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Support Vector Machine to Measure the Risk of Payment Delay on Construction Projects in Gaza Strip

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Abstract

Payment delay to contractors is a common cause of disputes in Gaza Strip construction industry. The aim of this paper is to formulate a model to measure the risk of payment delay in terms of cost overrun. Factors that contribute to the risk of payment delay were identified. 140 questionnaires were distributed to contractors. 113 (80.71%) questionnaires were received. Nine factors were identified to be the most important factors that are contributing to the risk of payment delay. A model to measure the risk of payment delay was formulated. Support Vector Machine (SVM) was used to develop the model. A hypothetical case study and structured interview with (31) contractors was used to build up the model. The nine factors that contribute to the risk of payment delay were used as input data and the total overrun cost due to payment delay was used as an output. The proposed model was able to predict the cost overrun due to payment delay with accuracy performance of 93.47%. The model can help to give early warning of cost overrun due to payment delay.

Keywords Payment Delay, Modeling, Support Vector Machine, Gaza Strip.

استخدام SVM لقياس خطر تأخير الدفعات على مشاريع التشييد في قطاع غزة

ملخص

يعتبر تأخير الدفعات للمقاولين من الاسباب الشائعة للنزاعات في صناعة البناء والتشييد في قطاع غزة. ان الهدف من هذه الدراسة هو صياغة نموذج لقياس مخاطر تأخير الدفعات من حيث زيادة التكلفة. لقد تم تحديد العوامل التي تساهم في مخاطر تأخير الدفعات. تمت الدراسة عن طريق توزيع 140 استبيان على المقاولين. وكان عدد من استجابوا للاستبيان هو 113 مقاول بنسبة (80.71 ٪). لقد تم تحديد تسعة عوامل لتكون من أهم العوامل التي تسهم في مخاطر تأخير الدفعات. لقد تم صياغة نموذج لقياس مخاطر تأخير الدفع. لقد تم استخدام طريقة SVM لتطوير هذا النموذج. تم استخدام دراسة حالة افتراضية و عمل مقابلات مع 31 مقاول لبناء النموذج. تم استخدام العوامل التسعة التي تساهم في خطر تأخير الدفع كبيانات مدخلة ، واستخدم التكاليف الاضافية بسبب تأخير الدفعات كمخرجات . كان النموذج المقترح قادرة على التنبؤ بمقدار التكلفة الاضافية وذلك بسبب تأخير الدفع بدقة تصل الى93.47 ٪ . يمكن للنموذج ان يساعد على إعطاء إنذار مبكر في حال زيادة التكاليف بسبب تأخير الدفعات.

كلمات مفتاحية: تأخير الدفعات، نمذجة، SVM، قطاع غزة.

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1. Introduction:

Risks and effects of payment delay in Gaza Strip are important topics that plague stakeholders in construction projects. Payment delay causes bad effects in the successful implementation of construction projects. Payment delay is defined as failure of a paymaster to pay within the period of honoring of certificates as provided in the contract [1]. The parties involved in the process of payment claim such as client, contractor, superintending officer, architect, quantity surveyor, banker and other construction players may cause a payment to be delayed. Construction delay can be observed by several indication factors. One significant factor is owners' performance in making payment to contractors. The extra time required for payments is clear evidence that company is in financial difficulties [2].
This paper aims to improve the contractor ability to overcome the bad impact of payment delay. The impacts and risk of payment delay were checked. A model to measure the risk of payment delay was developed.

2. The risk of payment delay:

According to Abu Shaban [3], most consultants and contractors stated that the projects suffered by the payment delay problems. In the Gaza Strip, payment delay leads to effect contractors' performance and cause time performance problem. This may also lead to disputes between owner and contractor. According to Chen et al. [4] regular disbursement of interim payment is a critical point for a contractor to keep them alive. Whether it is payment delay or not being paid in the amounts certified, it all literally means big problems to the contractors as cash flow will be effected.

Khosrowshahi [5] identified other risk factors that impact on cash flow to include payment delay and difficulty in obtaining the right amount of funds at reasonable interest rates. The other reason for withholding payment is that the owner being of poor means for the time being and defaults in making payment. Contractor in this case becomes suitable for the claims of interest charges on the payment delay [6].

The payment delay from owners will affect the cash flow of the contractor and retain age with held by the owner will also create cash flow problem to the payment delay problem is interrelated with the cash flow problem. Payment delay creates negative social impacts, leads to abandonment of projects, results in formal dispute resolution (litigation/ arbitration), and leads to bankruptcy or liquidation [7].

The speed of work depends largely to the efficiency and availability of workers. Most of contractors are using sub-contractors to do the construction work and when the payment delay to the sub-contractors, the sub-contractors have limited resource to work with and subsequently reduce the number of workers or stop work until they get payment from the contractors [8].

2.1 Causes of payment delay:

Oppong [9] stated that payment delay to contractors is the main cause for construction delay. Most of the contractors found it very difficult to bear the construction expenses when the payments are delayed [10]. The owner has related a group of delay factors; it is mainly due to financing issues and owner interference [11].

Ayudhya [2] had classified four main categories, which were administration, financial, technical, and inspection and other common and identified twenty-four causes of payment delay. The top five causes of delay in payment were owner financial problems, delay in work approval, major accidents, inaccurate bill of quantities and substandard workmanship. The causes of payment delay according to Abdul-Rahman et al. [12] are: the client's poor financial and business management, withhold of payment by client, contractor's invalid claim, delay in valuation and certification of interim payment by consultant, inaccuracy of valuation for work done, insufficient documentation and information for valuation, involvement of too many parties in the process of honoring certificates, heavy work load of consultant to do evaluation for work done, contractor's misinterpretation of client's requirement of variation order.

2.2 Remedies for payment delay:

One possible remedy to the payment delay problem by the employer in not paying in time is to allow for the contractor to claim for interest [13]. Contractors indicated that payment bonds, direct payments and the use of trust accounts were preferred solutions to the payment problems experienced by industry [14]. The right of suspension is an important remedy. The contractor has the right to stop work until the payment is made[15].

2.3 Payment delay in Gaza Strip construction industry:

Making progress payments to contractors on time is critical. Expediting the reviewing and approving of design documents, shop drawings, and payments to contractor can reduce any delay or cost overruns at the projects in Gaza Strip [16]. Most consultants and contractors stated that the project was sometimes delayed by payment delay from the owner. In the Gaza Strip, contractors usually suffer from this problem. Payment delay from owner to contractor lead to delay of contractors' performance and cause problem in time performance. This may also lead to disputes and claims between owner and contractor of project. All of that will affect the overall performance of project which has been implemented [3].

The financial difficulties are an effectual cause of construction disputes, because contractors always depend on the payments to be received on time in order to pay their obligations. The contractor tries to avoid failure by claiming the owner for payments that are not due yet. Because the Gaza Strip companies are of small size, any payment delay or any design changes can affect the company's ability and might lead to disputes and claims [17].

Most of Palestinian National Authority projects are funded by donors. Many construction companies have traditionally complained delay in collecting debts from donors as a direct impact of local business political environment. This cause is also directly related to cash flow management. With lack of capital and lack of financial resources, delay of collecting debts from donors makes the negative effect much worse [18].
El Karriri [19] study recommended the clients and consultants to minimize the due time of the payment which should not to be more than (20 days) from the submission of the payments request by the contractor. Abo Mostafa [20] stated that payment delay has high effect on labor productivity. This result is justified as payment delay has very bad effect on labor mood and consequently decreases its productivity.

This research introduces an influential tool to measure the impact of risk payment delay, which will help to evaluate real losses that affect the payment delay. This will help the owner to establish reasonable compensation for the payment delay.

2.4 Payment delay risks modeling:

Adams [21] presented an application of an expert elicitation model and Bayesian methods to the analysis of the risk of payment delays in international contracts set in a developing economy, and a determination of how differing perceptions about risks affect estimates about the risk. Expert opinions about the risk of payment delays are transformed into prior distributions about the risk using the relative likelihood method and combined with sample information about the risk for a Bayesian analysis of the risk. Kwon, et al. [22] formulated a model enabled to examine how payment delay affects the supplier's optimal work rate, the manufacturer's optimal payment, the supplier's and the manufacturer's expected discounted profits, and the expected project completion time.

General forecasting techniques are quantitative approaches that have been used. They can be either deterministic or stochastic. Examples of deterministic methods are regression methods (linear regression and multiple regressions). Econometric models moving average methods and exponential smoothing methods. Examples of stochastic methods are the maximum likelihood method, Box- Jankins models, and probability weighted moment (L-moment). For instance, it may mean the determination of the life cycle cost of a system from a mathematical model containing a number of parameters and based on case histories of similar projects [23].

2.5 Support vector machines (SVM):

The support-vector network is a new learning machine for two-group classification problems. The machine conceptually implements the following idea: input vectors are non-linearly mapped to a very high dimension feature space. In this feature space a linear decision surface is constructed. Special properties of the decision surface ensures high generalization ability of the learning machine. The idea behind the support-vector network was previously implemented for the restricted case where the training data can be separated without errors [24].

The theory that underlies support vector machines (SVM) represents a new statistical technique that has drawn much attention in recent years. This learning theory may be seen as an alternative training technique for polynomial, radial basis function and multi-layer percept classifiers. SVM are based on the structural risk minimization (SRM) induction principle [25].

The SVM deals with classification and regression problems by mapping the input data into high-dimensional feature spaces. Its central feature is that the regression surface can be determined by a subset of points or support-vectors (SV); all other points are not important in determining the surface of the regression[26].

2.6 The using of support vector machines in construction:

There are plenty of learning approaches for applications in the engineering fields. Scholars have utilized approaches such as neural networks, case based reasoning, and self-organizing feature map based optimization to deal with practical construction problems. SVM is one popular type of learning approach which has been utilized in the engineering fields, especially for pattern classification. Recently this approach has also been adapted for the construction industry, for example, for the solving of cost estimates, contract risk, and construction safety problems. Construction material suppliers are usually exposed to financial risks as a consequence of a high debt capital structure and the nature of the material import business. There is demand for a tool that is able to predict whether such a material supplier, based on its financial status, should use derivatives to hedge financial risks. A prediction model using the Support Vector Machine (SVM) was developed to determine whether employing risk hedging based on derivatives usage would be beneficial. The SVM prediction model, based on the kernel radial basis function and normalized data, yields a prediction accuracy rate of 80.65%. The evaluation, using logistics and small sets of data. A ten financial determinates are proven candidates for financial risk hedging. SVM prediction model appeared feasible for construction material suppliers to apply the model [27].

3. Methodology:

A questionnaire was designed based on the risk of payment delay. The questionnaire survey was developed to assess the views of contractors, as the contractor is the most effected party in construction project by the impact of payment delay. A literature review was conducted to identify the risk of payment delay. 18 factors were identified as an impact of payment delay on contractor based on the work of [2, 7-9, 11, 12].

The questionnaire was designed into two sections: section A, and section B. Section A is general information about the respondents. Section B include the effect and risk of payment delay on contractor which have 18 factors.

The respondents were asked to rank the importance individual impact of payment delay on Gaza construction contractors. The questionnaire is mainly based on Likert's scale of five ordinal measures from one (1) to five (5) according to level of importance.
The questionnaires should be based on a carefully prepared set of questions piloted and refined until the researcher is convinced of their validity. The questionnaire was tested in order to make sure that the questions were easily understood. The test was made by distributing six drafts of the questionnaire to expert contractors. In general, they agreed that the questionnaire is suitable to achieve the goals of the study.

The internal consistency of the questionnaire is measured by a scouting sample, through measuring the correlation coefficients between each paragraph in one field and the whole filed. The result is that P-values are less than 0.01, so the correlation coefficients of this field are significant at $\alpha = 0.01$. It can be said that the paragraphs of this field are consistent and valid to measure what it was set for. Cronbach's coefficient alpha test is used to measure the reliability of the questionnaire between each field and the mean of the whole fields of the questionnaire. The normal range of Cronbach's coefficient alpha value between (0.0) and (+1.0), and the higher values reflects a higher degree of internal consistency. The results shows that Cronbach's coefficient for all items equal (0.9076). This range is considered high; the result ensures the reliability of the questionnaire.

The target groups in this study are contractors who may be affected by impact of payment delay. According to the Palestinian Contractors Union (PCU) in Gaza Strip, there are 140 contracting companies are classified as first and second class in building field [3]. All the contracting companies are contacted to fill the questionnaire. The manager of each company was requested to fill the questionnaire. 140 questionnaires were distributed. 113 questionnaires were received (80.71%).

The results of the questionnaire were utilized to build up a model that was used to measure the risk of payment delay in terms of financial loss. Nine factors that affect the payment delay which have RII more than 70% were used to build up the model. Suport Vector Machine (SVM) was used to develop the model. To build the SVM model, thirty-one interviews were conducted with expert engineers working in contracting campanies. The contracting companies were chosen because they were the most hurters due to the effects of payment delay. The results of interviews was used as training data for the model.

4. Results and analysis:
36.3% of sample size were project managers, 31.9% were site engineers, 15.9% were office engineers and 15.9% for others. More than 35 % of the respondents have key positions in their organization that insure quality information.

Considering the respondent's experience, 26.5% of respondents have experience from "1 – 5 years", 31.0% have experience from "6 – 10 years ", 13.3% have experience from "10 – 15 years " , 29.2 % have experience "More than 15 years". It is clear that about a third of the respondents have experience more than 10 years.

4.1 The risk of payment delay:

Table 1 shows the opinion of the respondents about the effects of payment delay on contractor ranked according to the Relative Importance Index (RII) and mean value. The two higher ranked items are: “Delay of paying employees' salaries” with RII of (80.88%), and P-value equal (0.0) and “Time overrun of project” with RII (78.94%), and P-value equal (0.0). The Delay of paying employees salaries will de-motivate the contractor own staff to perform well which could damage the overall project progress. The time delay will occur due to lake of financial resource to purchase materials and to pay for subcontractors. Therefore, the planned activities will be delayed causing overall delay for the whole project.

The least two ranked factors are: “Increase dispute about the interpretation of the contract document” with RII (60.35%) and “Contract termination” with RII (55.04%). It is evident that the payment delay to the contractor should severely affect the project progress in terms of cost, time, and quality. The payment delay will further cause cost overrun due to difficulty to pay for subcontractors and suppliers. However, the high interest due to loan has low importance with RII (73.27%). This can be interpreted due to non-dependence of projects finance on loans. That is, most contactors are financing their projects from their budgets.

Table 1 *Effects of payment delay on contractor*

Factors	Mean	Standard Deviation	Relative index	T test	P-value	Rank
Delay of paying employees	4.04	0.976	80.88	11.369	0.000	1
Time overrun of project	3.95	0.943	78.94	10.670	0.000	2
Cash flow problems	3.91	1.090	78.23	8.888	0.000	3
The progress slow down until	3.85	0.984	76.99	9.178	0.000	4
Difficulties to procure	3.84	0.996	76.81	8.972	0.000	5
Difficulties to participate in	3.77	1.126	75.40	7.268	0.000	6
Difficulties with Sub-contractor to continue works	3.75	1.005	75.04	7.958	0.000	7
Cost overrun of project	3.73	1.063	74.51	7.258	0.000	8
Bad reputation	3.73	1.219	74.51	6.327	0.000	9
High interest rate due to	3.66	1.107	73.27	6.374	0.000	10
Forced to borrow from	3.58	1.171	71.50	5.221	0.000	11
Create more claims	3.57	0.925	71.33	6.511	0.000	12
Decrees productivity of labor	3.30	1.133	66.02	2.823	0.006	13
Shortage of equipment	3.21	1.004	64.25	2.249	0.026	14
Work suspension	3.17	1.217	63.36	1.469	0.145	15
Difficult to maintain	3.12	1.028	62.48	1.282	0.203	16
Increase dispute about the interpretation of the contract document	3.02	1.165	60.35	0.162	0.872	17
Contract termination	2.75	1.366	55.04	-1.928	0.056	18
Average	**3.55**	**0.659**	**71.05**	**8.919**	**0.000**	

Critical value of t at df (112) and significance level (0.05) equal (1.98)

The same interpretation can be applied to the low importance of factor “Forced to borrow from financial institutions.”

Its noted that the overall relative importance index of the effects of payment delay on contractor is (71.05%) which is greater than (60%), the P-value equal (0.0) which is less than (0.05), and the value of T test equal (8.919) which is greater than the critical value which is equal (1.98). This indicates that the participant’s opinions are (Positive) to the effects of payment delay on contractor and the contractor should use all of his effort to mitigate the payment delay effects.

5. Model formulation:

Through this paper, a model is formulated to measure the risk of payment delay of construction projects in Gaza Strip. A NeuroSolution software, was used as a standalone environment for support-vector machines (SVM) development and training. Moreover, for verifying this work, the plentiful trial and error process was performed to obtain the best model architecture. The support-vector network is a new learning machine for two-group classification problems. The machine conceptually implements the following idea: input vectors are non-linearly mapped to a very high dimension feature space. In this feature space, a linear decision surface is constructed. Special properties of the decision surface ensure high generalization ability of the learning machine. The idea behind the support-vector network was previously implemented for the restricted case where the training data can be separated without errors [24].

The theory that underlies support vector machines (SVM) represents a new statistical technique that has drawn much attention in recent years. This learning theory may be seen as an alternative training technique for polynomial, radial basis function and multi-layer percept classifiers. SVM are based on the structural risk minimization (SRM) induction principle [25]. The SVM deals with classification and regression problems by mapping the input data into high-dimensional feature spaces. Its central feature is that the regression surface can be determined by a subset of points or support-vectors (SV); all other points are not important in determining the surface of the regression [26].

According to Chen and Shih [26] the SVM, which originated as an implementation of Vapnik’s Structural Risk Minimization (SRM) principle, is now being used to solve a variety of learning, classification, and prediction problems. In many ways, SVM performs the same function as artificial neural network (ANN). For example, when both the input and output data are available (supervised learning in ANN), the SVM can perform classification and regression; but when only the input data are available, it can perform clustering, density estimation and principle component analysis. The SVM is more than just another algorithm. It has the following advantages over an ANN: It can obtain the global optimum, the over fitting problem can be easily controlled. Empirical testing has shown that the performance of SVMs is better than ANNs in classification [28, 29, 30].

5.1 SVM prediction model:

The sample size is taken from interview with expert engineers who are working in contracting companies which conduct business related to construction in Gaza Strip. Considering accessibility of data, this research includes interview with (31) construction companies.

Eighteen impacts of payment delay were ranked according to their mean and relative importance index (RII) as shown in Table 1. The highest nine (9) factors were chosen to estimate the financial loss that could be encountered by contractors due to payment delay. Table 2 shows the factors that have a mean above 3.7, which is considered as significant factor contributing to payment delay.

Table 2 *Impact of payment delay on contractor*

No.	Impacts of payment delay on contractor	Mean	Relative index %
1	Delay of paying employees salaries	4.04	80.88
2	Time overrun of project	3.95	78.94
3	Cash flow problems	3.91	78.23
4	Slow progress until payment is received	3.85	76.99
5	Difficulties to procure material and services	3.84	76.81
6	Difficulties to participate in new projects tender	3.77	75.40
7	Difficulties with Sub-contractor to continue works in project	3.75	75.04
8	Bad reputation	3.73	74.51
9	High interest rate due to loans	3.66	73.27

Therefore, nine factors are used to formulate the model that was used to measure the risk of payment delay in terms of financial loss. The nine factors were used in a suggested hypothetical case study to have the contractor's opinions about the impact of these factors. A hypothetical case study was designed by counseling and sharing the expert contractors. Whereas hypothetical case study was used due to non-availability of actual data from real case studies concerning the impact of payment delay in construction projects at Gaza Strip. The suggested hypothetical case study was as follow:

1. A company has executed a building construction project with a grand total cost of US$1million, twelve months project period, number of payments was twelve, i.e. one payment every month, and the value of each payment was $75 thousands. The value of final payment was $175 thousand including the retention amount.
2. A payment delay occurred in the last five payments. The payment was delayed for two months for each invoice payment.

The aim of the contractors interview was to collect data about the expected financial loss that resulted due to the effects of payment delay on contractors. The financial loss for the nine items were estimated based on contractor best judement accounting information. Also, the experts should estimate the total financial loss in ($US) of the hypothetical case study according to contractors points of view. Finally the collected data used in building up the model which was designed to measure the impact of payment delay on construction projects in Gaza Strip. The total financial loss in ($US) was used as output data in the model formulation process and the weights of nine factors affecteing the financial loss were used as input data.

5.2 Data encoding:

Support vector machines as artificial neural network only deal with numeric input data. Therefore, the raw data should be converted from the external environment [31]. This may be challenging because there are many ways to do it. In this paper, the data were converted to numeric form as shown in Table 3. The data collected through the hypothetical case study and interviews were the weights of the impact of payment delay on contractors for the nine factors based on contractors experts judgement.

5.3 Model formulation:

There are several types of (SVM) software that used to predict the future values based on the past data like SPSS, MATLAB, NeuroSolution …etc. The developed model in this paper is based on NeuroSolution for Excel program. NeuroSolutions has been used for its ease of use, speed of training, flexibility of building and executing the SVM model. The research depended on the flexibility to specify SVM type, learning rate, momentum, activation functions, and graphical interpretation of the results.

It also has multiple criteria for training and testing the model.

In NeuroSolutions, Support Vector Machines (SVMs) are implemented using the kernel Adatron algorithm. The kernel Adatron maps inputs to a high-dimensional feature space, and then optimally separates data into their respective classes by isolating those inputs that fall close to the data boundaries. Therefore, the kernel Adatron is especially effective in separating sets of data that share complex boundaries. NeuroSolutions constructs adaptive systems in a Lego style that is component by component. The components are chosen from palettes. This object-oriented methodology allows for the simple creation of adaptive systems by simply dragging and dropping components, connecting them, and then adjusting their parameters.

5.4 Data organization:

The first step in implementing the support vector machines model in NeuroSolution application is to organize the Neurosolution Excel spreadsheet by specifying the input factors that have been already encoded. The nine factors are; late payment of salaries, time overrun of project, cash flow problems, slows down the progress until payment is received, difficult to procure material and services, difficult to tender for new projects, sub-contractor refuse to continue works on the project, bad reputation of the contractor, and high interest rate due to loans.

5.5 Data set:

The available data were divided into three sets namely; training set, cross-validation set and test set. Training and cross validation sets are used in learning the model through utilizing training set in modifying the network weights to minimize the network error, and monitoring this error by cross validation set during the training process. However, test set does not enter the training process and it hasn't any effect on the training process, where it is used for measuring the generalization ability of the network, and evaluated network performance [32]. In the present study, the total available data is (31) exemplars (Interviews results) that are divided randomly into three sets with the following ratio: Training set (includes 15 exemplars ≈ 48%), Cross validation set (includes 8 exemplars ≈ 26%) and Test set (includes 8 exemplar ≈ 26%).

Table 3 *Encoding the impact of payment delay on contractors estimated cost (US$)*

Company	Factor 1	2	3	4	5	6	7	8	9	Total loss ($US)
	Delay of paying employees' salaries	Time overrun of project	Cash flow problems	Slow progress until payment is received	Difficulties to procure material and services	Difficulties to participate in new projects tender	Difficulties with Sub-contractor to continue works in project	Bad reputation	High interest rate due to loans	
1st	0.07	0.07	0.1	0.07	0.3	0.15	0.1	0.07	0.07	27500
2nd	0.04	0.08	0.03	0.06	0.08	0.04	0.06	0.04	0.57	25000
3rd	0.1	0.05	0.05	0.05	0.3	0.3	0.05	0.05	0.05	26000
4th	0.01	0.25	0.2	0.15	0.25	0.05	0.02	0.05	0.02	30000
5th	0.05	0.05	0.1	0.1	0.2	0.3	0.05	0.05	0.1	30400
6th	0.05	0.1	0.1	0.15	0.15	0.25	0.1	0.05	0.05	30300
7th	0.1	0.1	0.15	0.05	0.25	0.05	0.15	0.1	0.05	27000
8th	0.1	0.15	0.17	0.07	0.08	0.11	0.09	0.2	0.03	30500
9th	0.09	0.18	0.05	0.16	0.14	0.12	0.09	0.1	0.07	26500
10th	0.1	0.15	0.05	0.1	0.25	0.1	0.15	0.05	0.05	34500
11th	0.1	0.05	0.1	0.15	0.25	0.1	0.05	0.05	0.15	31000
12th	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.12	26300
13th	0.17	0.15	0.19	0.09	0.18	0.02	0.07	0.02	0.11	25500
14th	0.05	0.15	0.2	0.2	0.2	0.05	0.05	0.05	0.05	30700
15th	0.1	0.05	0.05	0.1	0.2	0.1	0.1	0.1	0.2	28500
16th	0.1	0.1	0.15	0.15	0.1	0.2	0.1	0.05	0.05	28000
17th	0.05	0.05	0.15	0.15	0.2	0.15	0.1	0.05	0.1	25700
18th	0.05	0.09	0.13	0.1	0.12	0.2	0.05	0.06	0.2	29500
19th	0.03	0.07	0.1	0.11	0.15	0.21	0.07	0.07	0.19	27200
20th	0.1	0.01	0.01	0.05	0.6	0.01	0.2	0.01	0.01	28300
21st	0.07	0.12	0.06	0.11	0.06	0.32	0.12	0.07	0.07	34700
22nd	0.1	0.1	0.05	0.07	0.11	0.12	0.23	0.12	0.1	27700
23rd	0.06	0.09	0.09	0.15	0.15	0.11	0.11	0.11	0.13	30100
24th	0.05	0.2	0.1	0.05	0.3	0.05	0.1	0.02	0.13	27500
25th	0.1	0.05	0.15	0.15	0.2	0.05	0.05	0.1	0.15	29400
26th	0.1	0.14	0.09	0.14	0.14	0.18	0.06	0.05	0.1	33500
27th	0.05	0.15	0.15	0.15	0.15	0.05	0.15	0.1	0.05	30600
28th	0.05	0.1	0.1	0.2	0.1	0.1	0.2	0.05	0.1	25800
29th	0.09	0.02	0.04	0.13	0.13	0.19	0.13	0.08	0.19	33000
30th	0.3	0.1	0.1	0.15	0.05	0.02	0.08	0.1	0.1	28900
31st	0.1	0.1	0.25	0.15	0.05	0.05	0.1	0.1	0.1	26700

5.6 Model training, cross-validation and testing:

The support vector machine was built by selecting the type of network, number of epochs. The objective of training support vector machine (SVM) networks is the same objective of training the neural network. The model training starts with selecting the (SVM) network type also a thousand epochs and ten runs were limited. Ten runs in each one 3000 epochs were applied, where a run is a complete presentation of 3000 epochs, each epoch is a one complete presentation of all of the data[33]. However, in each run, new weights were applied in the first epoch and then the weights were adjusted to minimize the percentage of error in other epochs. To avoid overtraining for the network during the training process, an option of using cross-validation was selected, which computes the error in a cross validation set at the same time that the network is being trained with the training set.

The cross-validation data is used during the training but for monitoring not to train the network, instead to check the learning of the network during the training; and the testing data is used to validate the training network after finishing training process [32]. The testing data is totally a different set of data that the network is unaware of; after finishing the training process testing data is used for validation and generalization of the trained network. If the network is able to generalize rather precisely the output for this testing data, then it means that the neural network is able to predict the output correctly for new data and hence the network is validated. Moreover, the amount of data that is to be used for training and testing purposes depends on the availability of the data, but in general the training data is 2/3rd of the full data and the remaining is used for testing purposes. The cross-validation data can be 1/10th of the training data [34].

The best model that provided more accurate payment delay risk estimation without being overly complex was structured of (SVM) includes nine input factors and one output (Total payment delay risk in $US). The training data set was used to get network weights to bring its output closer to the desired output. The weights after training contain meaningful information. Whereas before training, they have random values and have no meaning. Data from interviews with (15) contracting companies were used for training purposes. A Neurosolution train tool was used for training the adopted model according to the weights adopted. The cross validation data set was used to monitor the network, instead to check the learning of the network during the training. Data from eight (8) contracting companies' interviews were used for cross validation purposes.

The testing data set was used for generalization that is to produce better output for unseen examples. Data from eight (8) contracting companies' interviews were used for testing purposes. A Neurosolution test tool was used for testing the adopted model according to the weights adopted. Table 4 presents the results of eight contracting company's interviews. The actual risk in ($US) of tested interviews results is compared with estimated risk in ($US) from support vector machine (SVM) model. An absolute error and absolute percentage error are also presented.

Table 4 *Results of SVM network model for testing sample sizes*

Inter view No.	Actual Risk ($)	Estimated Risk ($)	Absolute Error (AE) ($)	Absolute Percentag e Error (APE) %
24th	27,500	28,974.	1,474.5	5.36
25th	29,400	29,679.	279.26	0.95
26th	33,500	30,091.	3,408.9	10.18
27th	30,600	29,353.	1,246.1	4.07
28th	25,800	28,264.	2,464.7	9.55
29th	33,000	29,300.	3,699.5	11.21
30th	28,900	27,507.	1,392.6	4.82
31st	26,700	28,337.	1,637.8	6.13
		Average	1,950.4	6.53

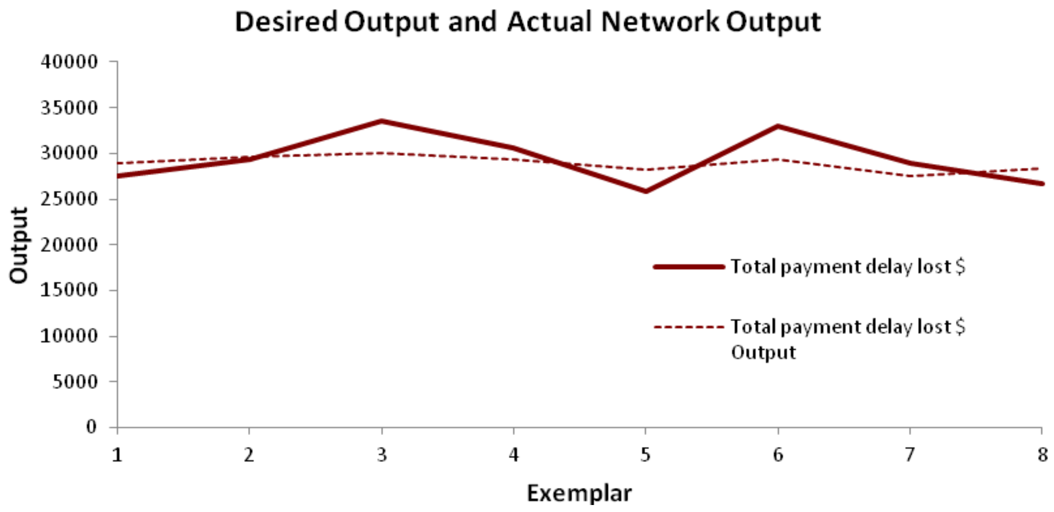

Figure 1 *Actual and estimated payment delay risk for test set*

Figure 1 describes the actual payment delay risk compared with estimated payment delay risk for test set. It is noted that there is a convergence between the two lines.

Table 5 shows the MAE for the selected model, and to calculate the (MAE) for testing set, the following procedure is followed.

MAE=(1,474.56+279.26+3,408.96+1,246.17+ 2,464.77+3,699.50+1,392.63+1,637.89)/8 =1950.47

The mean absolute error (MAE) equals (US$ 1,950.47) which is acceptable for projects worth one million dollars. However, it is not a significant indicator for the model performance because it proceeds in one direction for the hypothetical case study that supposed for this model, where the mentioned error may be small if the total cost of the project is over one million.

Table 5 shows the (MAPE) for the selected model, and to calculate the (MAPE) for testing set, the following procedure is followed.

$$\text{MAPE} = \frac{5.36+0.95+10.18+4.07+9.55+11.21+4.82+6.13}{8}$$

= 6.53

The Mean Absolute Percentage Error (MAPE) for the test results which equals (6.53%), this result can be expressed in another way by accuracy performance (AP) according to Wilmot and Mei [35] which is defined as (100−MAPE) %.

AP= 100% - 6.53% = 93.47%

That means the accuracy of adopted model for payment delay risk in building projects is (93.47%). The result is acceptable for projects worth one million dollars.

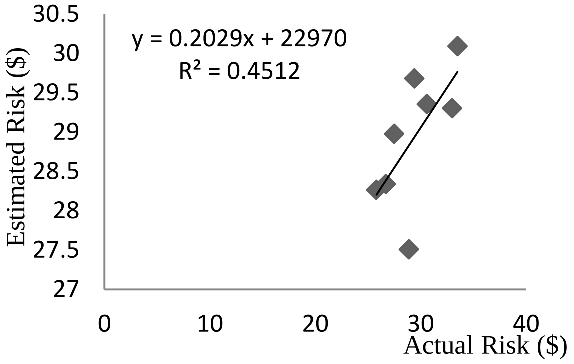

Figure 2 *Linear regression of actual and estimated risk of payment delay*

Regression analysis was used to ascertain the relationship between the estimated payment delay risk and the actual payment delay risk. The results of linear regression are illustrated graphically in Figure 2. The correlation coefficient R is (0.672) for testing set, indicating that there is a good linear correlation between the actual and the estimated risk of payment delay.

The results of performance measures are presented in Table 5, where the accuracy performance of adopted model is (93.47 %). In which the average error is (6.53%).

Table 5 *Results of performance measurements*

Item	MAE	MAPE	AP	r
SVM Model	US$ 1,950.47	6.53%	93.47 %	0.672

Figure 3 describes the actual payment delay risk comparing with estimated payment delay risk for all 31 contracting companies interviews. It is noted that there is a convergence between the two lines.

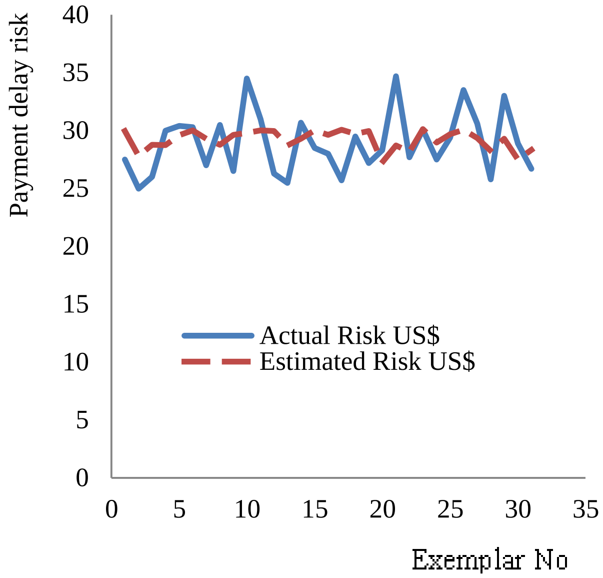

Figure 3 *Comparison between actual and estimated payment delay risk (x10^3 US$)*

In order to ensure the validity of the model in measuring the effect of payment delay, many statistical performance measures were conducted i.e.; Mean Absolute Error (MAE) = (US$ 1,950.47), Mean Absolute Percentage Error (MAPE) = (6.53%), Accuracy Performance (AP) = (93.47%) and Correlation Coefficient I = (0.672).

6. Conclusion:

The factors that are contributing to the risk of payment delay in construction projects in the Gaza Strip were identified. The top nine risks that affect the payment delay have been used to build the SVM model through the estimation of the financial loss percentage of each factor effect on payment delay.

The SVM model was developed to measure the risk of payment delay in the Gaza Strip. The model input factors are: late payment of salaries, time overrun of project, cash flow problems, slow down the progress until payment is received, difficult to procure material and services, difficult to tender for new projects, sub-contractor refuse to continue works on the project, bad reputation of the contractor, and high interest rate due to loans. The total cost loss in $US was used as output.

The model was able to measure the risk of payment delay in terms of US dollars losses. The accuracy performance of the adopted SVM model was 93.47%. The model performed well and no significant difference was discerned between the estimated output and the actual payment delay value. The average percentage error of this model is 6.53%. The model can be improved if actual case studies were used to train the model.

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