Grey Relational Analysis and Support Vector Regression for Crime Rates Forecasting with Economic Indicators

Razana Alwee, Siti Mariyam Hj Shamsuddin, Roselina Sallehuddin

***Abstract*—** Crime rates forecasting is an important area in the field of criminology. Linear models, such as regression and econometric models are commonly applied in crime rates forecasting. Due to the complexity of econometric models, time series method has been considered as a promising alternative tool for crime rates forecasting. Crime rates forecasting with economic indicators requires the use of annual data, which is often insufficient for standard time series methods. In addition, the selection of appropriate economic indicators is also important to ensure the accuracy of the forecasting results. Therefore, a forecasting model with features selection that is robust for small training data is needed to improve the performance of the crime rates forecasting. Hence, this study proposes the use of grey relational analysis and support vector regression in crime rates forecasting. Grey relational analysis is used to select the best data series to represent each economic indicator and to rank the economic indicators according to its importance. After that, the support vector regression is used to select the significant economic indicators and forecast the crime rates. Particle swarm optimization is used to estimate the support vector regression parameters. The proposed method is found to produce better forecasting accuracy as compared to multiple linear regression in forecasting property crime rates.

***Keywords*—**Grey relational analysis, support vector regression, particle swarm optimization, crime forecasting.

I. Introduction

CRIME forecasting is a prime focus in the field of criminology [1]. Research on crime forecasting has increased because of the potential and effectiveness of forecasting in crime prevention programs [2]. Due to this encouraging progress, in 2003, Journal of Forecasting issued a special section on crime forecasting consisting of six papers as well as an introduction to crime forecasting [3]. Crime forecasting model can be developed using multivariate model that involves the use of more than one variable. For example, economic indicators such as unemployment rates, gross domestic product and consumer price index are among the variables that are frequently used in crime forecasting. By including other variables in the model, multivariate models have the ability to forecast new patterns that have never been observed in the past [4].

Normally, annual data are required for forecasting crime rates with economic indicators. This is because crime rates and economic indicators are changed on annual basis. However, the annual crime data are usually insufficient for standard time series methods. Therefore, regression and econometric models are often used by researchers to forecast crime rates with economic indicators. A linear relationship is typically used in regression and econometric models. There are several researchers that used economic indicators in econometric and regression models to forecast crimes. Gross domestic product was used to forecast theft and handling of stolen goods, burglary and robbery [5], consumption and unemployment were used to forecast residential burglary [6], and consumer price index and unemployment rate were employed to forecast homicide, robbery and property crime rates [4]. In addition to the economic indicators, the researchers also used other data such as criminal justice variables and demographic variable [6], the conviction rate and the number of police officers [5], population density, proportion of population aged 17 to 24, and Gini coefficient [4].

Time series forecasting is one of the ongoing active research area. Over the past few decades, there are a lot of research that has been done for the development and enhancement of forecasting models [7]. The application of time series models for crime forecasting is still rare despite being considered as promising alternative to the complex econometric models. Some of the time series methods used by researchers for crime forecasting are ARIMA [8], exponential smoothing [9], and artificial neural network [10]-[12]. However, the time series methods are used to forecast crime level using daily [11], weekly [8] and monthly data [9]-[10],[12], where the data is sufficient. The annual data usually have a small number of observations and is less appropriate to be used with standard time series models that usually require a substantial number of observations. Therefore, in order to forecast crime rates with economic indicators, the time series model that can deal with small data set is needed.

In forecasting, selection of features that are used as input to the forecasting model is very important because it will

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influence the accuracy of the forecasting results. Therefore, for crime rates forecasting with economic indicators, selection of the significant economic indicators is very important to produce accurate model. One of the commonly implemented methods is the statistical correlation analysis. However, statistical correlation analysis frequently requires sufficient data to determine the distribution of data and to ensure statistical significance. In addition, statistical methods also require assumption that data distribution is linear, exponential or logarithmic, and errors are normally distributed with zero means [13]. Grey relation analysis (GRA) is a mathematical method of analysis based on geometry proposed by [14]. Unlike statistical methods, GRA can be applied in any condition without the requirements such as a particular sample size or statistical law [13], [15]-[16]. Thus, GRA is an alternative method that can be applied to identify relationships between economic indicators and crime rates.

Despite the advantages, GRA can only rank the features according to their significance to the crime rates. Therefore, another method is needed to model these features. Artificial neural network (ANN) is a popular and commonly applied method in time series forecasting [7]. However, this method suffers from several problems such as the need for controlling numerous parameters, uncertainty in solution (network weights), and the danger of over fitting. A common practice that involves trial and error process is time consuming and produces uncertain results. ANN also requires sufficient data to produce a good model [17]. Support vector regression (SVR), a nonlinear model to solve regression problems was proposed by [18] in order to overcome the drawbacks of ANN. There are four factors that contributed to the success of SVR which are good generalization, global optimal solution, the ability to handle nonlinear problems, and the sparseness of the solution. This has made SVR very robust with small training data, nonlinear, and high-dimensional problems [19]. Despite the advantages, SVR also has some drawbacks. For example, SVR model parameters must be set correctly as it can affect the regression accuracy. Inappropriate parameters may lead to over-fitting or under-fitting [20]. In order to overcome this problem, researchers use particle swarm optimization (PSO) to estimate the parameters of SVR model [21]-[23]. PSO has the ability to escape from local optima, easy to implement and has fewer parameters to be adjusted [24].

In this study, grey relational analysis (GRA) and support vector regression (SVR) are used to select the significant economic indicators for the crime rates forecasting models. PSO is used to estimate the parameters of SVR model. GRA and SVR are suitable for limited data. First, GRA is used to select the best data series to represent each economic indicator. After that, GRA ranks each economic indicator according to its importance or priority. On the other hand, SVR will choose the optimal economic indicators and forecast the property crime rate. This study uses United State (US) property crime rate. As for the economic indicators, unemployment rates (UR), gross domestic product (GDP), consumer price index (CPI) and consumer sentiment index (CS) are selected.

The remainder of this study is organized as follows. Related work on crimes and economic conditions is first discussed in Section II. In Section III, the grey relational analysis, support vector regression, particle swarm optimization and the proposed method, GRA_PSOSVR are described. Section IV describes the data set and model evaluation. The experimental results are presented in Section V. Finally, a brief conclusion is drawn in Section VI.

II. Related Work on Crimes and Economic Conditions

Economic conditions are often considered to be related to crimes, especially property crimes. In literatures, many studies have been done by researchers in order to relate the economic conditions with crimes. The unemployment rate is often selected by the researchers in their studies to represent the economic conditions [25]. A study using a country level panel data set from Europe found that unemployment has a positive influence on property crimes [26]. Meanwhile, another study based on UK annual regional data has discovered that unemployment is an important explanatory variable for crimes motivated by economic gain [27]. Results produced by some other studies also found significant relationship between unemployment and crimes. Among the findings are motor vehicle theft is significantly associated with the unemployment rate [28], and is also co integrated with male youth unemployment [29]. Another finding shows that unemployment has a positive effect on burglary, car theft and bike theft [30]. Meanwhile, a study in Israel found that unemployment has a relationship with homicide [7].

Unemployment, especially among youth and young adults are also found to influence crimes. According to a study on the United States arrest data, unemployment has a negative relationship with homicides for youth and young adults (16 - 24 years) and a positive relationship to adults (25 years and above). In the case of property crimes, unemployment has a positive relationship with theft crimes among youth and young adults (16 - 24 years) [31]. Another study investigated the relationship between crime with male adult (26 - 64 years) and youth (16 - 25 years) unemployment in Britain [32]. The results indicate that youth unemployment and adult unemployment are both significantly and positively related to burglary, theft, fraud and forgery as well as total crime rates. Male adult unemployment is found to be consistently related to robbery rates.

In addition to unemployment, other economic indicators such as consumer price index, gross domestic product and consumer sentiment index were also studied by the researchers to examine the relationship between economic conditions with crimes. Several researchers used the consumer price index to measure the inflation [33]-[34]. Inflation reduces the purchasing power and increases the cost of living. A study on the impact of inflation rate on crime in the United States using the modified Wald causality test found that the crime rate is co integrated with inflation and unemployment rates [34]. Further, another study which examined the linkages between inflation, unemployment and crime rates in Malaysia revealed that inflation and unemployment are positively related to the crime rate [33]. Meanwhile, for gross domestic product, a study to explain the relationship between national crime rates with social and economic variables has found that robbery and homicide have significant negative relationships with gross domestic product [35]. Whilst, a study on the consumer sentiment index has discovered that the consumer sentiment has significant negative effects on robbery and property crime rates [25].

In summary, economic conditions and their relationship to crimes are undeniable. However, in the literature there are several economic indicators studied by researchers. Researchers use different methods and data which vary the results of the studies. It is difficult to determine which economic indicators have the most influence on the crimes. The purpose of this study is to propose a method for identifying important economic indicators that influence the crime rates. Four economic indicators are considered which are unemployment rate, consumer price index, gross domestic product and consumer sentiment. The important economic indicators that have been identified can be used for forecasting purposes.

III. Methodology

In this section, grey relational analysis (GRA), support vector regression (SVR) and particle swarm optimization (PSO) are explained as a basis for further discussion on the proposed method, GRA_PSOSVR.

A. Grey Relational Analysis

Grey relation analysis (GRA) is an analysis method in Grey system theory which was founded by Professor Deng Julong [14],[36]. This method is based on geometrical mathematics and compliance with the principles of normality, symmetry, entirety and proximity [37]-[38]. GRA is a distinct similarity measurement that uses data series to obtain grey relational order to describe the relationship between the related series [39]. It can be used to measure the correlations between the reference series and other compared series. In this study, the reference series is the property crime rate, while the compared series is the economic indicators (consumer price index, unemployment rate, gross domestic product, and consumer price index). The relative distance between a compared series and the reference series, which is referred to as grey relational grade (GRG) represents the degree of influence between these series. A small distance indicates a significant influence [13]. GRG is a numeric value between 0 and 1. GRG value close to 1 indicates that there is a strong relationship between the two series. The GRA has been applied in a variety of fields such as medical [39]-[40], economic [16], [41]-[43], social [44]-[46] and manufacturing [15],[47]-[48].

The following are the basic steps in GRA [49]:

Step 1: Determine compared series (X_i) and reference series (X_0)

$$X_0 = \{x_0(1), x_0(2), \ldots, x_0(n)\}$$
$$X_i = \{x_i(1), x_i(2), \ldots, x_i(n)\}, \; i = 1,2, \ldots, m$$

Step 2: Use (1) to transform the series to dimensionless form.

$$x_i^*(k) = \frac{x_i(k) - \min_k x_i(k)}{\max_k x_i(k) - \min_k x_i(k)}, \quad i = 1, .., m, k = 1, .., n \quad (1)$$

where n is the number of experimental data items, m is the number of compared series, $x_i(k)$ is the original data series, $x_i^*(k)$ is the dimensionless form of data series, $\min_k x_i(k)$ is the smallest value of $x_i(k)$ and $\max_k x_i(k)$ is the largest value of $x_i(k)$.

Step 3: Use (2) to calculate the grey relational coefficient between X_0 and X_i, which reflects the degree of influence of two compared series at one time.

$$\xi_{0i} = \frac{\min_i \min_k |x_0^*(k) - x_i^*(k)| + \rho \max_i \max_k |x_0^*(k) - x_i^*(k)|}{|x_0^*(k) - x_i^*(k)| + \rho \max\limits_i \max_k |x_0^*(k) - x_i^*(k)|} \quad (2)$$

where $\rho \in (0,1)$, which is called distinguishing coefficient. Generally, $\rho = 0.5$. According to the mathematical proof, the value of ρ does not affect the rank of the grey relational grade [50].

Step 4: Calculate the grey relational grade (GRG), which is the average value of grey relational coefficient using (3),

$$r_{0i} = \frac{1}{n} \sum_{k=1}^{n} \xi_{0i}(k) \quad (3)$$

where r_{0i} represents the level of correlation between the reference series and the compared series. The grey relational order is constructed based on the calculated value of GRG, r_{0i}. Order obtained is a list of priorities in selecting a series closely related to the reference series, X_0. Generally, $r > 0.9$ indicates a marked influence, $r > 0.8$ a relatively marked influence, $r > 0.7$ a noticeable influence, and $r < 0.6$ a negligible influence [37].

B. Support Vector Regression

Support vector regression (SVR) is a nonlinear model to solve regression problems. SVR training process is equivalent to the process of solving the linearly constrained quadratic programming problems that provides a unique optimal value with no local minimum problem. The solution consists sparseness, as only the essential data are used to solve the regression function. Lagrangian multipliers are introduced to solve the quadratic programming problem. The SVR model is given by (4) [51]:

$$f(\mathbf{x}) = (\mathbf{z}.\, \phi(\mathbf{x})) + b \quad (4)$$

where $\mathbf{z}$ is the weight vector, b is the bias value and $\phi(\mathbf{x})$ is the kernel function.

SVR used ε-insensitivity loss function which can be expressed as (5),

$$L_\varepsilon(f(\mathbf{x}) - y) = \begin{cases} |f(\mathbf{x}) - y| - \varepsilon, & \text{if } |f(\mathbf{x}) - y| \geq \varepsilon \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

where ε is the region for ε-insensitivity. Loss is accounted only if the predicted value falls out of the band area. The SVR model can be constructed to minimize the following quadratic programming problem (6),

$$\min: \; \frac{1}{2}\mathbf{z}^T\mathbf{z} + C \sum_i (\xi_i + \xi_i^*)$$
$$\text{subject to} \begin{cases} y_i - \mathbf{z}^T\mathbf{x}_i - b \leq \varepsilon + \xi_i \\ \mathbf{z}^T\mathbf{x}_i + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \quad (6)$$

where i = 1, 2, ..., n is the number of training data, $(\xi_i + \xi_i^*)$ is the empirical risk and $\frac{1}{2}\mathbf{z}^T\mathbf{z}$ is the structure risk preventing over-learning and lack of applied universality, and C is the regularization parameter.

After selecting proper regularization parameter (C), width of band area (ε) and kernel function (K), the optimum of each parameter can be resolved though Lagrange function. The commonly used kernels are linear kernel, polynomial kernel, radial basis function (RBF) or Gaussian kernel and sigmoid kernel. Equation (7), (8), (9), and (10) are the equations for linear kernel, polynomial kernel [20], RBF kernel [52] and sigmoid kernel [53], respectively.

Linear kernel,

$$K(x_i, x_j) = x_i^T x_j \tag{7}$$

Polynomial kernel,

$$K(x_i, x_j) = (1 + x_i . x_j)^d \tag{8}$$

RBF kernel,

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right) \tag{9}$$

Sigmoid kernel,

$$K(x_i, x_j) = \tanh\left[v(x_i, x_j) + \alpha\right] \tag{10}$$

The type of kernel function influences the parameters of SVR kernel. The kernel function and parameters of SVR kernel function should be set properly because it can affect the regression accuracy. Inappropriate parameters may lead to over-fitting or under-fitting [20]. This study uses the RBF kernel function because it is suitable for solving most forecasting problems [22]. The RBF kernel is also effective and has a fast training process [54]. There are three important parameters to be determined for the RBF kernel function [23]:

i. Regularization parameter C
   C is a parameter for determining the tradeoff cost between minimizing training error and minimizing model complexity.
ii. Kernel parameter (γ)
   γ represents the parameter of the RBF kernel function.
iii. The tube size of ε-insensitive loss function (ε)
   ε is the approximation accuracy placed on the training data points.

These parameters must be set correctly, in order to produce accurate estimation model. In this study, the parameters are determined through particle swarm optimization (PSO).

C. Particle Swarm Optimization

Particle swarm optimization (PSO) is one of the stochastic optimization methods introduced by Kennedy and Eberhart in 1995 [55]. This method is based on the natural evolution process which uses swarming strategies in bird flocking and fish schooling. PSO is population-based which consists of particles. Initially, the particles are randomly generated. Each particle has a position and velocity, which represents a potential solution to a problem in D-dimensional space. The position and velocity of ith particle are denoted by $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ and $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$, respectively. While solving the search problem, each particle explores the search space by moving in the previous direction, which is its previous best particle ($p$best) and the best solution for the entire population ($g$best). The velocity and position of each particle are updated by using (11) and (12) respectively [56]-[57].

$$v_{ij}(t+1) = w.v_{ij}(t) + c_1.rand1_{ij}.\left(pbest_{ij}(t) - x_{ij}(t)\right) + c_2.rand2_{ij}.\left(gbest_j(t) - x_{ij}(t)\right) \tag{11}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{12}$$

where $v_{ij}(t)$ is the velocity of ith particle at iteration t, $x_{ij}(t)$ is the position of ith particle at iteration t, j=1, 2,…, D, is the dimension of the search space, w is the inertia weight to balance the global and local search abilities of particles. Suitable selection of inertia weight can balance the global and local search and thus reduce the number of iterations in order to find the optimal solution [58]. c_1 and c_2 are two learning factors which control the influence of the social and cognitive components, rand1_{ij} and rand2_{ij} are two uniform random numbers generated independently within the range of [0, 1], $p\text{best}_{ij}(t)$ is the best previous position yielding the best fitness value for ith particle at iteration t, and $g\text{best}_j$ is the global best particle by all particles at iteration t. After changing the position of the particle, the fitness value of the particle is evaluated. The $p$best and $g$best are updated based on the current position of the particles. As this process is repeated, the whole population evolves toward the optimum solution.

The steps in the implementation of the PSO are as following [59]:

Step 1: Initialize the positions and velocities of all the particles randomly in the D-dimensional search space by uniform probability distribution function.
Step 2: Evaluate the fitness values of the particles.
Step 3: Update $p$best for each particle: if the current fitness value of the particle is better than its $p$best value, set the $p$best equal to the current position of the particle.
Step 4: Update $g$best: if the current fitness value of the particle is better than the $g$best value, then set $g$best equal to the current position of the particle.
Step 5: Update the velocity and position of each particle using (11) and (12), respectively.
Step 6: Repeat steps 2 to 5, until a stopping criteria is met, such as a sufficient good fitness value or maximum number of iterations.

The explanation on how PSO is used to estimate the parameters of SVR model is given in the next section.

D. PSO for SVR parameters estimation (PSOSVR)

There are three parameters to be estimated for the SVR model, C, γ and ε. The ith particle is represented by the three-dimensional vectors, $X_i = (x_{i1}, x_{i2}, x_{i3})$ and $V_i = (v_{i1}, v_{i2}, v_{i3})$, where the first, second and third dimensions of the vectors refer to C, γ and ε, respectively. Fig. 1 and 2 show the architecture of PSOSVR model [60] and the flowchart of PSOSVR, respectively. In this study, PSO is used in conjunction with k-fold cross-validation to reduce the adverse effects of over fitting phenomenon. In k-fold cross-validation, the training data set is randomly divided into k subsets of equal size. The regression function is built with a given set of parameters (C, γ, ε) using the k-1 subsets and the model performance is measured by the one remaining subset (validation data set). Each subset is used once for validation and the process is repeated k times. In this study, root mean squared error (RMSE) is selected to be the performance criterion, and the 5-fold cross-validation is utilized to evaluate the performance of the model [22],[60]. The average of RMSE on the validation set from k trials is used as a measure of fitness. The RMSE is defined as (13).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \quad (13)$$

where n is the number of validation data; y_t is the actual value and $\hat{y}_t$ is the predicted value.

In this study, the population size is set to 10 and the value of c_1, c_2 is set to 2 [22],[60]-[62]. The inertia weight, w is decreased along with the iterations according to (14) [63]-[64].

$$w(iter) = wmax - \frac{wmax - wmin}{itermax} * iter \quad (14)$$

where *iter* is the number of iterations, *wmax* is set to 0.9, *wmin* is set to 0.1 and maximum number of iterations, *itermax* is set to 50. The range of ε is determined based on the value of the data, which is the percentage of the mean of the training output (y_i, i=1, 2, 3, …n). The lower and upper bounds of ε are set as (15)and (16) [52].

$$lower_{bound} = \frac{0.001}{n}\sum_{1}^{n} y_i \quad (15)$$

$$upper_{bound} = \frac{0.15}{n}\sum_{1}^{n} y_i \quad (16)$$

where, y_i is the training output and n is the number of training data. Meanwhile, the range for C and γ are set arbitrarily. The searching ranges for the parameters C, γ and ε are as shown in Table I. PSO algorithm will be run 31 times and the value of parameters that produce the smallest forecasting error on testing data set will be selected as the optimum values for parameters of SVR model.

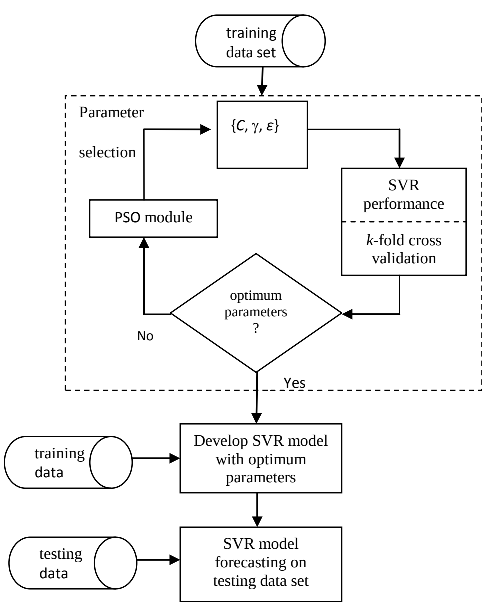

Fig. 1. Architecture of PSOSVR

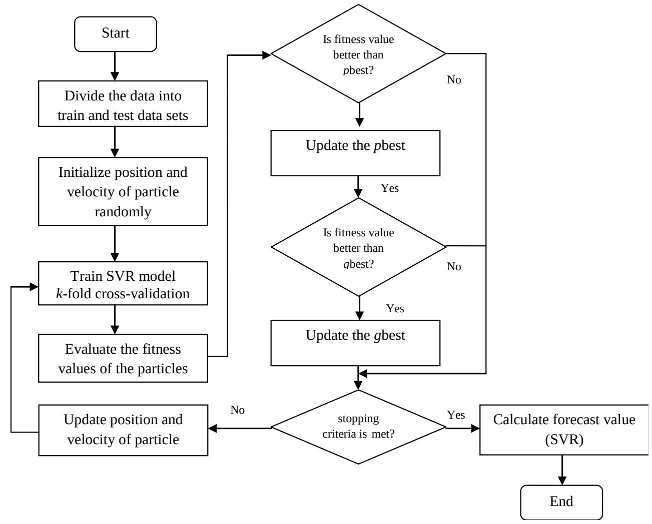

Fig. 2. Flowchart of PSOSVR

TABLE I. THE RANGE FOR C, γ AND ε

SVR parameter	Searching Range
C	2^{-1} - 2^{7}
γ	2^{-4} - 2^{2}
ε	0.0006 - 0.0954

E. The Proposed Method (GRA_PSOSVR)

In this study GRA is used for two purposes. First, it is implemented to determine the best data series to be used as experimental data. The second purpose is to select features in determining the best input features to be used in PSOSVR model, where in this case the features are significant economic indicators. The combination of GRA and PSOSVR is able to reduce the economic indicators that are not important by selecting the significant economic indicators only. The significant economic indicators are chosen based on their ability to enhance the forecasting accuracy and increase the speed of the learning process. Fig. 3 shows the three main steps in the proposed model. The steps are:

Step 1: *Select the best data series to represent the economic indicators*. There are several candidate data series that can be used to represent each economic indicator. However, only one data series is required. For each economic indicator, GRA is used to rank all the candidate data series (compared series). The rank is based on the GRG value. The data series with the greatest GRG value is selected to represent the economic indicator in step 2.

Step 2: *Rank the economic indicators*. In this step, the GRA is used to examine the relationship between each economic indicator and the reference series (property crime rate). The economic indicators (compared series) will be arranged according to their importance to the reference series based on the GRG value.

Step 3: *Select the significant economic indicators*. This step is intended to select the significant economic indicators for property crime rate using PSOSVR model. Fig. 4 shows the flowchart in this step. A different set of economic indicators is used as inputs to the PSOSVR model. Starting with all available economic indicators, the least important economic indicators will be removed one at a time from the list of input. PSOSVR model with the current list of input is trained using the training data set. After that, the model is applied to the test data set to forecast the crime rate. The forecasting error is calculated using four types of quantitative error measurements, namely root mean square error (RMSE), mean square error (MSE), mean absolute percentage error (MAPE), and mean absolute deviation (MAD).

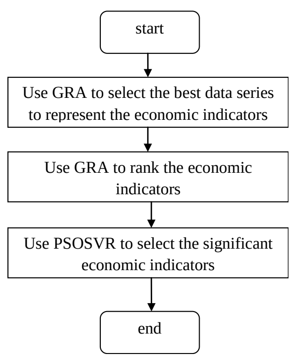

Fig. 3. Flowchart to select the significant economic indicators

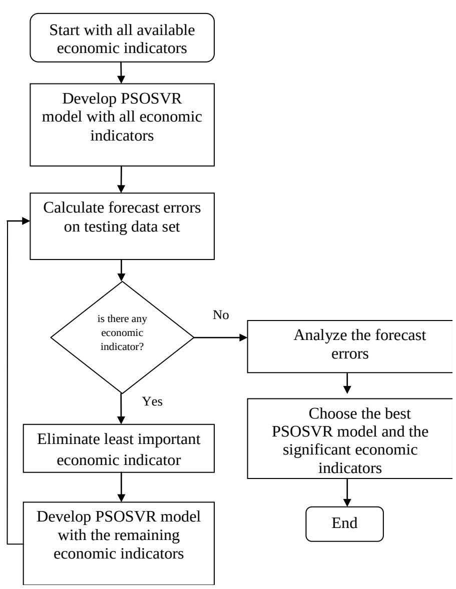

Fig. 4. Flowchart to select the significant economic indicators

After all the necessary PSOSVR models have been developed, the best model is determined based on error measurements, RMSE, MSE, MAPE, and MAD. If the results given by the four error measurements are inconsistent, then MAPE is chosen as a benchmark [65]-[66]. The economic indicators in the list of input for the best model are selected as the significant economic indicators.

IV. Data Set and Model Evaluation

This section describes the data set used and the model evaluation carried out in this study.

A. Data Set

This study uses data of annual property crime rate, consumer price index, gross domestic product, consumer sentiment index and unemployment rate from 1961 to 2009 in United States. In addition to economic indicators, one year lagged selected violent crime rate (robbery rate, murder and nonnegligent manslaughter rate, forcible rape rate or aggravated assault rate) is used as feature in the forecasting model. The crimes data were downloaded from the Uniform Crime Reporting Statistics web site (http://www.ucrdatatool.gov), while economic indicators data were obtained by downloading the data from Economic Research Federal Reserve Bank of St. Louis web site (http://research.stlouisfed.org). There were 30 data series for the unemployment rate, 15 data series for gross domestic product, 16 data series for the consumer price index and two data series for the consumer sentiment index.

The data is then divided into training and testing data set. The training data set is used to develop the PSOSVR model while testing data set is used to evaluate the forecasting performance of the PSOSVR model. In this study, 90 percent of the data will be used for training (1961 to 2004) and 10 percent as testing data set (2005 to 2009).

B. Model Evaluation

The forecasting performance of the proposed method is validated through comparison with a multiple linear regression model (MLR). MLR is a popular linear model in crime forecasting and is often used for multivariate analysis. The performances of both models are evaluated based on the testing data set using four different measurements as follows:

i. Descriptive statistics

Graph of actual values and forecasting of testing data set is plotted in order to see the pattern of model predictions compared to the actual data patterns. A box plot diagram is used to check the forecasting errors. Box plot is used to see the dispersion of error values such as the position of median whether it is close to zero, and to ensure that there are no extreme values in error.

ii. Quantitative error measurements

Four types of quantitative error measurements are conducted, namely root mean square error (RMSE), mean square error (MSE), mean absolute percentage error (MAPE), and mean absolute deviation (MAD). Formula (17), (18), (19), and (20) are the equations for RMSE, MSE, MAPE and MAD, respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \quad (17)$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \quad (18)$$

$$MAPE = \sum_{t=1}^{n}\left|\frac{y_t-\hat{y}_t}{y_t}\right| \times \frac{100}{n} \quad (19)$$

$$MAD = \sum_{t=1}^{n}\frac{|y_t-\hat{y}_t|}{n} \quad (20)$$

where n is the number of testing data, y_t is the actual value and $\hat{y}_t$ is the predicted value.

iii. Paired sample *t*-test

The paired sample *t*-test is performed to prove that there is no significant means difference between the forecasting values and the actual data. Two hypotheses to be defined are the null hypothesis (H_0) and the alternative hypothesis (H_1). Let $\mu_1$represents the mean of actual data, μ_2 is the mean of forecasting values of the forecasting model and $(\mu_1 - \mu_2 = \mu_D)$ is the difference of means. The hypothesis,

$H_0 : \mu_D = 0$

$H_1 : \mu_D \neq 0$

The test statistic is shown by (21), in which student t is distributed with $n_D - 1$ degrees of freedom.

$$t = \frac{\bar{y}_D - \mu_D}{s_D/\sqrt{n_D}} \quad (21)$$

where $\bar{y}_D$ is a sample mean difference, s_D is a sample standard deviation of the difference, and n_D is a sample size. The mean of forecasting values is equal to the mean of actual values, if the hypothesis test fails to reject the null hypothesis. It indicates that the model is appropriate to be used as forecasting model since it represents the real situation.

iv. Chi-square goodness-of-fit test

The chi-square goodness-of-fit test is carried out to ensure that the forecasting values are distributed according to the actual data of property crime rates. The hypothesis are,

H_0 : the forecasting value conforms to the distribution of the actual data

H_1 : the forecasting value does not conforms

The test statistic is given by (22),

$$\chi_0^2 = \sum_{i=1}^{k}\frac{(F_i - E_i)^2}{E_i} \quad (22)$$

where F_i and E_i are the forecasting value and the actual value at time i, respectively. The null hypothesis is rejected if the calculated χ_0^2 is greater than the critical value, $\chi^2_{\alpha,k-s-1}$, where α is the level of significant and k-s-1 is degree of freedom. s is the number of parameters of the hypothesized distribution estimated by the sample statistics. Here, s=0, since no parameter is estimated from the data.

V. RESULT AND DISCUSSION

In this study, four economic indicators have been used to develop forecasting model for property crime rate. In the first stage, GRA functionality is to find the best data series to be employed. Table II and III show top ranked ten unemployment and gross domestic product data series relationship with property crime rate, respectively. The unemployment rate for 20 to 24 years data series is the chosen data series to represent unemployment rate. This result is consistent with the findings by [31] in such that young adult unemployment has a relationship with theft (property crime). As for the gross domestic product, grey relational grade of these data series are not much different, so any of these data series can be selected to represent the gross domestic product. Real gross domestic product is used in previous study [5]. However, this study selects the data series with the largest GRG value. Gross domestic product in United States natural log of billions of chained 2005 US dollars has the highest GRG value and is chosen to represent gross domestic product.

Table IV shows the top ten consumer price index data series relationship with property crime rate. The CPI for all urban consumer apparel data series is chosen to represent consumer price index for property crime rate. Previous studies used the percentage of change in the annual consumer price index [4] and consumer price index in the United States [34]. Consumer price index in the United States is ranked sixth with the GRG value of 0.603. This study found that the CPI for all urban consumers-apparel is more influential to the property crime as compared with other data series for the consumer price index. Youths and young adults (16 - 24 years) are those who often keep up to date with the latest fashions and apparels. These groups of people are often labeled as to be likely to commit crimes [28] due to unemployment but possessed greater desires and needs for the latest apparel, which may lead them to commit crimes, especially property crime.

TABLE II. THE RANK OF UNEMPLOYMENT DATA SERIES

Data Series	GRG	Rank
Unemployment Rate - 20 to 24 years	0.634	1
Unemployment Rate - 20 to 24 years, Men	0.625	2
Unemployment Rate - 20 to 24 years, Women	0.621	3
Unemployment Rate - 16 to 19 years, Women	0.614	4
Natural Rate of Unemployment	0.609	5
Unemployment Rate - 25 to 34 years	0.6051	6
Unemployment Rate - 25 to 34 years, Women	0.6038	7
Unemployment Rate - Women	0.6033	8
Unemployment Rate - 25 years and over	0.6004	9
Unemployment Rate - Men	0.6000	10

TABLE III. THE RANK OF GROSS DOMESTIC PRODUCT DATA SERIES

Data Series	GRG	Rank
GDP in United States Natural Log of Billions of Chained 2005 US Dollars	0.686	1
Real GDP-Natural Log of Billions of Chained 2005 Dollars	0.685	2
GDP- Natural Log of Billions of Dollars	0.683	3
Current Price GDP in United States Natural Log of Billions of United States Dollars	0.683	4
Gross Domestic Purchases Natural Log of Billions of Dollars	0.682	5
Nominal Potential GDP Natural Log of Billions of Dollars	0.681	6
GDP: Chain-type Price Index Natural Log of Index 2005=100	0.681	7
GDP: Chain-type Price Index	0.627	8
GDP in United States	0.617	9
Real GDP	0.617	10

TABLE IV. THE RANK OF CONSUMER PRICE INDEX DATA SERIES

Data Series	GRG	Rank
CPI for All Urban Consumers: Apparel	0.662	1
CPI for All Urban Consumers: Commodities	0.622	2
CPI for All Urban Consumers: Transportation	0.613	3
CPI for All Urban Consumers: Food	0.605	4
CPI for All Urban Consumers: All Items	0.603	5
CPI in the United States	0.603	6
CPI for All Urban Consumers: All Items Less Food & Energy	0.602	7
CPI for All Urban Consumers: Alcoholic beverages	0.596	8
CPI for All Urban Consumers: Services	0.592	9
CPI for All Urban Consumers: Shelter	0.592	10

Table V shows the rank of consumer sentiment index data series relationship with property crime rate. There is only a little difference in the GRG values between the data series. University of Michigan Consumer Sentiment- Natural Log of Index 1st Quarter 1966=100 data series is selected to represent consumer sentiment. Previous researcher used the annualized index of consumer sentiment (1966 = 100) values as their measure of consumer sentiment [25].

TABLE V. THE RANK OF CONSUMER SENTIMENT INDEX DATA SERIES

Data Series	GRG	Rank
University of Michigan: Consumer Sentiment- Natural Log of Index 1st Quarter 1966=100	0.626	1
University of Michigan: Consumer Sentiment- Index 1st Quarter 1966=100	0.624	2

In the second stage, GRA is used as features selection to remove the irrelevant economic indicators. Table VI shows the rank of economic indicators based on GRG. The GRG for gross domestic product and unemployment rate are similar to three decimal places which is 0.675. This indicates that both indicators have the same level of priority. Since they have the highest GRG values, it implies that both of them are most significant factors. Whereas the GRG obtained for the consumer sentiment index (CS) is 0.623 which is relatively low as compared to other economic indicators. Therefore, it can be concluded that, by comparing to other economic indicators, the consumer sentiment index is the least influencing economic indicators for the property crime rate.

TABLE VI. THE RANK OF ECONOMIC INDICATORS

Data Series	GRG	Rank
Gross Domestic Product	0.675	1
Unemployment Rate	0.675	2
Consumer Price Index	0.664	3
Consumer Sentiment Index	0.623	4

In order to select the significant economic indicators, crime forecasting models have been developed using PSOSVR model. In addition to economic indicators, two crime indicators are also used in the forecasting models. One year lagged of property crime rate and one year lagged of selected violent crime are employed. One year lagged is to allow crime rates to change according to the patterns of criminal behavior. The one year lagged crime rate has a positive effect on the change in current crime trend [4]. The selection of one year lagged of violent crime is based on GRA as shown in Table VII. Table VII shows that the robbery rate has the highest GRG value, 0.743. Therefore, the robbery rate was selected to represent the one-year lagged of violent crime in forecasting model. Robbery is a violent crime which is motivated by economic gain. Perhaps that is the reason why robbery is more influential to property crime rate as compared to other violent crimes.

TABLE VII. THE RANK OF ONE-YEAR LAGGED OF VIOLENT CRIMES

Data Series	GRG	Rank
Robbery rate	0.743	1
Murder and nonnegligent manslaughter rate	0.673	2
Violent Crime rate	0.653	3
Forcible rape rate	0.643	4
Aggravated assault rate	0.579	5

There are five models with a different set of economic indicators developed for property crime rate. Table VIII shows the RMSE, MSE, MAPE and MAD for property crime rate models. The minimum errors are obtained from the model with three economic indicators, namely consumer price index, gross domestic product, and unemployment rate. The SVR parameters (C, σ, ε)=(38.4363, 0.0625, 0.0062). Therefore, consumer price index, gross domestic product, and unemployment rate are selected as significant economic indicators for property crime rate.

The proposed method, GRA_PSOSVR is compared with MLR to evaluate its forecasting performance. Table IV shows the difference across significant economic indicators selected by the MLR model and GRA_PSOSVR. For the MLR model, the significant economic indicators are consumer sentiment index, unemployment rate and consumer price index. The economic indicators selected by the MLR and the GRA_PSOSVR are different because both models differ in term of relationship existing among the data. For example MLR has linear relationship while GRA_PSOSVR has nonlinear relationships.

TABLE VIII. THE PERFORMANCE OF PSOSVR MODELS

Economic Indicators	RMSE	MSE	MAPE	MAD
Consumer price index, Gross domestic product, Unemployment rate, Consumer sentiment index	261.76	68518.96	7.26	231.16
Consumer price index, Gross domestic product, Unemployment rate	**22.93**	**525.68**	**0.50**	**15.68**
Gross domestic product, Unemployment rate	28.20	795.38	0.66	20.66
Gross domestic product	58.39	3409.84	1.07	33.18
No economic indicator	168.43	28367.78	4.87	155.75

TABLE IX. SELECTED SIGNIFICANT ECONOMIC INDICATORS BY MLR AND GRA_PSOSVR

Method	Economic Indicators
MLR	Consumer sentiment index, Unemployment rate, Consumer price index
GRA_PSOSVR	Consumer price index, Gross domestic product, Unemployment rate

Table X and Fig. 5 show the comparative values between the actual values and forecasted values of property crime rate. The predicted values obtained from GRA_PSOSVR are closer to the actual value and have a similar pattern with the actual data in comparison to MLR. Fig. 6 shows box plot of forecast errors. Based on the box plot, GRA_PSOSVR model was found to have smaller forecast errors than MLR with a median closer to zero.

TABLE X. COMPARISON OF ACTUAL VALUE AND FORECAST VALUE OF PROPERTY CRIME RATES

Year	Actual value	GRA_PSOSVR	MRL
2005	3431.5	3439.569	3494.5
2006	3334.5	3347.165	3336.1
2007	3263.5	3257.103	3246.4
2008	3211.5	3208.763	3383.9
2009	3036.1	3084.623	3078.1

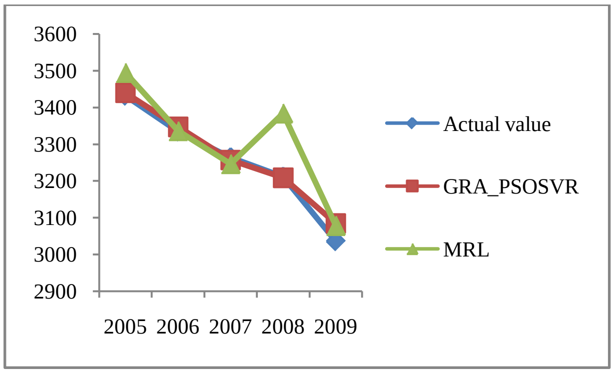

Fig. 5. Forecasting of Testing Data Set

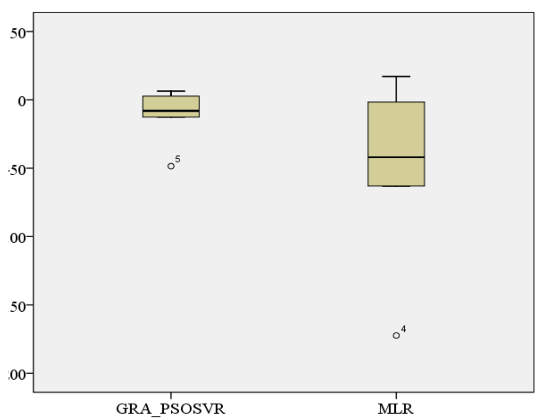

Fig. 6. Forecasting of Test Data Set

Paired sample *t*-test is used to compare the actual data of property crime rate with the forecast values of the proposed model, GRA_PSOSVR, and MLR. The test is conducted to ensure that there is no statistically significant difference of means between the actual data and the forecast values from the forecasting models. Table XI shows the paired samples correlations of paired samples *t*-test. The correlation between actual values and forecast values of GRA_PSOSVR is 0.992, which is highly correlated and higher than the correlation between actual values and forecasted values of MLR. This result indicates that GRA_PSOSVR represents the actual data better than MLR. Meanwhile, Table XII shows the results of paired samples *t*-test. The results show that between the actual data and the forecasted values from the forecasting models, the *P-value* > 0.05 (0.285 and 0.190). The difference between the upper and lower value for 95% interval is ranging between negatives and positives values. This result indicates that the hypothesis test fails to reject the null hypothesis which implies that there is no statistically significant difference of means between the actual data of property crime rates and the forecasted values. However, GRA_PSOSVR shows smaller mean, standard deviation and standard error mean as compared to MLR.

Table XIII summarized the results obtained from the chi-square test. H_0 is not rejected, since the calculated χ_0^2 for GRA_PSOSVR is less than the critical value, $\chi_{0.05,4}^2$ (0.86 < 9.49), when the value of α=0.05. The result indicates that the forecasted values from GRA_PSOSVR are conformed to the distribution of the actual data. However, for MLR, H_0 is rejected due to the calculated χ_0^2 (11.6) is greater than $\chi_{0.05,4}^2$ (9.49) which means that the forecasted values from MLR are not fitted to the actual data. In addition, RMSE, MSE, MAPE and MAD by GRA_PSOSVR for property crime rate model are found to be smaller than MLR as shown in Table XIV. Therefore, the assumption that can be made is that GRA_PSOSVR is able to give better forecasting performance in comparison to MLR.

Based on the model evaluation that has been carried out, we can conclude that the proposed method, GRA_PSOSVR is suitable to be employed in crime rates forecasting with economic indicators because it has better forecasting performance as compared to MLR. The optimal parameters are very important for the accuracy of SVR models. The use of PSO has facilitated the searching process for the optimal parameters of SVR model. MLR only identifies features based on a linear relationship, but the GRA_PSOSVR is able to identify important features based on non-linear relationships in the data. The features selection based on non-linear relationship has been able to produce forecast model with better accuracy.

TABLE XI. PAIRED SAMPLES CORRELATIONS

Pair	Correlation	Sig.
1	0.992	0.001
2	0.883	0.047

(Legend: Pair 1: Actual data and GRA_PSOSVR; Pair 2: Actual data and MLR)

TABLE XII. PAIRED SAMPLES TEST

Pair	Paired Differences					
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference: Lower	Upper	Sig.(2-tailed)
1	-12.02	21.8	9.96	-39.12	15.08	0.285
2	-52.38	74.2	33.19	-144.5	39.8	0.190

(Legend: Pair 1: Actual data and GRA_PSOSVR; Pair 2: Actual data and MLR)

TABLE XIII. CHI-SQUARE TEST

Model	Calculated Value χ_0^2	Critical Value, $\chi_{0.05,4}^2$	Decision
GRA_PSOSVR	0.86	9.49	Do not reject H_0
MLR	11.08	9.49	Reject H_0

TABLE XIV. COMPARISON OF ERRORS

Model	**RMSE**	**MSE**	**MAPE**	**MAD**
MLR	84.55	7148.96	1.83	59.22
GRA_PSOSVR	22.93	525.68	0.50	15.68

VI. CONCLUSION

This paper has presented the use of GRA and SVR in the selection of economic indicators to forecast the property crime rates. PSO is used to estimate the SVR parameters. The proposed method, GRA_PSOSVR is used to identify and obtain the significant economic indicators for the property crime rates. The rank of each economic indicator on the crime rates can be obtained using GRA. PSOSVR is used to select the significant economic indicators and to forecast the crime rates. Gross domestic product is the economic indicator that has the strongest relationship with property crime rate, followed by unemployment rate, consumer price index and consumer sentiment index. The significant economic indicators for property crime rate are gross domestic product, unemployment rate, and consumer price index. The GRA_PSOSVR also shows a better forecasting performance than MLR. Even though this study only focuses on the economic indicators, the GRA_PSOSVR can also be used to study other indicators that may have relationships with crime, such as demographic and social indicators. In conclusion, GRA_PSOSVR can be used as alternative method that is suitable to be applied in the crime rates forecasting.

ACKNOWLEDGMENT

This work is supported by Universiti Teknologi Malaysia under GUP (Vote No. Q.J130000.2628.08J02). Authors would like to thank Research Management Centre (RMC) Universiti Teknologi Malaysia, for the research activities and *Soft Computing Research Group* (SCRG) for the support and motivation in making this study a success.

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