.00 | 68.00 |
| 69.00 | 67.68 | 69.03 | 69.40 | 69.00 | 69.00 | 69.00 | 69.00 | 69.00 | 69.00 | 69.00 | 69.00 | 69.00 | 69.00 |
| 19.00 | 20.51 | 18.96 | 19.00 | 18.08 | 19.00 | 19.00 | 19.00 | 17.47 | 19.00 | 19.00 | 19.00 | 19.00 | 19.00 |
| hidden neurons | 1.00 | 5.00 | 10.00 | 15.00 | 20.00 | 30.00 | 40.00 | 50.00 | 60.00 | 70.00 | 80.00 | 90.00 | 100.00 |
| RMSE | 1.28 | 0.30 | 0.93 | 1.20 | 0.16 | 0.20 | 0.19 | 0.50 | 6.17 | 5.24 | 0.07 | 0.72 | 0.34 |
| MAE | 1.17 | 0.24 | 0.37 | 0.38 | 0.14 | 0.05 | 0.05 | 0.19 | 2.66 | 2.43 | 0.02 | 0.19 | 0.09 |
| MAPE | 2.80 | 0.57 | 0.35 | 0.57 | 0.30 | 0.21 | 0.06 | 0.63 | 9.21 | 6.65 | 0.06 | 0.27 | 0.15 |

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| Due d'ate d'autout | | Model No. | | | | | | | | | | | |
|-------------------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|
| Predicted output | V-63 | V-64 | V-65 | V-66 | V-67 | V-68 | V-69 | V-70 | V-71 | V-72 | V-73 | V-74 | V-75 |
| 83.00 | 82.28 | 84.04 | 62.05 | 79.35 | 78.37 | 81.95 | 82.57 | 64.16 | 91.30 | 69.95 | 79.19 | 119.6 0 | 85.31 |
| 70.00 | 69.52 | 73.08 | 51.16 | 69.83 | 63.89 | 69.52 | 67.71 | 54.01 | 93.72 | 52.95 | 70.09 | 94.75 | 68.84 |
| 30.00 | 30.97 | 33.67 | 35.35 | 31.02 | 32.79 | 26.96 | 28.03 | 26.29 | 30.58 | 25.03 | 23.86 | 22.03 | 31.08 |
| 25.00 | 26.67 | 29.48 | 30.55 | 26.66 | 27.86 | 22.54 | 23.83 | 24.20 | 30.22 | 20.05 | 19.63 | 16.82 | 27.47 |
| 21.00 | 23.22 | 15.50 | 32.80 | 20.65 | 18.23 | 21.12 | 21.36 | 21.23 | 22.04 | 94.47 | 23.82 | 1.87 | 20.01 |
| 32.00 | 32.21 | 29.56 | 29.44 | 40.82 | 36.24 | 59.58 | 72.42 | 29.30 | 41.79 | 21.78 | 19.78 | 42.33 | 33.26 |
| 142.00 | 144.7 2 | 118.0 7 | 132.3 8 | 141.5 0 | 151.6 9 | 148.0 1 | 142.7 6 | 141.7 6 | 143.7 3 | 144.8 5 | 138.6 9 | 135.6 3 | 143.9 3 |
| 63.00 | 62.86 | 63.54 | 71.40 | 60.84 | 64.34 | 54.89 | 60.47 | 63.30 | 53.64 | 46.10 | 69.26 | 59.89 | 63.54 |
| 83.00 | 83.15 | 80.78 | 88.03 | 80.49 | 84.50 | 77.76 | 82.50 | 72.01 | 59.56 | 86.81 | 89.40 | 82.35 | 91.00 |
| 36.00 | 36.49 | 37.89 | 45.27 | 35.70 | 36.43 | 36.79 | 37.26 | 52.57 | 39.24 | 39.89 | 39.40 | 43.77 | 29.55 |
| 83.00 | 82.88 | 84.72 | 80.68 | 79.52 | 79.80 | 83.46 | 82.87 | 88.07 | 83.94 | 68.40 | 79.15 | 82.21 | 81.43 |
| 68.00 | 68.20 | 70.67 | 68.02 | 65.73 | 69.67 | 71.18 | 67.21 | 65.64 | 71.26 | 52.22 | 75.51 | 69.80 | 68.65 |
| 69.00 | 69.21 | 71.81 | 69.11 | 66.01 | 70.31 | 72.65 | 68.65 | 65.94 | 68.09 | 53.16 | 66.06 | 69.98 | 72.75 |
| 19.00 | 19.61 | 18.86 | 18.45 | 22.00 | 41.55 | 33.86 | 18.62 | -3.37 | 17.90 | 3.95 | 79.33 | 26.86 | 19.35 |
| No of hidden neurons | 1.00 | 5.00 | 10.00 | 15.00 | 20.00 | 30.00 | 40.00 | 50.00 | 60.00 | 70.00 | 80.00 | 90.00 | 100.0 0 |
| RMSE | 1.12 | 6.97 | 9.56 | 3.18 | 7.18 | 9.07 | 10.87 | 10.59 | 10.07 | 22.80 | 17.03 | 13.97 | 3.20 |
| MAE | 0.78 | 4.01 | 7.17 | 2.35 | 4.65 | 5.50 | 3.81 | 7.37 | 6.62 | 15.17 | 8.89 | 9.74 | 2.32 |
| MAPE | 2.16 | 7.58 | 15.30 | 5.66 | 14.31 | 15.93 | 11.11 | 18.73 | 12.04 | 46.10 | 33.23 | 24.31 | 4.75 |

Table 7-7: Performance of test sample Model V using (nftool and Scaled Conjugate Gradient Algorith

| Table 7-8: Second | elected models | s for Model V | using Matlab | (nftool) |
|--------------------------|----------------|---------------|--------------|----------|
|--------------------------|----------------|---------------|--------------|----------|

| Model No | RMSE | MAE | MAPE (%) | Training Algorithm |
|------------|-------|-------|----------|-----------------------|
| Model V-37 | 0.309 | 0.183 | 0.437 | Levenberg |
| Model V-60 | 0.018 | 0.066 | 0.058 | Bayesian |
| Model V-63 | 0.778 | 1.120 | 2.163 | Scaled |

7.4 Developing of Model V Using Regression Excel Tool

Linear regression analysis is used to predict the output of dependent variable (variation payment delay) on the basis of the independent variables, which are: Claim review (X1), Payment processed by employer (X2), Variations orders evaluation and approval (X3), Payment amount (X4), Balance of contingency in the contract (X5), Available contingency in the contract (X6), Extension of time occurrence (X7), Contractor experience (X8), Consultant experience (X9), and Work progress (X10). All the values of independent and dependent variables are known from historical data as explained previously in Section (4.2). Linear regression analysis is used to predict the output of dependent variable (Variation payments) on the basis of the independent variables mentioned above. The linear regression equation output is as presented in Equation (7-1):

Y = -68.825 + 0.92*X1 + 0.952*X2 + 0.984* X3 + 0*X4 + 0*X5 + 0*X6 - 1.193*X7 + 0.137*X8 + 0.095*X9 - 0.02*X10 (7-1)

The goodness of fit for the Regression Model is shown in Table (7-9) based on 95% confidence interval. The Multiple R value represents the correlation coefficient of determination with a value of 0.999 showing a strong linear relationship between the predicted output and targets. The calculated R-squared value of 99.8% is representing the goodness of fit for the above equation. This means that 99.8% of the variance in the dependent variable (variation payment delay) is explained by the model indicating a high predictive power for the model. The adjusted R squared is equal to 99.7% and it represents R squared value in term of the number of variables in the model. As shown both values are very close to each other. The computed standard error is equal to 2.963%, this tells that the average distance for the predicted points falls about 2.963% from the regression line, this result shows very good prediction power of the model. The obtained P-value of 1.656×10^{-101} (considered extremely significant) and reflecting the probability for obtaining an R squared value of 99.8%.

Table (7-10) shows the variables codes, coefficients, the standard error along with the lower and upper bounds of the confidence interval of each variable. The table shows that five out of eleven variables (54.5%) have positive biased coefficients, three out of eleven (27%) have negative biased coefficients, and three have zero values. As shown in the table for a 95% confidence prediction interval, about 95% of the observations should fall within coefficient \pm 2*standard error from the regression line, these ranges of confidence intervals are expected to comprise the right value of the coefficient for each variable of the regression model. Table (7-11) shows the P-values of the regression model which examine the effect of each independent variable on the dependent variable and its significance to the model. The results show that four variables are considered significant including the constant which are: Claim review, Payment by owner, and Variations orders evaluation and approval. These variables show very low p-values (less than 0.05) indicating a high significance. On the other hand, seven variables are considered as not significant showing high p-values (more than 0.05), one of these seven is extension of time, and it was input as binary (0, 1)

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variable and it is included in the regression equation with low coefficient amount. The most three non-significant variables are real variables entered in the model as payment amounts in Bahraini dinar which are: Payment amount, Balance of contingency in the contract, and Allocated contingency in the contract, these factors will not be included in the model because their coefficients are equal to zero. The other three non-significant factors are work progress, Contractor experience, and Consultant experience; these factors are included in the model with very low values of their coefficients. This may be due to their indirect relationship to payment delay.

| Table 7-9: Goodness of Fit for Model V-76 | | | | | | | |
|---|-----------------------------|--|--|--|--|--|--|
| Regression Statistics | Goodness of Fit ≥ 0.80 | | | | | | |
| Multiple R | 0.999 | | | | | | |
| R Square | 0.998 | | | | | | |
| Adjusted R Square | 0.997 | | | | | | |
| Standard Error | 2.963 | | | | | | |
| P-value | 1.656E-101 | | | | | | |
| Observations | 91 | | | | | | |

| Code | Variables | Coefficient | Standard Error | Lower 95% | Upper 95% |
|------|---|-------------|-------------------|--------------|--------------|
| С | Constant | -68.825 | 7.249 | -83.250 | -54.400 |
| X1 | Claim review(days) | 0.920 | 0.044 | 0.833 | 1.007 |
| X2 | Payment process by owner (days) | 0.952 | 0.021 | 0.909 | 0.994 |
| X3 | Variation orders evaluation and approval (days) | 0.984 | 0.006 | 0.972 | 0.996 |
| X4 | Payment amount (BD) | 0.000 | 0.000 | 0.000 | 0.000 |
| X5 | Balance of contingency in the contract (BD) | 0.000 | 0.000 | 0.000 | 0.000 |
| X6 | Allocated contingency in the contract (BD) | 0.000 | 0.000 | 0.000 | 0.000 |
| X7 | Extension of time (binary) | -1.193 | 1.610 | -4.397 | 2.011 |
| X8 | Contractor experience (years) | 0.137 | 0.205 | -0.271 | 0.544 |
| X9 | Consultant experience (years) | 0.095 | 0.377 | -0.655 | 0.845 |
| X10 | Work Progress (delay in days) | -0.020 | 0.017 | -0.055 | 0.014 |

Table 7-10: Regression coefficients for Model V-76

Table 7-11: Significant and non-significant variables Model V-76

| Code | Variables | | P-value | Significance |
|------|---|--------|------------|-----------------|
| С | Constant | -9.495 | 9.378E-15 | Significant |
| X1 | Claim review(days) | 21.073 | 2.147E-34 | Significant |
| X2 | Payment process by owner (days) | 44.931 | 1.593E-58 | Significant |
| X3 | Variation orders evaluation and approval (days) | | 4.527E-103 | Significant |
| X4 | Payment amount | -0.241 | 0.810 | Not Significant |
| X5 | Balance of contingency in the contract | 0.823 | 0.413 | Not Significant |
| X6 | Allocated contingency in the contract | 0.481 | 0.632 | Not Significant |
| X7 | Extension of time | -0.741 | 0.461 | Not Significant |
| X8 | Contractor experience (years) | 0.669 | 0.506 | Not Significant |
| X9 | Consultant experience (years) | 0.252 | 0.802 | Not Significant |
| X10 | Work progress (delay in days) | -1.177 | 0.243 | Not Significant |

Accordingly, the model is modified by eliminating the non-significant factors and including only the significant independent factors as per the model result which are: Claim review (days), Payment process by owner (days) and Variation orders evaluation and approval (days), as presented in Equation (7-2).

Y = -63.647 + 0.924 * X1 + 0.940 * X2 + 0.982 * X3

(7-2)

The goodness of fit for the Regression Model for equation (7-2) is shown in Table (7-12) based on 95% confidence intervals. The Multiple R value is equal to 0.999 showing a very good linear relationship between the predicted output and targets. The calculated R-squared value is equal to 99.8% which is indicating a great predictive power of the model. The adjusted R squared is equal to 0.998. The computed standard error is equal to 2.923%, this result asses a high precision of the prediction by the model. The obtained P-value of 5.9×10^{-114} (considered extremely significant) and reflecting the probability for obtaining an R squared value of 99.8%. Table (7-13) shows the variables codes, coefficients, the standard error along with the lower and upper bounds of the confidence interval of each variable. The table shows that three out of four variables (75%) have a positive biased coefficients, and one out of four (25%) have negative biased coefficient value ± 2 *Standard error from the regression line, these ranges of confidence intervals are expected to comprise the right value of the coefficient for each variable of the regression model.

Table 7-12: Goodness of Fit for Model V-76Using Equation (9-2)

| Regression Statistics | | | | | |
|-----------------------|----------|--|--|--|--|
| Multiple R | 0.999 | | | | |
| R Square | 0.998 | | | | |
| Adjusted R Square | 0.998 | | | | |
| Standard Error | 2.923 | | | | |
| P-value | 5.9E-114 | | | | |
| Observations | 91 | | | | |

| Cable | 7-13:] | Regression | Coefficients | for Model | V-76Using | Equation (| 9-2) |
|--------------|----------------|------------|--------------|-----------|-----------|------------|------|
| | | 0 | | | 0 | 1 \ | |

| Code | Variables | Coefficient | Standard Error | Lower 95% | Upper 95% |
|------|---|-------------|----------------|-----------|-----------|
| С | Constant | -63.647 | 1.276 | -66.182 | -61.111 |
| X1 | Claim review(days) | 0.924 | 0.033 | 0.858 | 0.989 |
| X2 | Payment process by owner (days) | 0.940 | 0.018 | 0.904 | 0.977 |
| X3 | Variation orders evaluation and approval (days) | 0.982 | 0.005 | 0.972 | 0.993 |

The test sample cases (14 cases) are used to validate the regression models of Equation (7-1) and Equation (7-2). The test sample along with the estimated output and the performance errors are shown in Table (7-14) and (7-15) for Equation (7-1) and (7-2), respectively. As shown in Table (7-14), the performance error values for Equation (7-1) are for RMSE of 0.918, MAE of 0.842, and MAPE of 1.943. While Table (7-15) shows the performance error values for Equation (7-2) as follows: RMSE of 1.110, MAE of 0.958 and MAPE of 2.806%. It is noticed that there is a remarkable matching between the two curves for Equation (7-1), which is reflecting very good performance for the regression equation. On the other hand, Equation (7-2) results are showing relatively less matching. Therefore, it is recommended to choose Equation (7-1) for the regression model (Model V-76). Thus, Equation (7-1) is modified by excluding the variables with zero coefficient, it becomes:

Y = -68.825 + 0.92*X1 + 0.952*X2 + 0.984*X3 - 1.193*X7 + 0.137*X8 + 0.095*X9 - 0.02*X10(7-3)

Table 7-14: Test Sample of The Regression Model (Model V-76) Using Equation (7-1)

| Case No. | Target output (days) | Predicted output (days) | Square Error | Absolute error | Percentage error% |
|-------------|-------------------------|-------------------------|--------------|----------------|-------------------|
| 1 | 83 | 81.447 | 2.412 | 1.553 | 0.019 |
| 2 | 70 | 68.660 | 1.796 | 1.340 | 0.019 |
| 3 | 30 | 31.002 | 1.004 | 1.002 | 0.033 |
| 4 | 25 | 26.088 | 1.184 | 1.088 | 0.044 |
| 5 | 21 | 21.937 | 0.878 | 0.937 | 0.045 |
| 6 | 32 | 32.878 | 0.771 | 0.878 | 0.027 |
| 7 | 142 | 141.167 | 0.694 | 0.833 | 0.006 |
| 8 | 63 | 63.755 | 0.570 | 0.755 | 0.012 |
| 9 | 83 | 83.331 | 0.110 | 0.331 | 0.004 |
| 10 | 36 | 37.099 | 1.207 | 1.099 | 0.031 |
| 11 | 83 | 82.255 | 0.555 | 0.745 | 0.009 |
| 12 | 68 | 67.465 | 0.286 | 0.535 | 0.008 |
| 13 | 69 | 68.453 | 0.299 | 0.547 | 0.008 |
| 14 | 19 | 19.152 | 0.023 | 0.152 | 0.008 |
| Performance | | | RMSE | MAE | MAPE (%) |
| | | | 0.918 | 0.842 | 1.943 |

 Table 7-15: Test Sample of the Regression Model (Model V-76) Using Equation (7-2)

| Case | Target output | | Ì | Absolute | Percentage |
|------|---------------|-------------------------|--------------|----------|------------|
| No. | (days) | Predicted output (days) | Square Error | Error | Error (%) |
| 1 | 83 | 82.007 | 0.986 | 0.993 | 1.196 |
| 2 | 70 | 69.241 | 0.576 | 0.759 | 1.084 |
| 3 | 30 | 31.327 | 1.761 | 1.327 | 4.423 |
| 4 | 25 | 26.417 | 2.008 | 1.417 | 5.668 |
| 5 | 21 | 23.081 | 4.331 | 2.081 | 9.910 |
| 6 | 32 | 33.697 | 2.880 | 1.697 | 5.303 |
| 7 | 142 | 141.605 | 0.156 | 0.395 | 0.278 |
| 8 | 63 | 64.027 | 1.055 | 1.027 | 1.630 |
| 9 | 83 | 83.667 | 0.445 | 0.667 | 0.804 |
| 10 | 36 | 37.513 | 2.289 | 1.513 | 4.203 |
| 11 | 83 | 82.547 | 0.205 | 0.453 | 0.546 |
| 12 | 68 | 67.817 | 0.033 | 0.183 | 0.269 |
| 13 | 69 | 68.799 | 0.040 | 0.201 | 0.291 |
| 14 | 19 | 19.699 | 0.489 | 0.699 | 3.679 |
| D. (| | | RMSE | MAE | MAPE (%) |
| | Performance | | | 0.958 | 2.806 |

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7.5 Comparison and Discussion of Model V Results

Table (7-16) show the comparison between the selected models developed for variation payment delay using MATLAB (nntool), MATLAB (nftool) and Excel Regression analysis tool. As per the computed results the best performance model is the neural network Model V-60 using MATLAB nftool with 80 neurons in hidden layer as shown in Figure (7-1) based onBayesian Regulation algorithm and tan-sigmoid function. The best performance for the training sample of this model is at 145 epochs with MSE of 1.50×10^{-5} as shown in Figure (7-2), and R value of 0.999 as shown in Figure (7-3).Model V-60 is having an error values for RMSE of 0.066, MAE of 0.018 and MAPE of 0.058%. In the second place comes the neural network Model V-14 with 5 neurons based onBayesian Regulation algorithm and tan-sigmoid function. Model V-14 has a minimum value for RMSE of 0.304, MAE of 0.248 and MAPE of 0.586%. Finally, in the third place the regression model (Model V-76) with RMSE value of 0.918, MAE value of 0.842 and MAPE value of 1.943%. The ANN using MATLAB nftool shows relatively better results than Matlab nntool and regression model.

| Table 7-10. Comparison of the belieted winders for (winder v) | | | | | | | |
|---|-------|-------|-------|-------|------------------|---------------|--|
| Model No | RMSE | MAE | MAPE% | R | Туре | Tool | |
| Model V-14 | 0.304 | 0.248 | 0.586 | 0.999 | Neural Network | MATLAB nntool | |
| Model V-60 | 0.066 | 0.018 | 0.058 | 1 | Neural Network | MATLAB nftool | |
| Model V-76 | 0.918 | 0.842 | 1.943 | 0.998 | Regression Model | ExcelATP | |

Table 7-16: Comparison Of the Selected Models for (Model V)



Figure 7-1: ANN Diagram for Model V-60







Figure 7-3: R square value for Model V-60

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8. Conclusions and Recommendations

8.1 Conclusions

Two models are developed in this study for the prediction of interim payment delay (Model I) and prediction of variation payment delay (Model V). Models development is achieved through several steps starting by choosing the type of model, dividing the data set, choosing the software used to build the model, entering the dependent and independent variables, choosing the different parameters for each type of model and finally training and testing the models to choose the best model. Model I and Model V are developed using eleven and ten independent variables, for seventy and seventy-six trial models, respectively, using different parameters, programs and Modeling techniques including artificial neural models and regression models. For Model I for interim payment delay (days), the best performance model is a neural network Model I-48 developed using MATLAB nftool. This model is having 10 neurons in the hidden layer, and it is based onBayesian Regulation algorithm, and tan-sigmoid function. It has the minimum error results of RMSE of 1.520, MAE of 0.969 and MAPE of 3.767%. In the second place the regression model Model I-70 with RMSE of 3.928, MAE of 3.655 and MAPE of 11.944%. While for Model V for variation payment delay, the best performance model is neural network Model V-60 developed using MATLAB nfool. This model is having 80 neurons in the hidden layer and it is based onBayesian Regulation algorithm, and tan-sigmoid function. It has performance model is neural network Model V-60 developed using MATLAB nfool. This model is having 80 neurons in the hidden layer and it is based onBayesian Regulation algorithm, and tan-sigmoid function. It has performance of 0.066, MAE value of 0.018 and MAPE value of 0.058%. In the second place the regression model Model V-76 with RMSE value of 0.842, MAE value of 0.918 and MAPE value of 1.943%.

Finally, as the results show by comparing the Neural Networks and linear regression approach, it is shown that the estimation accuracy of Neural Networks approach gives relatively better results than linear regression analysis for payment delay (days) for governmental building construction projects.

8.2 Recommendations

This study has shown the important role each of the contract parties has on the occurrence of payment delay, some practices can increase the risk of payment delay while others can help in eliminating the risk, in this section some recommendations are presented to help contract parties in overcoming this issue:

- 1-MoW is recommended to use the developed models in this study to enhance the current payment process by predicting the payment delay risk in days and trying to avoid it by taking proper measures during the planning stage of projects.
- 2-It is recommended for MoW to use an electronic approval system to speed up the approval process and enhance communication. This can be implemented using an electronic signature to avoid the normal and slow cycle of hard documents approval.
- 3-Consultant is recommended to monitor the payments of the main contractor to the subcontractors and suppliers to avoid any payment delay to these parties in the project.
- 4-Contractor is recommended to use the models presented in this study in order to predict the delay in payment and to know when to make early claim of payments along with full required documents to avoid delay. Moreover, knowing the amount of delay risk for the contractor can help him to arrange the enough cash needed prior beginning of the project to avoid financial problems.
- 5-Contractor is recommended to use the model to have a good view about the expected payment delays in project, and to plan a cash flow programme that is applicable during construction stage.

8.3 Limitation of the Study:

The major limitation of this study is lack of data which is manifested in inadequate cases in payment delay. The study is also limited to one directorate of MoW, which is concerned with the building construction section; other directorates concerned with road and sanitary section are not covered. Another limitation is the scope of contractors being covered by the questionnaire by including only contractors of class A and B, and excluding other classes.

8.4 Future Recommended Studies

- 1-To Study the payment delay disputes of construction projects in Bahrain courts, and the remedies actions (verdicts) taken for those whose payments were delayed in each law case. A Model can be created thereafter to predict the remedies by ranking the factors taken from all these cases to create a clear picture for the payment delay compensation, and the most type of payment that is facing delay or nonpayment.
- 2-To develop payment delay models for governmental construction projects with more data and by including other types of payments such as advanced and final payment.

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