A Type-2 Fuzzy Hybrid Expert System for Commercial Burglary

M.H. Fazel Zarandi(✉), A. Seifi, H. Esmaeeli, and Sh. Sotudian

Department of Industrial Engineering, Amirkabir University of Technology, Tehran, Iran
{zarandi,aseifi,h.esmaili,shahab7290}@aut.ac.ir

Abstract. In this paper, an interval type-2 fuzzy hybrid expert system is proposed for commercial burglary. This method is the combination of Sugeno and Mamdani inference system. After identifying the system domain, the inputs and output of the system are determined. Then the k-nearest neighborhood functional dependency approach is used to select the most important variables for the system. The indirect approach is used to fuzzy system modeling by implementing the Kwon validity index for determining the number of rules in the fuzzy clustering approach. Next, the output membership values are projected onto the input spaces to generate the membership values of input variables, and the membership functions of inputs and output are tuned. Then, the type-1 fuzzy hybrid system has been implemented. After that, we transformed the type-1 fuzzy hybrid rule base into an interval type-2 fuzzy hybrid rule base for enhancing the robustness of the system. For generating interval type-2 fuzzy hybrid rule base, the Gaussian primary MF with an uncertain standard deviation and a fixed mean is used. In order to validate our method, we developed two system modeling techniques and compared the results with the proposed interval type-2 fuzzy hybrid expert system. These techniques are multiple regression, and type-1 fuzzy expert system. The results of this study show that the proposed interval type-2 fuzzy hybrid expert system has a better performance in comparison to type-1 fuzzy and multiple regression models.

Keywords: Type-2 fuzzy modeling · Interval type-2 fuzzy hybrid system · Commercial burglary

1 Introduction

Stores are first-choice striking targets for burglary and break-in robbery. Although residential burglaries are more than non-residential burglaries, businesses generally suffer higher rates of victimization. The first International Crimes against Business Survey (ICBS), discovered that store burglary rates, comprising attempted burglary, ten times those of households [1]. There is a little research on developing an expert system for burglary specifically on commercial burglary. The crimes related to properties have a remarkable proportion of recorded offending. Residential burglary is an issue that has been researched for many times. Studies of burglary for the cognitive process have been used in property selection at the scene of the crime [2]. A number of useful American studies of burglary appeared in the 1970s [3]. Specific focus on the burglar's

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targets evaluation at the scene of the crime has appeared in the 1980s. In that decade a valuable database has made up for building studies. Maguire and Bennett interviewed 40 convicted burglars and categorized them by distinguishing between their targets [4]. In this interview, burglars described which targets were attractive and which ones were deterrent. Nee and Taylor experiments showed that burglars selected their targets by evaluating some characteristic like ease, speed, etc. [2].

For commercial burglaries, Gavin Butler interviewed with burglars who were in prison. His goal was establishing why people commit this type of offense and to recognize the type of choices associated in deciding how to perform it, with special reference to security systems [3]. At first, candidates were asked for their viewpoints on location. They could select one of three stores, all belonging to a major high street. They were on a high street, in a shopping mall, and the other was a superstore located in the suburb and on the main road. The results are shown in Table 1 [3]. Table 1 shows that the superstore was the most popular target because it located in the suburb and police stations are in town. For the store on the high street and the shopping mall, because they could have safety employees, high security, and they would be difficult to enter.

Table 1. Choice a store for the purpose of commercial burglary [3]

	Selections	Percent
High street	1	14.3
Shopping mall	1	14.3
Superstore	5	71.4
Total	7	100.0

Expert systems, as a subset of AI, are computer programs that imitate the reasoning process of a human expert [5]. Due to this ability, expert systems have been successfully used for many real-world applications, including modeling, medical diagnosis, scheduling and controlling [6–8]. During the last decade, business owners have come to rely upon various types of intelligent systems to make safety decisions. These models, however, have their own limitations due to the noise and complex dimensionality of data. Therefore, the result may not be convincing. It should be noted that type-2 fuzzy sets can model and minimize the effects of uncertainties in these models. The additional parameters of type-2 fuzzy sets over those in type-1 fuzzy sets provide the former with additional design degrees of freedom that make it possible to minimize the effects of uncertainties [9]. Moreover, the effects of uncertainties can be minimized by optimizing the parameters of the type-2 fuzzy sets during a training process.

The aim of this research is to develop an interval type-2 fuzzy hybrid expert system for commercial burglary. To achieve this objective, this paper proposes an IT2 fuzzy hybrid system, which is the combination of Mamdani and Sugeno methods.

The paper is organized as follows: Sect. 2 reviews the fuzzy sets and systems. Section 3 describes the problem statement of commercial burglary. Section 4 presents the design approach of interval type-2 fuzzy hybrid system. In Sect. 5, the proposed interval type-2 fuzzy hybrid expert system for commercial burglary is developed. In Sect. 6, the evaluation of proposed system is presented. Finally, Sect. 7 concludes the paper with some remarks about the contribution as well as future work possibilities.

2 Fuzzy Systems

Fuzzy set theory was first introduced by Zadeh in 1965. Fuzzy logic systems (FLSs) are well known for their ability to model system uncertainties. A type-1 fuzzy set in the universe X is determined by $\mu_A(x)$ which is a membership function that takes values between [0, 1] [10]:

$$A = \{(x, \mu_A(x)) | x \in X\} \tag{1}$$

In some problems, the vagueness of information is too high to model the problem with type-1 fuzzy sets, so type-2 fuzzy sets are used to model these systems. The type-2 fuzzy theory was introduced by Zadeh as an extension of type-1 fuzzy theory [10]. In type-2 fuzzy sets, each element is represented by two membership functions, which are named primary and secondary membership functions.

Interval-valued type-2 and generalized type-2 fuzzy are two kinds of type-2 fuzziness. Interval-valued type-2 fuzzy is a special type-2 fuzzy, where the upper and lower bounds of membership are crisp and the spread of membership distribution is ignored considering the assumption that membership values between upper and lower values are uniformly distributed (Fig. 1) [11].

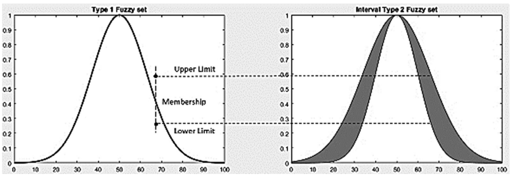

Fig. 1. Type-1 and type-2 fuzzy sets.

A type-2 fuzzy set $\tilde{A}$ can be defined as [11]:

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \mu_{\tilde{A}}(x, u)/(x, u) J_x \subseteq [0, 1] \tag{2}$$

When all $\mu_{\tilde{A}}(x, u)$ are equal to 1, then $\tilde{A}$ is an interval type-2 FLS. The special case of (2) might be defined for the interval type-2 FLSs [11]:

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} 1/(x, u) J_x \subseteq [0, 1] \tag{3}$$

The most important application of fuzzy sets theory is rule-based fuzzy logic systems (FLSs). A rule-based type-2 fuzzy logic system is comprised of four elements: rules, fuzzifier, inference engine and output processor (Defuzzifier and Type reducer) that are inter-connected. The difference between T1 FLS and T2 FLS is in the output processing module. Figure 2, represents the structure of a T2 FLS [11].

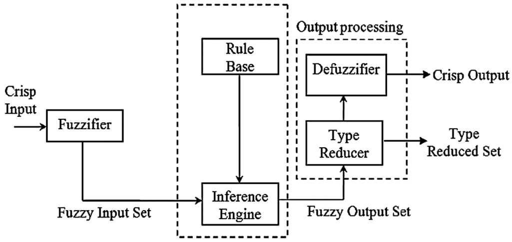

Fig. 2. Type-2 fuzzy logic system [11]

3 Problem Description

Security and protection of properties have been important issues at all times. Stores always have been an attractive target for burglars. Therefore, the owners of these commercial buildings are willing to improve the safety of their properties. In this paper, we have analyzed the safety situation of 120 branches of a chain store in an Asian country which asked its name not to mention in this paper. The goal of this paper is finding the branches which are susceptible to burglary using the type-2 fuzzy hybrid expert system. After finding the susceptible branches, we can enhance their degree of safety. We used 7 inputs and 1 output which are selected by negotiation with the experts. The output is the total value of stolen properties (in thousands of dollars) and the inputs are as follows:

(1) Employee: Number of safety employees in each branch,
(2) The degree of safety: we assigned 1, 2 or 3 for the degree of safety according to safety situations of each region. The safety situations of each region are elicited from police reports,
(3) Safety budget: The annual safety budget which assigned for each branch (in thousands of dollars),
(4) Distance: Distance between each branch and nearest police stations (km),
(5) Sale: Total annual sales (million dollars),
(6) Assets: Total assets for each branch (million dollars),
(7) Customer: Number of customers (in thousands).

4 Designing the Type-2 FLS

There are two very different approaches for selecting the parameters of a type-2 FLS [11]. The first one is the partially dependent approach. In this approach, at first a best possible type-1 FLS is designed and then, used to initialize the parameters of a type-2 FLS. In the second method, all parameters of the type-2 FLS are tuned from scratch without using an existing type-1 design. This approach is totally independent.

One advantage of the first approach is good initialization of the parameters of the type-2 FLS. we need fewer parameters for tuning and smaller search space for each variable since the baseline of type-1 fuzzy sets imposes constraints on the type-2 sets.

Therefore, in this approach, the computational cost is less than the second approach. Moreover, type-2 FLSs designed with the first approach are able to perform better than the corresponding type-1 FLSs [12]. Furthermore, the type-2 FLS has a larger number of degrees of freedom because it is more complex. The additional dimension provided by the type-2 fuzzy set enables a type-2 FLS to produce more complex input–output map without the need to increase the resolution. [13].

This paper is based on the partially dependent approach. After designing type-1 fuzzy system, we introduced a type-2 fuzzy rule base with uncertain standard deviation and interval-valued membership function. This system uses the similar rules of the type-1 FLS and the difference is just that the if-part and then-part are type-2.

The procedures of a development of the proposed system are as follows:

(1) Determination of input and outputs variables of the system.
(2) Feature selection.
(3) Determination of the number of rules and clustering the output space.
(4) Projection of membership values of the output onto the inputs.
(5) Tuning the parameters of the type-1 MFs of the inputs and output variables.
(6) Transforming type-1 fuzzy rule base to interval type-2 fuzzy rule base.
(7) Tuning the parameters of interval type-2 MF of the inputs and output variables.
(8) Performance evaluation.

4.1 Determination of Input and Output Variables

The identification of input and output variables is generally done by studying the domain of a problem and also by negotiation with experts. There are an unbounded number of possible candidates which should be restricted to definite numbers. In this step, the designers and experts attempt to specify the most pertinent input and output variables.

4.2 Feature Selection

Since many pattern recognition techniques were originally not designed to manage large amounts of irrelevant features, using Feature Selection (FS) techniques has become a necessity in many applications. The objectives of feature selection are numerous, the most important ones are: (1) to avoid overfitting (b) to provide cost-effective models and (c) to gain a deeper insight into the underlying processes that generated the data [14]. In this paper, the k-nearest neighborhood functional dependency (KNN-FD) approach proposed by Uncu and Türkşen [15] has been used. This FS algorithm combines features wrapper and feature filter approaches in order to identify the substantial input variables in system with continuous domains. This technique makes use of functional dependency concept, correlation coefficients and K-nearest neighborhood (KNN) method to implement the feature filter and feature wrappers. All of these methods independently pick out the significant input variables and the input variable combination, which yields the best result with respect to their corresponding evaluation function, is selected as the winner [15]. The results of this FS method indicate that all of the input variables are usable and we cannot omit any of them.

4.3 Determination of the Number of Rules and Clustering the Output Space

In the fuzzy clustering algorithms, we should use a cluster validity index to determine the most suitable number of clusters. In this paper, Kwon validity index [16] is used. This index is defined as:

$$V_K(U, V, X) = \frac{\sum_{i=1}^{c} \sum_{j=1}^{N} u_{ij}^2 \|x_j - v_i\|^2 + \frac{1}{c} \sum_{i=1}^{c} \|v_i - \bar{v}\|^2}{\min_{i \neq k} \|v_i - v_k\|^2}, \tag{4}$$

Where $\bar{v} = \frac{\sum_{j=1}^{N} x_j}{N}$. An optimal cluster number is found by solving $\min_{2 \le c \le N-1} V_K$ to produce the best clustering performance for the dataset X. Kwon index is modified to accommodate Mahalanobis distance norm instead of Euclidean one [13]. This cluster validity index is implemented to determine the most suitable number of clusters (rules). The best number of clusters based on this cluster validity index is obtained 3. So, the proposed fuzzy system contains 3 rules.

The proposed system is a combination of Mamdani and Sugeno inferences. In the Sugeno method, the observation is crisp. On the other hand, in Mamdani inference system the antecedents and consequents of the rule-based system are fuzzy sets, and there is no function. So, we clustered the output data and then generated the primary membership grades of the output clusters. For this goal, we used Sugeno and Yasukawa method [17]. We first partition the output space and then obtain the input space clusters by "projecting" the output space partition onto each input variable space, separately. We consider one of the most suitable and traceable fuzzy clustering algorithms, i.e., GK clustering for performing the process of encoding the output space.

4.4 Projection of Membership Functions of Output onto Input Spaces

After clustering the output space, the suitable membership functions should be determined for the input variables. One approach is to set the membership grade of each input equal to its corresponding output membership grade acquired by the output data clustering process [18]. Accordingly, for each output data, all the corresponding input variables will have the similar membership grade. The problem with this method is that the membership functions are not convex and for shaping the convex membership functions, a further approximation is needed. In addition, the output membership grade at each sample point is not necessarily the same as the input membership grades. For these reasons, we have used the proposed approach of Fazel Zarandi [18] for projection of membership functions of output onto input spaces. At first, we determined the interval in which the input membership functions adopt value 1 (i.e. $\overline{S_1 S_2}$ Fig. 3). Next, the optimum value of S_1^* and S_2^* are determined by classifying the data point using GK clustering by given m and c and analyzing the objective function of the classification algorithm. For more details please refer to [13].

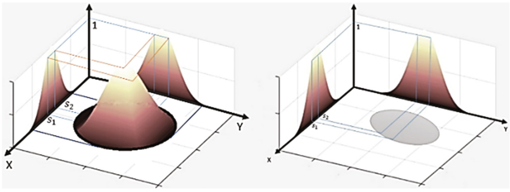

Fig. 3. Projection of output onto the input spaces [18]

4.5 Tuning the Parameters of Type-1 Membership Functions

Type-1 FLSs contain parameters that can either be pre-specified or can be tuned during a training process. Tuning the parameters of the fuzzy model is essential to reach better results. As a matter of fact, as Liang and Mendel [19] state, a perfect FLS should have $f(x) = d$, where, d is the desired output, but generally there exist errors between the desired and actual output. Therefore, tuning the parameters of the FLS for reducing the system errors is necessary.

In this paper, the proposed tuning algorithm by Liang and Mendel [19] is used. This method tunes all of the parameters related to a Gaussian type-1 FLS and uses a steepest-descent as optimization method. Given an input–output training pair $\left(x^{(i)}, y^{(i)}\right), x^{(i)} \in R^G$ and $y^{(i)} \epsilon R$, a type-1 fuzzy is designed so that the following error function is minimized [19]:

$$e(t) = \frac{1}{2}\left[f\left(x^{(i)}\right) - y^{(i)}\right]^2 \quad i = 1, \ldots, N \tag{5}$$

4.6 Transformation Type-1 to Interval Type-2 Membership Functions

For transforming a type-1 fuzzy set to an interval type-2 fuzzy set with uncertain standard deviation, we consider the case of a Gaussian primary membership function having a fixed mean m_f^S and uncertain standard deviation that takes values in $[\sigma_{f_1}^S, \sigma_{f_2}^S]$, [11], i.e.,

$$u_f^S(x_f) = exp\left[-\frac{1}{2}\left(\frac{x_f - m_f^S}{\sigma_f^S}\right)\right], \quad \sigma_f^S \in [\sigma_{f_1}^S, \sigma_{f_2}^S] \tag{6}$$

Where $f = 1, \ldots, G; G$ is a number of antecedents; $S = 1, \ldots, D;$ and D is number of rules. The upper membership function is:

$$\bar{u}_f^s(x_f) = \begin{cases} 1, & x_f = m_f^s \\ N\left(m_f^s, \sigma_{f_2}^s, x_f\right), & otherwise \end{cases} \tag{7}$$

and $N\left(m_f^s, \sigma_{f_2}^s, x_f\right)$ is defined as follows:

$$N\left(m_f^s, \sigma_{f_2}^s, x_f\right) \cong exp\left[-\frac{1}{2}\left(\frac{x_f - m_f^s}{\sigma_{f_2}^s}\right)\right] \tag{8}$$

Finally, the lower membership function is:

$$\underline{u}_f^s(x_f) = \begin{cases} 1, & x_f = m_f^s \\ N\left(m_f^s, \sigma_{f_1}^s, x_f\right), & otherwise \end{cases} \tag{9}$$

4.7 Tuning the Parameters of Interval Type-2 Membership Functions

Tuning the parameters of the interval type-2 FLS is essential for decreasing the system errors. Since $f(x)$ is determined by upper and lower membership functions and centroids of IT2 fuzzy sets, we focus on tuning these parameters which are what we mean by tuning IT2 FLS [19]. We used the proposed tuning algorithm by Liang and Mendel [19] for tuning all of the parameters related to the Gaussian IT2 FLS. Since an interval type-2 FLS can be characterized by two fuzzy basis function expansions, we can focus on tuning the parameters of just these two type-1 FLSs.

5 The Proposed IT2 Fuzzy Hybrid Expert System

In this section, we present a hybrid type-2 fuzzy model for commercial burglary. After identifying the structure of the problem, a hybrid reasoning method is developed. This method is a combination of Mamdani and Sugeno inference. Furthermore, the antecedents of hybrid reasoning method are interval type-2 fuzzy sets. We create an interval type-2 FLS from the type-1 FLS. The hybrid interval type-2 FLS uses singleton fuzzification, product t-norm, product inference, and center-of-sets type-reduction. It also uses the same number of fuzzy sets and the same rules as the type-1 FLS. The only difference now is that the antecedent and consequent sets (Only in Mamdani inference) are type-2 which has a fixed mean and an uncertain standard deviation that takes on values in an interval, i.e., [11].

While in Mamdani inference system the antecedents and consequents of the rule-based system are fuzzy sets, in TSK inference method, consequents are functions. Therefore, in TSK system, we have used Fazel Zarandi et al. [9] approach for determining the consequents of type-1 TSK fuzzy system.

The defuzzification step in Mamdani method is done at the end of inference, whereas in TSK there is no defuzzification step. We use some defuzzification methods such as centroid, bisector, mom and Yager for a custom operation. The best result of this system is obtained by Yager defuzzification method. In TSK system, the model output of each rule is aggregated by taking the weighted average of the output of each rule for upper and lower bound in the fuzzy rule base. This step is used separately for upper and lower membership functions for TSK system. After finding the output of each inference, the final output of the model is obtained by combining the outputs of TSK and Mamdani systems as follow:

$$Out_{final} = \beta \times Out_{Sugeno} + (1 - \beta) \times Out_{Mamdani} \tag{10}$$

Where $\beta \in [0, 1]$. We have used the Gradient descent method for tuning this parameter. The best result of proposed system is obtained by $\beta = 0.43$.

In this research 120 data points have been selected which 96 data points are used for generating rules and the rest for testing the model. Figure 4, shows the rule base and inference mechanism for the proposed IT2F hybrid system, where the value of stolen property is the output of the model. Table 2 shows the antecedent parameters of interval type- 2 fuzzy hybrid expert system. In this table, $\bar{v}_{11}$, $\bar{\sigma}_{11}$ and $\underline{\sigma}_{11}$ are the fixed mean, upper bound standard deviation and lower bound standard deviation, respectively. Table 3 demonstrates the consequent parameters of the TSK and the Mamdani system after tuning.

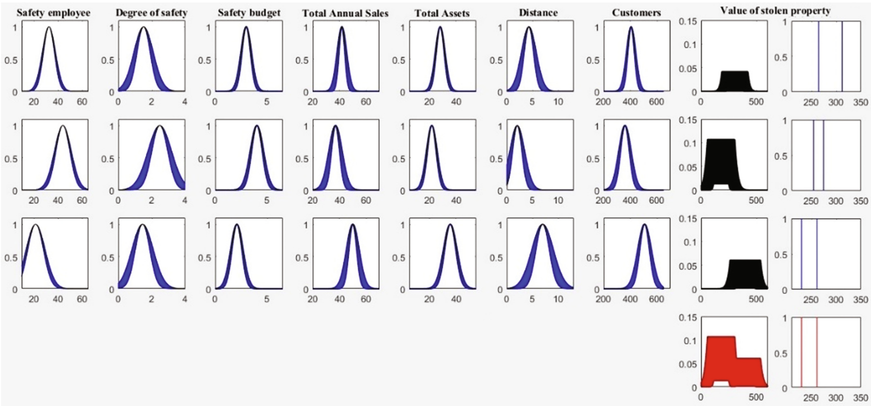

Fig. 4. The hybrid interval type-2 rule base

Table 2. The consequent parameters of the TSK and the Mamdani system after tuning.

Rules	Mamdani	TSK			
Rule 1	$\bar{v}_{1c} = 303.61$	$a_{11} = -2.28$	$a_{12} = -29.87$	$a_{13} = -22.25$	$a_{14} = 0.48$
	$\bar{\sigma}_{1c} = 46.26$	$a_{15} = 1.03$	$a_{16} = 9.47$	$a_{17} = 0.08$	$b_1 = 324.37$
	$\underline{\sigma}_{1c} = 18.51$				
Rule 2	$\bar{v}_{2c} = 180.17$	$a_{21} = -2.07$	$a_{22} = -29.65$	$a_{23} = -22.03$	$a_{24} = 0.37$
	$\bar{\sigma}_{2c} = 58.01$	$a_{25} = 1.01$	$a_{26} = 9.38$	$a_{27} = 0.06$	$b_2 = 315.10$
	$\underline{\sigma}_{2c} = 23.20$				
Rule 3	$\bar{v}_{3c} = 397.29$	$a_{31} = -2.37$	$a_{32} = -30.84$	$a_{33} = -22.57$	$a_{34} = 0.64$
	$\bar{\sigma}_{3c} = 57.78$	$a_{35} = 1.23$	$a_{36} = 9.73$	$a_{37} = 0.23$	$b_3 = 355.46$
	$\underline{\sigma}_{3c} = 23.11$				

Table 3. The antecedent parameters of the system after tuning

Rules	Membership function parameters						
Rule 1	$\bar{v}_{11} = 32.46$	$\bar{v}_{12} = 1.51$	$\bar{v}_{13} = 2.98$	$\bar{v}_{14} = 41.89$	$\bar{v}_{15} = 28.06$	$\bar{v}_{16} = 4.28$	$\bar{v}_{17} = 405.86$
	$\bar{\sigma}_{11} = 5.49$	$\bar{\sigma}_{12} = 0.58$	$\bar{\sigma}_{13} = 0.51$	$\bar{\sigma}_{14} = 3.59$	$\bar{\sigma}_{15} = 3.67$	$\bar{\sigma}_{16} = 1.46$	$\bar{\sigma}_{17} = 34.71$
	$\underline{\sigma}_{11} = 4.39$	$\underline{\sigma}_{12} = 0.38$	$\underline{\sigma}_{13} = 0.43$	$\underline{\sigma}_{14} = 2.15$	$\underline{\sigma}_{15} = 2.93$	$\underline{\sigma}_{16} = 0.87$	$\underline{\sigma}_{17} = 24.29$
Rule 2	$\bar{v}_{21} = 43.92$	$\bar{v}_{22} = 2.47$	$\bar{v}_{23} = 4.01$	$\bar{v}_{24} = 37.12$	$\bar{v}_{25} = 21.87$	$\bar{v}_{26} = 2.02$	$\bar{v}_{27} = 359.85$
	$\bar{\sigma}_{21} = 7.01$	$\bar{\sigma}_{22} = 0.71$	$\bar{\sigma}_{23} = 0.65$	$\bar{\sigma}_{24} = 3.59$	$\bar{\sigma}_{25} = 4.02$	$\bar{\sigma}_{26} = 1.46$	$\bar{\sigma}_{27} = 46.56$
	$\underline{\sigma}_{21} = 5.60$	$\underline{\sigma}_{22} = 0.46$	$\underline{\sigma}_{23} = 0.51$	$\underline{\sigma}_{24} = 2.15$	$\underline{\sigma}_{25} = 3.22$	$\underline{\sigma}_{26} = 0.87$	$\underline{\sigma}_{27} = 32.59$
Rule 3	$\bar{v}_{31} = 21.51$	$\bar{v}_{32} = 1.44$	$\bar{v}_{33} = 2.09$	$\bar{v}_{34} = 50.05$	$\bar{v}_{35} = 35.57$	$\bar{v}_{36} = 6.96$	$\bar{v}_{37} = 506.58$
	$\bar{\sigma}_{31} = 7.92$	$\bar{\sigma}_{32} = 0.65$	$\bar{\sigma}_{33} = 0.61$	$\bar{\sigma}_{34} = 4.82$	$\bar{\sigma}_{35} = 5.16$	$\bar{\sigma}_{36} = 2.12$	$\bar{\sigma}_{37} = 51.63$
	$\underline{\sigma}_{31} = 6.34$	$\underline{\sigma}_{32} = 0.42$	$\underline{\sigma}_{33} = 0.47$	$\underline{\sigma}_{34} = 2.89$	$\underline{\sigma}_{35} = 4.13$	$\underline{\sigma}_{36} = 1.27$	$\underline{\sigma}_{37} = 36.14$

6 Performance Evaluation

For evaluating the performance of the proposed system, the entire dataset is divided into two sets (training and test dataset). The training set consists of 96 samples. The test set contains 24 samples. These samples are used to check the performance of the proposed system. Moreover, for validation of the system, we compared our model's result with the result of multiple regressions model and T1 fuzzy model. We have used Minitab for analyzing the regression model. The regression model is as follows:

$$y = 344.36 - 2.34x_1 - 30.05x_2 - 22.45x_3 + 0.57x_4 + 1.17x_5 + 9.62x_6 + 0.11x_7 \quad (11)$$

The comparison of our proposed model with multiple regression approaches and type-1 fuzzy model is shown in Table 4. We used the Root Mean Square Error (RMSE) criteria. Where:

$$RMSE = 2\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y_i^*)^2} \quad (12)$$

Results show that our proposed IT2F hybrid expert system has less error and high accuracy than other methods.

Table 4. Root mean square error of the systems

Systems	Multiple regression	Type-1 fuzzy model	Proposed model
RMSE	0.055	0.081	0.049

7 Conclusion

In this paper, an interval type-2 fuzzy hybrid rule-based expert system is developed for commercial burglary. The proposed system is the combination of Sugeno and Mamdani inference system. This model is tested on a chain store in an Asian country. The experimental tests reveal that the model successfully estimates the value of stolen properties for each branch. We developed a multiple regression, and type-1 fuzzy system and compared their results with the proposed system. We concluded the proposed IT2 fuzzy hybrid expert system has a better performance in comparison to type-1 and multiple regression models. For future works, this method in general type-2 fuzzy hybrid expert system can be considered.

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