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Public Procurement Crisis of Iraq and its Impact on Construction Projects

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ABSTRACT

The public procurement crisis in Iraq plays a fundamental role in the delay in the implementation of construction projects at different stages of project bidding (pre, during, and after). The procurement system of any country plays an important role in economic growth and revival. The paper aims to use the fuzzy logic inference model to predict the impact of the public procurement crisis (relative importance index and Likert scale) was carried out at the beginning to determine the most important parameters that affect construction projects, the fuzzy analytical hierarchy process (FAHP) to set up, and finally, the fuzzy decision maker's (FDM) verification of the parameter for comparison with reality. Sixty-five construction projects in Iraq have been selected, and the most crucial crisis variables were used for calculating the weights and their importance, using the fuzzy logic inference model to verify the crisis parameters and the extent of their impact in preparation for predicting the mathematical model of public procurement parameters. After the algorithm had been completed, it was noted that the fast, messy genetic algorithm produced a little difference between training and testing (0.012% and 0.0057%), which is more reliable for predicting mean results from models. The paper's major conclusion is that 18 crisis factors in public procurement through different stages affect construction projects in Iraq.

Keywords: Crisis, Public procurement, Construction projects.

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أزمات العقود العامة في العراق وتأثيرها على مشاريع البناء

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الخلاصة

تلعب أزمة العقود العامة في العراق وظيفة أساسية أدت إلى تأخير التنفيذ في معظم مشاريع البناء وفي مراحل مختلفة من عطاءات المشروع (ما قبل المناقصات ، أثناء المناقصات وبعد المناقصات) ، يلعب نظام العقود لأي بلد دورًا مهمًا في نمو الاقتصاد واحياؤه. الهدف من هذا البحث هو تحديد وجمع وتحليل عوامل الأزمات في نظام العقود العامة لجمهورية العراق وفعالية هذه العوامل ومدى تأثيرهاعلى مشاريع البناء التي تنفذها الشركات (العامة والخاصة والأجنبية). تم تنفيذ نموذج الاستدلال المنطقي الغامض للتنبؤ بتأثير الأزمات العامةلمنظومة العقود ، تم استخدام (مؤشر الأهمية النسبية ومقياس ليكرت) في البداية لتحديد أهم العواملالمسببة للأزماتوالتي لها تأثير على مشاريع البناء ، وكذلك استخدام عملية التسلسل الهرمي التحليلي الغامض (FAHP) لإعداد الموديل ، وأخيرا ، التحقق من صانع القرار الضبابيFDMلعوامل المقارنة مع الواقع من خلال اخذ نموذج ل 65 مشروع انشائي تم تنفيذها في العراق ، تم استخدام أكثر المتغيرات الحاسمة للأزمات ، وحساب الأوزان وأهميتها ، باستخدام نموذج الاستدلال المنطقي الغامض للتحقق من عوامل الأزمةعندما اكتملت الخوارزمية ، لوحظ أن الخوارزمية الوراثية السريعة الفوضوية أنتجت اختلافًا قليلاً بين التدريب والاختبار أكثر هي 0.012 ٪ و 0.0057 ٪ والتي أكثر موثوقية للتنبؤ بالنتائج المتوسطة من النماذج. استنتج من هذا البحثان هنالك 18 من العوامل المسببة للأزمات في العقود العامة من خلال المراحل المختلفة لمشاريع البناءفي العراق تؤثر على مرحلة التنفيذ.

الكلمات المفتاحية : الأزمات، العقود العامة، المشاريع الأنشائية.

1. INTRODUCTION

Many research gaps require familiarity with typical crises in public procurement. The difficulty is finding the most relevant knowledge of the initial standard crisis factors that significantly impact the final objective of any new guesswork in the conceptual public procurement crisis model. These parameters must be quantifiable and qualified. It is difficult to predict a procurement crisis parametrically and conceptually in the context of a project when there are insufficient variables and information to consider. How this might impact the goal of the construction project is unknown. Every project's planning and feasibility study involves a conceptual forecast (time, cost, and company performance), which can significantly impact the total construction objectives. Conceptual project costing is the appraisal of the entire project and is solely based on the project's first general conceptions **(Smith et al., 2013).** On the other side, insufficient input might have a negative impact in situations where there is subjectivity, ambiguity, and uncertainty. Fuzzy logic is a helpful tool for forecasting **(Abbasnia et al., 2008; Lin and Feng, 2008).**
Making decisions and controlling processes. The fuzzification representation engine is the four primary components of fuzzy logic utilized to compare the effectiveness of the proposed model.

The creation and regulations of MFs get increasingly challenging as the issue becomes more complicated **(Araque et al., 2008).** According to several scholars, solving this problem is a challenging task. Determining the precise cost parameters is challenging due to the optimization problem's above-described challenges. A significant development in creating a reliable integrated model for conceptual costing **(Kamalabadi et al., 2007).** The objective of the paper is to identify, collect, and analyze the crisis factors in the public procurement system of Iraq and the effectiveness of these factors in construction projects that are implemented by companies (public, private, and foreign) **(Saifan et al., 2016; Liang, 2006).** This work aims to determine the most procurement factors that affect the construction projects in Iraq through different stages (pre-, during and after).

2. METHODOLOGY

The Hybrid Genetic Algorithm HGA is a cutting-edge tool for large-scale permutation issues in machine learning and optimization that takes a population-based approach **(Marsh and Fayek, 2010).** It is an enhancement over hereditary anarchist algorithms, first created to address linkage issues in simple genetic algorithms (sGAs) brought on by a parameter-coding issue that can result in inferior solutions. Large-scale permutation issues can be solved effectively using H.G.A., which uses messy chromosomes to produce strings of varying lengths, as opposed to sGA, which depicts potential answers as fixed-length strings. The HGA algorithm has two types of loops (input and output). We refer to the out-put loop as an -era (k). First, a competitive template is generated (for example, a fixed-bit string created randomly or specifically for a given challenge) **(Noori and Rasheed, 2023)**. The inner loop is then activated. Build blocks Filter (B.B.F.), also known as the primordial phase, phase 1, and initialization phase, are the three phases that make up the inner loop of the HGA algorithm. The HGA differs from other genetic systems in that it may deliberately change build blocks (B.B.s) in the primordial phase to get "excellent" solutions and, perhaps, the global optimum **(Ding and He, 2004).**

All feasible BBs of order k are present in sufficiently large data sets during the initiation phase. At this point, HGA runs the probabilistically complete initialization (PCI) procedure, which creates n chromosomes at random and determines the fitness values of each one **(Plebankiewicz, 2009; Rashidi and Brilakis, 2011).** Building block filtering and threshold selection are the two procedures that make up the primordial phase. In the beginning phase, "bad" genes that do not belong to B.B.s are eliminated, resulting in a population with a high percentage of "good" genes that belong to BBs. Operations are more akin to straightforward GA during the juxtaposing phase. A high-quality generation that might include the ideal answer is created using a cut-and-splice operator and a good gene selection process. Once the inside loop is complete, the subsequent outer loop can begin. So far, The best solution is to replace the competitive template, which serves as the new competitive model for the subsequent outside loop. Up until the most significant number of eras (kmax) is reached, the entire process is repeated. The HGA may also work with epochs in addition. A whole process that starts with the first era and ends with the most eras is carried out by an epoch. The user must provide the maximum number of epochs (emax) as illustrated in **Figs. 1** and **2**.

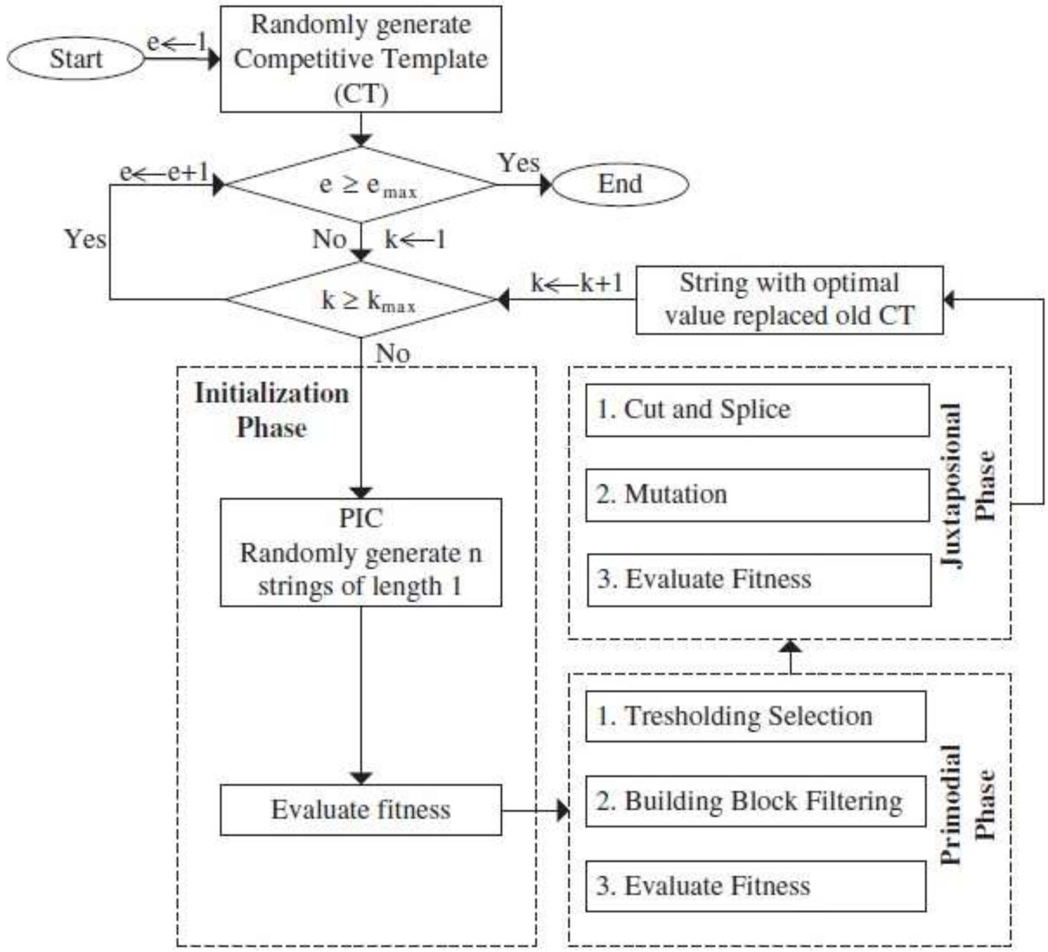

Figure 1. Hybrid Genetic Algorithm (H.G.A)

3. WEIGHTED SUPPORT VECTOR MACHINES (W.S.V.M)

W.S.V.M., or fuzzy support vector machine, was its previous name, Fuzzy Support Vector Machine (FSVM3). As the weighting value, each training data point in W.S.V.M. addresses a fuzzy membership. The original SVM treats all training points in a particular class equally. **(Nassar and Erzaij, 2022)** Yet, different data sets typically have different levels of importance in the series forecasts, which was suggested to enhance SVM's capacity to reduce the impact of outliers and irrelevant data. A weighting value is assigned to each input point in SVM in W.S.V.M., allowing different input points to contribute differently to the linearity of the regression (LR). In cost series prediction issues **(Shankar and Rao, 2010),** older training data points are given the lowest weights to reduce their impact. The W.S.V.M.'s mathematical description is explained in the following section. Given an S number of data points, training, and associated weights, where is the vector input, is the intended output, is a weighted for data point (,)(= 1..., m), and a tiny non-negative () represents the low bound of weights. The following optimization problem, Eqs. (1–4) must be resolved to use the W.S.V.M. for regression analysis (**Soltani and Haji, 2007).**

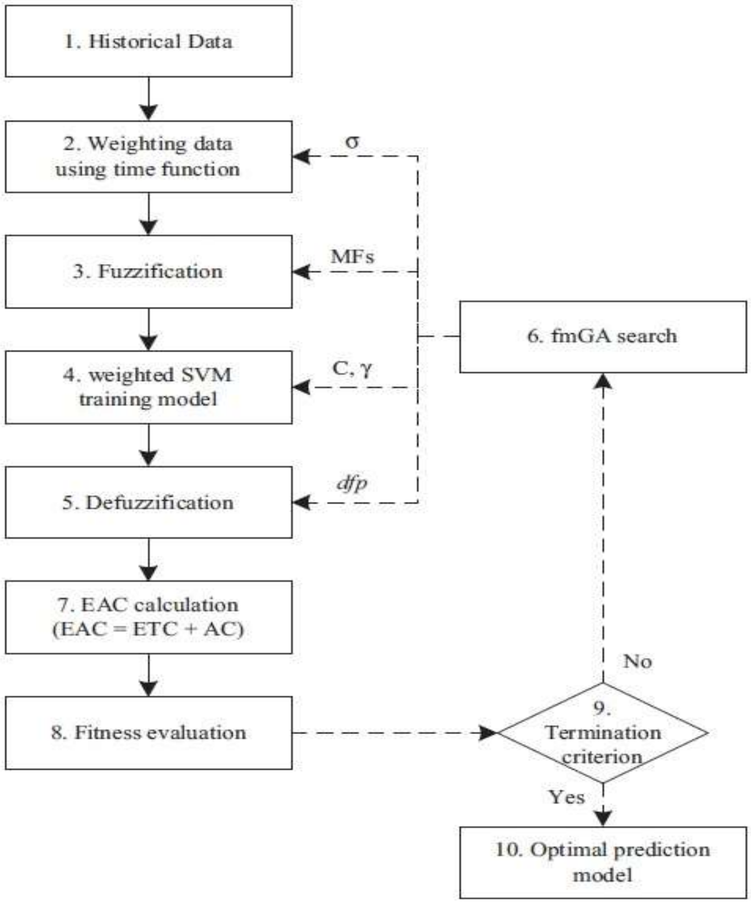

Figure 2. Procedure of Hybrid Genetic Algorithm model

Min $= \frac{1}{2} ww + c \sum_{i=1}^{1} s_i(\varsigma_i + \varsigma_i^*)$ (1)

Substitute to $y_i - (w\emptyset(x_i + b) \leq \varepsilon + \varsigma_{i\,,}$ (2)

$Substituteto\ (w\emptyset(x_i + b) - y_i \leq \varepsilon + \varsigma_{i,}$ (3)

$Substituteto \varsigma_i + \varsigma_i^* + \leq 0,$ (4)

where

C is the penalty factor.

$\emptyset$(x) denotes the high-dimension feature space, which is mapped from the input space (x) (up and low) to the training error. For W.S.V.M., the smallest weight value decreases the effect on the factors. **(Yang and Wang, 2007)**

Thus, the corresponding data points $\emptyset$ () are considered a decrease relative to the Levant. Optimizing problems can be transformed into the shown dual form, Eq.s (5 to 10):

Max=$\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_1 - \alpha_i^*)(\alpha_j - \alpha_j^*)k(x_i, x_j) - \varepsilon \sum_{i=1}^{l}(\propto_i - \alpha_{l_i}^*) + \sum_{i=1}^{il} y_i(\propto_i - \alpha_{i_l}^*)$ (5)

Substitute to $\sum_{i=0}^{l} \boldsymbol{\alpha_i y_i = 0}$, $0 \leq \propto_i \leq \boldsymbol{s_i ci = 1}, \ldots\ldots, \boldsymbol{l}$ (6)

and the KKTC for optimality is given as

$\alpha_l^-(\varepsilon + \varsigma_i^- - y_i + w^- x_i + b^-) = 0, i = 1 \ldots\ldots., l$ (7)

$$\alpha_i^{\cdots}(\varepsilon + \varsigma_i^{\cdots} - y_i + w^{-}x_i + b^{-}) = 0, i = 1 \ldots \ldots .., l \quad (8)$$

$$(s_i c - \propto_i^{-})\varsigma_i^{-} = 0, \; i = 1 \ldots \ldots ., l \quad (9)$$

$$(s_i c - \propto_i^{\cdots})\varsigma_i^{\cdots} = 0, \; i = 1 \ldots \ldots ., l \quad (10)$$

where denotes the support value of the training data point. ik (x_i,x_j) is a kernel function that controls how data is mapped from the input space to the feature space. The crisis management functions f(c_i) might be chosen for the determination of the W.S.V.M.'s s_i in sequential learning and inference methods (such as crisis management), in which points from the recent past are weighted more severely than other points in the past that proposed three cost functions (line, quad, and exp). These three cost functions were used to anticipate financial cost series problems; Eqs. (11–13) demonstrate the effectiveness of this method in outperforming SVM.

$$si = f1(ci) = \frac{1-\sigma}{t_m - t_1} + \frac{t_m\sigma - t_1}{t_m - t_1} \quad (11)$$

$$si = fq(ci) = (1\sigma)\left(\frac{t_i - t_1}{t_m - t_1}\right)^2 + \sigma \quad (12)$$

$$si = fe(ci) = \frac{1}{1 + e^{(\sigma - 2\sigma(t_i - t_1/t_l - t_1)}} \quad (13)$$

The tradeoff between margin maximization and violation error reduction was decided by penalty factor C for W.S.V.M. It was observed that this problem needed to be handled properly. Kernel parameters, such as gamma, which must also be correctly calibrated to increase predicted accuracy, were another concern. Additionally, setting the weighting data option is another reason for using a Weighted Support Vector Machine (W.S.V.M.). Finally, three parameters must be improved: the penalty crisis (C), the kernel factors (), and. To address this issue, an optimized approach (such as HGA) may be employed to simultaneously determine all of the parameters optimum values **(Mahjoob et al., 2016; Zahraie and Tavakolan, 2007).**

3.1 Data Collection

This model's data collection sets came from 18 public procurement Causes of a crisis Construction, as given in **Table 1.**

3.2 Data Weighting

The tradeoff between margin maximization and violation error reduction was decided by penalty parameter C for W.S.V.M. It was observed that this was a problem that needed to be handled personally. Another concern was kernel parameters, such as gamma, that must be correctly calibrated to increase the predicted accuracy (**Zhang et al., 2005; Van, 2022),** generated randomly, and the end code (F.M.G.A.) as given in **Tables 1 to 4.**

Table 1. Crisis factors affected the Construction project

Factors	Description
F1	There is sufficient time between the announcement and the date of submitting the bid and sending the clarification to all potential bidders (in writing).
F2	Delayed approval of the federal budget and corruption in contractual proceed.
F3	Procurement plan to manage the bidding during the life cycle of a project and untrue feasibility studies
F4	Classification Companies private, public and Registration
F5	Completion of tender documents, drawings, and technical specifications with estimated price updated
F6	The interference of political parties in public procurement and corruption in processing.
F7	Inadequate training of the individuals who carry out the evaluation process.
F8	Inquiries and pre-bidding conferences with Deviation, Reservation, and Omission.
F9	The award decision is made solely based on the criteria stipulated in the tender documents.
F10	The reliability of the financial performance and other criteria of the competitive companies
F11	Evaluation forms do not cover all aspects like regulations may overlap on the one hand and EPC.
F12	Review payments and process payments in a timely manner.
F13	Effective and fair processes are in place to promptly settle disputes during the contract implementation period, Handling disputes.
F14	Committing to the amounts allocated in the budget or distributing them in a timely manner.
F15	Decision-making is slow and complicated.
F16	Lack of clarity in designs and technical specifications.
F17	Poor communication between the project parties and the contractor.
F18	Schedule and Scope Change.

3.3 Fuzzification

This step converted The normalized input qualities into the appropriate membership grade. This crisp to fuzzy quantity mapping is accomplished using a set of membership functions (MF) generated using a code (H.G.A.). These shapes can be constructed using the summit points and widths of the trapezoidal and triangular MF shapes utilized in this study. The summit and width representation method was used to fuzzify entire MF sets (SWRM). to learn more about the summit and width representation method (SWRM) and the fuzzification procedure **(Kuo and Lu, 2013; Hosseini and Soltanpour, 2022)**

3.4 Weighted Support Vector Machine (W.S.V.M)

In this phase, W.S.V.M. is installed to manage fuzzy input-output mapping. For the W.S.V.M., which trains on this data collection as shown in **Fig. 3** to develop the projected model, the membership grades generated by the fuzzification procedure serve as input fuzzy **(Yin and Hou, 2016; Adeli and Wu, 2018)**.

Table 2. Values crisis time factors affected Ten construction projects

Factors	Projects									
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
F1	1	1	1	1	1	1	1	1	3	1
F2	1	2	1	1	1	1	1	3	2	1
F3	1	1	2	3	2	1	2	3	3	1
F4	2	1	2	3	1	1	1	2	1	2
F5	2	2	3	2	2	2	2	2	2	2
F6	1	2	1	2	2	1	1	1	1	1
F7	2	2	3	2	2	2	2	2	2	2
F8	1	1	2	3	3	3	1	3	3	1
F9	2	2	3	2	2	2	2	2	2	2
F10	2	2	1	1	2	2	2	1	1	2
F11	2	2	1	1	3	2	1	3	2	2
F12	2	2	3	2	3	1	1	2	3	2
F13	3	3	1	1	2	2	3	1	3	3
F14	1	1	2	3	3	1	1	3	1	1
F15	1	1	1	2	2	2	2	2	2	1
F16	2	1	2	3	1	1	1	2	1	2
F17	2	2	3	2	2	2	2	2	2	3
F18	2	1	2	3	2	3	2	3	2	3

The F.M.G.A. algorithm produces and optimizes the kernel parameters (g) and penalty (C) used by W.S.V.M. The radial basis function kernel (RBF kernel) was a workable initial alternative in this investigation. It should also be mentioned that this study made use of the SVM source code found in the Library for Support Vector Machines (LIBSVM).

Table 3. Values crisis performance factors affected one of Ten construction projects

	Factors	F1	F2	F3	F4	F5	F6	F7	F8
projects	P1	2	1	2	1	2	1	2	1
	P2	2	2	1	2	1	1	2	1
	P3	2	2	2	1	1	1	3	2
	P4	1	1	2	1	1	2	2	1
	P5	2	2	1	1	1	1	2	1
	P6	1	1	2	2	1	1	2	1
	P7	1	3	1	2	1	1	2	1
	P8	2	2	1	1	2	1	2	1
	P9	2	2	1	1	1	1	2	1
	P10	2	2	1	2	2	1	2	1

Table 4. Values crisis cost factors affected one of Ten construction projects

	Factors	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13
projects	P1	2	3	2	2	1	2	1	2	1	2	1	1	2
	P2	3	2	3	1	3	1	2	1	1	1	2	2	3
	P3	2	3	2	2	2	2	3	1	1	2	2	3	2
	P4	1	2	1	3	1	3	1	2	1	3	3	2	1
	P5	2	1	2	2	2	2	2	1	2	2	2	1	2
	P6	3	3	3	3	3	3	3	1	3	3	3	3	3
	P7	2	3	2	2	2	2	3	3	1	2	2	3	2
	P8	1	2	1	3	1	3	1	2	1	3	3	2	1
	P9	2	1	2	2	2	2	2	1	2	2	2	1	2
	P10	3	3	3	3	3	3	3	1	3	3	3	3	3

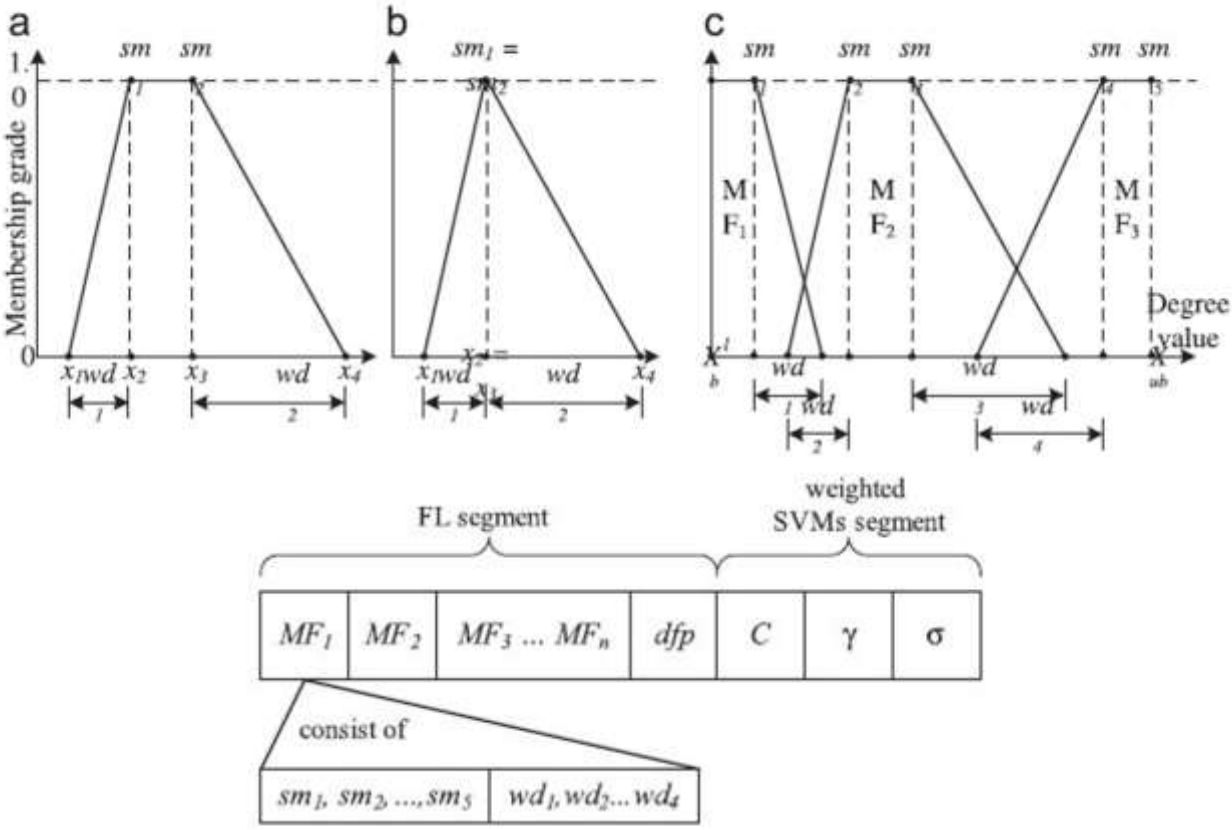

Figure 3. Membership function (trapezoidal, triangle, and complete MFset)

where:

MF_1 is the membership function i-th; **Sm** is the summit point j-th of MF; **WD_1** is the width j-th of MF; ***dfp*** is the de-fuzzification factor; **C** is the penalty parameter; **γ** is RBF kernel parameter; **σ** is the lower bound of weighting data factor

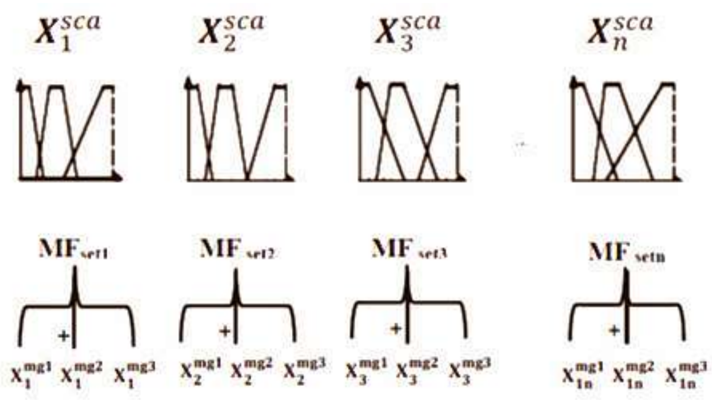

Figure 4. Fuzzification Process

where: X_{ij}^{sca} is the scaled input pattern; $\mathbf{X}_{\mathbf{ij}}^{\mathbf{mgk}}$ is the membership grade k of X_{ij}^{sca} ; **i** is the number of cases; **j** is the number of the input pattern; **k** is the number of MF_S in one complete membership set

3.5 Defuzzification

Once the training process is over, the W.S.V.M. output number has been stated in terms of the fuzzy output, and it must be converted into crisp numbers using models. To achieve this, models build a randomly generated dfp sub-string and encode it using HGA. This evolutionary method uses a common denominator for W.S.V.M. output **(Cheng et al., 2012; Alroomi et al., 2005)**, which makes it simple to comprehend and apply. **Fig. 4** shows the fuzzy process using HGA.

3.6 H. G.A Searching

The fit test figures of (MF_S, dfp, penalty factors C), RBF kernel parameters g, and the weighted data factors s are simultaneously searched for using the model, HGA. The five components that make up the chromosomes in H.G.A. that indicate a potential solution for factors study are the MF substring, dfp substring, penalty factors substring, kernel factors substring, and low bound of weighting data substring. A binary string represents the chromosome. **Fig. 4** depicts the chromosomes' structure. In the chromosomal design, each binary's **(Cheng et al., 2012; Serbane, 2013)** necessary length must also be specified beforehand. The parameters and number of bits required for the building cost are listed in **Table 5**.

Table 5. Cost, time, and performance crisis factors affected the construction project

Parameters	U.b	L.b	No of Bits
Mf set	-	-	38a
C cost	170	0	4
C time	80	0	6
C performance	130	0	4
dfp	1	0.00001	8
γ	1	0.011	9
σ	1	0.38	7

3.7 Fitness Evaluation

The fitness function in F.M.G.A. was developed to evaluate the fitness of generalization features and model correctness (**Attalla and Wu, 2003).** This function offers the best-fitting MF shape, W.S.V.M. parameters, and effective defuzzification. The fitness function combines model complexity with accuracy, as seen in Eq. (14)

$$f\,fi\,¼ = \frac{1}{c^{aw} * s^{er} + c^{cw} * mc} \quad (14)$$

where c^{aw} represents the accuracy weighting coefficient, s^{er} represents the prediction error between actual output and desired output, c^{cw} represents the complexity weighting coefficient, and mc represents model complexity, which can be quantified by counting the number of support vectors. The optimization process aims to minimize the prediction error (s^{er}) in the training data set. However, to avoid over-fitting, reducing the model complexity (mc) by limiting the number of support vectors is needed. In other words, the fitness function represents a trade-off between model accuracy and model generalization **(Shaw et al., 2005).**

4. RESULTS AND DISCUSSION

Once the termination requirement is satisfied, the loop ends. This indicated that the input/output mapping relationship had been found by the predicted model with the best tuning settings. After the training procedure is complete, the model is prepared to predict new facts.

Table 6. Optimal prediction modeler

Factors	Data set	Result		
		RMSE	AA %	MAPE %
Cost	Training	0.768	97.12	35
	Testing	0.746		
	%	0.022		
Time	Training	0.619	97.08	36
	Testing	0 607		
	%	0.012		
Performance	Training	0.668	96.98	35.8
	Testing	0.646		
	%	0.022		

5. CONCLUSIONS

This research examines projects using a fuzzy logic inference model to anticipate the public procurement crises of the project input to the model. This study includes a collection of crisis management teams for building projects gathered from earlier research and fieldwork. The objective is to examine the advantages of integrated crisis management approaches and determine the project's expected score. The crisis management variables from a panel of professionals were assessed and rated based on influence level intervals and questionnaire forms. It was noted that the hybrid genetic algorithm (H.G.A.) produced a slight difference between training and testing of 0.022%, 0.012, and 0.022%. The technique was applied to a dataset of 10 construction projects, so the results gathered from the hybrid model are reliable predictions.

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