

Long-term Business Cycle Forecasting Using Intuitionistic Fuzzy Least-squares Support Vector Regression

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Abstract—Long-term business cycle forecasting is a very important issue in economic evaluation. This study presents a novel intuitionistic fuzzy least-squares support vector regression (IFLS-SVR) model for accurately forecasting long-term index of business cycle. Traditional support vector regression (SVR) and least-squares support vector regressions (LS-SVR) have been successfully applied in forecasting problems especially complex/nonlinear system. In this paper, the prediction model adopts two least-squares support vector regressions with intuitionistic fuzzy sets to approach fuzzy upper and lower bounds respectively, and then approach the crisp predict values. Genetic algorithms (GAs) are also employed in order to select two parameters of IFLS-SVR models. In this study, IFLS-SVR, LS-SVR and SVR are employed for the Taiwan business index forecasting. Empirical results indicate that the IFLS-SVR has better performance in terms of forecasting accuracy. Therefore, the IFLS-SVR model can efficiently provide credible long-term prediction for the Taiwan business index forecasting

Keywords- long-term business cycle forecasting; intuitionistic fuzzy support vector regression; support vector regression; least-squares support vector regressions

I. INTRODUCTION

Accuracy forecasting long-term business cycle is an important issue in economic research. Business cycle is often determined by a panel of macroeconomic experts from analyzing movements in the set of components making up the Commerce Department's coincident variables of economic activity. Index of business cycle can be easily observes that has nonregular business cycle in past serial time, and index of business cycle belongs nonlinear data set especially in Taiwan. For accuracy measuring/forecasting, stochastic/statistics method is usually employed to analysis business cycle. Many researches have devoted to study of business cycle ([17], [18], [4], [32], [33], [27], and [20]). However, it is difficult to predict the business cycle with time serial, and many researches forecast short-term index of business cycle for reducing complexity. The difficulty derives from assumptions made by the probability distributions and a lack of adequate business

cycle models for long-term prediction. Moreover, in real world information usually belongs vague, uncertain, imprecise and incomplete. In Taiwan the index of business cycle is composed of nine exogenous variables. This may make the index of business cycle exist some uncertain factors. Hence, to overcome the problem intuitionistic fuzzy sets (IFSs) and generalization of fuzzy interval data is employed to represent Taiwan business cycle which uses five lights/intervals to represent different economic actives. In order to handle the uncertain situation and insufficient vague information, a concept IFSs developed by [1] is introduced in this paper. The fundamental characteristics of IFSs are that the values of its membership function and non-membership vague values rather than exact numbers. Therefore, it could be used to simulate any activities and process requiring human expertise and knowledge, which are inevitably imprecise values.

In this paper, we discuss multivariate fuzzy nonlinear regression by support vector regression (SVR). SVR [30] has been extended so as to solve forecasting problems and has provided many exciting results especially nonlinear regression and time series problems with the introduction of Vapnik's ϵ -insensitive loss function. Unlike most of the traditional technology SVR implement neural network models, and SVR adopts the structural risk minimization principle which seeks to minimize an upper bound of the generalization error rather than minimize the training error. In recent years, SVR schemes have been extended to cope with forecasting problems, and have provided many promising results in customer demand [19], finance ([29], [16], and [14]) intermittent demand [13], tourism demand [25], air quality ([22] and [21]), wind speed [24], plant control systems [31], rainfall [12], prices for the electricity market [8] and flood control [35]. Furthermore, for representing fuzzy data the support vector fuzzy regression machines have been proposed by[11]. This method modified the principle of SVR which changes convex optimization problems to multivariate fuzzy linear regression models. And the support vector interval regression networks (SVIRNs) are proposed by [15] which can efficiently handle interval output data. Yao and Yu [34] develop a fuzzy regression based on asymmetric support vector machines which extend the support vector fuzzy regression machines. Chuang [7] extended SVIRNs develops

interval support vector interval regression networks (ISVIRNs) which can handle interval input/output data. Hao and Chiang [9] develops a fuzzy regression analysis by support vector learning. In this paper we proposed a novel IFLS-SVR to forecast index of business cycle. Our proposed method find upper and lower bound by LS-SVR respectively, and use intuitionistic fuzzy sets technology to approach training data. Our proposed method can get benefit LS-SVR. In addition to our method adopts genetic algorithms (GAs) to search optimal parameters of LS-SVR. This make our method can obtain better performance.

II. RELATED WORKS

A. IFSs Theroy

Fuzzy sets theory, proposed by Zadeh [36], has shown successful applications in various fields. In this theory, the membership of an element to a fuzzy set is a single value between zero and one. But in reality, it may not always be certain that the degree of non-membership of an element to a fuzzy set is just equal to 1 minus the degree of membership, i.e. there may be some hesitation degree. Thus, as a generalization of fuzzy sets, the concept of IFSs was introduced by [1]. Bustince and Burillo [6] showed that this notion coincides with the notion of vague sets (VSs).

The IFSs is as an extension of fuzzy sets. An IFSs A in a fixed set E is an objective with the expression

$$A = \{ \langle x, \mu_A(x), \nu_A(x) \rangle | x \in E \}, \quad (1)$$

where the functions $\mu_A : E \rightarrow [0,1]$ and $\nu_A : E \rightarrow [0,1]$ denote the degree of membership and the degree of non-membership of the element $x \in E$, respectively. For every $x \in E$,

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1 \quad (2)$$

when $\mu_A(x) + \nu_A(x) = 1$, for every $x \in E$, then the IFSs will degenerate to a fuzzy set. Hence, we can consider a fuzzy set with its membership function $u_A(x)$, having the IFSs expression as

$$A = \{ \langle x, \mu_A(x), 1 - \mu_A(x) \rangle | x \in E \} \quad (3)$$

under the condition of $\nu_A(x) = 1 - \mu_A(x)$, for every $x \in E$.

For each IFSs A in E , "hesitation degree" has consideration. We call the hesitation degree of an element $x \in E$ in A by the following expression:

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x), \quad (4)$$

We can consider $\pi_A(x)$ as a hesitancy degree of x to A . From (4) it is evident that

$$0 \leq \pi_A(x) \leq 1 \text{ for all } x \in E. \quad (5)$$

Therefore, to describe an intuitionistic fuzzy set completely; we need at least two functions from the triplet ([2][3]): (1) membership function; (2) non-membership function; (3) hesitation degree.

B. Least-squares Support Vector Regressions with Genetic Algorithm

A successful method for regression problem is the least squares support vector regression ([26] and [28]), which attempts to minimize the sum square errors (SSEs) of training data set while simultaneously minimizing the margin error. The LS-SVR approach is to approximate an unknown function by a training data set $\{(x_i, y_i), i=1, \dots, N\}$. The regression function can be formulated as follows:

$$y = f(x) = w^T \phi(x_i) + b \quad (6)$$

where $\phi(x_i)$ denotes the feature of the inputs, and w and b indicate coefficients. LS-SVR introduces a least squares version to SVR by formulating the regression problem as

$$\begin{aligned} \text{Min } J_1(w, b, e) &= \frac{1}{2} \|w\|^2 + \frac{1}{2} C \sum_{i=1}^N e_i^2 \\ \text{subject to} \end{aligned} \quad (7)$$

$$y_i = w^T \phi(x_i) + b + e_i, i = 1, 2, \dots, N$$

Introduce the Lagrangian as

$$L_1(w, b, e, \alpha) = J_1(w, b, e) + \sum_{i=1}^N \alpha_i (y_i - w^T \phi(x_i) - b - e_i). \quad (8)$$

where α is the Lagrangian multiplier vector. The conditions for optimality are

$$\begin{aligned} \frac{\partial L_1}{\partial w} = 0 &\Rightarrow w = \sum_{i=1}^N \alpha_i \phi(x_i), \\ \frac{\partial L_1}{\partial b} = 0 &\Rightarrow \sum_{i=1}^N \alpha_i = 0, \\ \frac{\partial L_1}{\partial e_i} = 0 &\Rightarrow e_i = \frac{1}{C} \alpha_i, i = 1, \dots, N, \\ \frac{\partial L_1}{\partial \alpha_i} = 0 &\Rightarrow y_i = w^T \phi(x_i) + b + e_i, i = 1, \dots, N. \end{aligned} \quad (9)$$

Herein, $k(x_i, x_j)$ denotes a Kernel function whose value equals the inner product of two vectors, x_i and x_j , in the feature space $\phi(x_i)$ and $\phi(x_j)$, meaning that $k(x_i, x_j) = \phi^T(x_i) \phi(x_j)$. Any function that satisfies Mercer's condition [23] can act as the Kernel function. This work uses the Gaussian function. Hence, we can denote the $K = (k_{ij})_{N \times N}$, $k_{ij} = k(x_i, x_j)$, and $V = \text{diag}\{1/C, 1/C, \dots, 1/C\}$, LS-SVR can be described as

$$\begin{bmatrix} A & 1 \\ 1^T & 0 \end{bmatrix} \begin{bmatrix} \alpha \\ b \end{bmatrix} = \begin{bmatrix} y \\ 0 \end{bmatrix}, \quad (10)$$

where $A = K + V$. Hence, the regression model (see (6)) is found by solving (10). The resulting LS-SVR becomes then

$$f(x) = \sum_{i=1}^N \alpha_i k(x, x_i) + b. \quad (11)$$

Note that in the case of Gaussian kernels, one has only two additional tuning parameters (C , σ), which is less than for standard SVR.

The experiment uses genetic algorithms (GA) [10] to search optimal parameter of LS-SVR. In this study, binary encoding is specified in GA search. The size of the population is set fifty. The roulette wheel selection principle is used to select chromosomes for reproduction. In the crossover operation,

chromosomes are paired randomly. The single-point-crossover principle is employed in the GA search. In this study, the probabilities of crossover and mutation are set to 0.5 and 0.1, respectively. By the GA search the optimal parameters C and σ can be obtained. To minimize forecasting error of the LS-SVR model, the negative values of $MAPE$ were treated as the objective values of the GA; thus, each iteration generates a smaller $MAPE$ value. The parameter search procedure is conducted until the stop criterion is reached. The two parameters resulting in the smallest validation error are then used to develop a appropriate LS-SVR model. Finalized forecasting vales are obtained by LS-SVR. Finally, after comparison with the testing data, the testing errors are obtained.

III. INTUITIONISTIC FUZZY LEAST-SQUARES SUPPORT VECTOR REGRESSIONS

The IFLS-SVR approach has mainly different with LS-SVR/SVR which constructs the intuitionistic fuzzy sets to represent uncertain degree of data. IFSs D_i in a fixed set E is an objective with the expression

$$D_i = \{ \langle X_i = (x_i, y_i), \mu_D(y_i), \nu_D(y_i) \rangle | X \in E \}, i \in 1, \dots, N. \quad (12)$$

In this paper, intuitionistic fuzzy generator or fuzzy complement is created from Yager generating function [5]. The fuzzy complement functional is defined as:

$$N(\mu(y_i)) = g^{-1}(g(1) - g(\mu(y_i))) \quad (13)$$

where $g(\cdot)$ is an increasing function and $g: [0,1] \rightarrow [0,1]$.

Yager class can be generated by using the following function in the above (13)

$$g(y_i) = y_i^\alpha \quad (14)$$

So, Yager's intuitionistic fuzzy complement is written as:

$$N(y_i) = (1 - y_i^\alpha)^{1/\alpha}, \alpha > 0 \text{ where } N(1)=0, N(0)=1. \quad (15)$$

Non-membership values are calculated from Yager's intuitionistic fuzzy complement $N(y_i)$. Thus, with the help of Yager's intuitionistic fuzzy complement, IFSs becomes:

$$D_i = \{ \langle X_i = (x_i, y_i), \mu_D(y_i), (1 - \mu_D(y_i)^\alpha)^{1/\alpha} \rangle | X \in E \}. \quad (16)$$

and the hesitation degree is :

$$\pi_D(y_i) = 1 - \mu_D(y_i) - (1 - \mu_D(y_i)^\alpha)^{1/\alpha} \quad (17)$$

In IFLS-SVR, based on the expert's viewpoints the membership function can be determined, and then the hesitation degree can be obtained by (16). Following we can use definition of triangular fuzzy numbers (TFNs) to approach the intuitionistic fuzzy lower (IY_{Li}) and upper bounds (IY_{Ui}) with $\alpha=0.5$ which can be formulated as following:

$$IY_{Li} = Y_{Li} + (Y_{Ci} - Y_{Li}) \times (\mu_D(y_i) + \pi_D(y_i)) \quad (18)$$

$$IY_{Ui} = Y_{Ui} - (Y_{Ui} - Y_{Ci}) \times (\mu_D(y_i) + \pi_D(y_i)) \quad (19)$$

where Y_{Li} is lower bound of TFNs, Y_{Ci} is the mode of TFNs, and Y_{Ui} is upper bound of TFNs. Fig. 1 shows that the data point construct intuitionistic fuzzy lower and upper bounds.

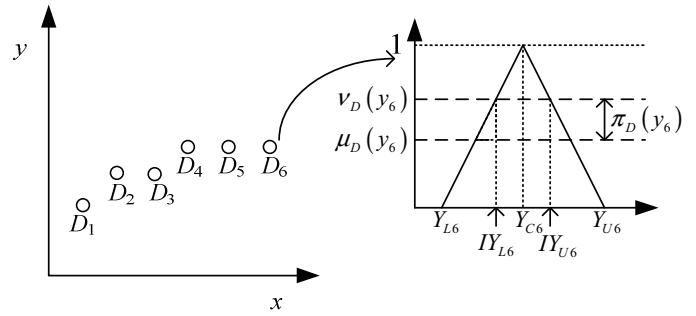


Figure 1. Illustration of construction of the intuitionistic fuzzy sets.

Then, in the IFLS-SVR model the intuitionistic fuzzy lower and upper regression lines must be constructed by the LS-SVR method with the lower bound of $\{(x_i, IY_{Li}), i=1, 2, \dots, N\}$ and the upper bound of $\{(x_i, IY_{Ui}), i=1, 2, \dots, N\}$, respectively, which can be written as follows:

$$Y_L(x_i) = w_{Li}^* + b_L = \sum_{i=1}^N \alpha_{Li} k(x, x_i) + b_L. \quad (20)$$

where the Lagrange multipliers, α_{Li} and an optimal weight vector w_{Li}^* of the lower bound regression hyperplane can be estimated by (6):

$$Y_U(x_i) = w_{Ui}^* + b_U = \sum_{i=1}^N \alpha_{Ui} k(x, x_i) + b_U. \quad (21)$$

where the Lagrange multipliers, α_{Ui} , and an optimal weight vector w_{Ui}^* of the upper bound regression hyperplane can be estimated by (7). Then the fuzzy prediction model uses (20) and (21) to estimate the estimated central vale $Y_C(x_i)$ by a simple calculation as follows:

$$Y_C(x_i) = \sum_{i=1}^N ((\alpha_{Li} + \alpha_{Ui}) K(x, x_i) + b_L + b_U) / 2. \quad (22)$$

Furthermore, the IFLS-SVR model uses GA algorithms to select the two parameters of LS-SVR. Fig. 2 shows the flowchart of the proposed IFLS-SVR model.

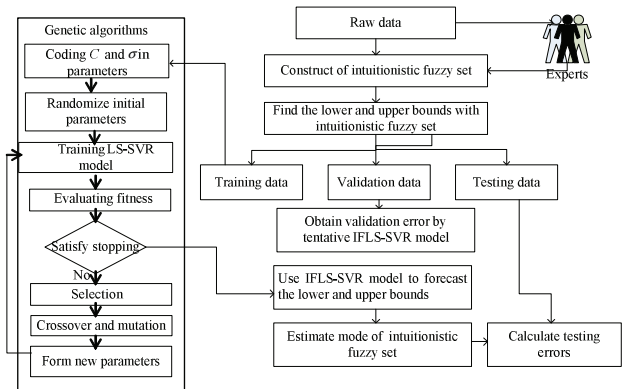


Figure 2. A flowchart of the IFLS-SVR

IV. NUMERICAL EXAMPLES AND EXPERIMENTAL RESULTS

To represent the vague characteristics of business cycles index in Taiwan, the Council of Economic Planning and Development uses five business lights to indicate the various degrees of business cycles. Table I shows the lights, intervals, and meanings of economic activities of the different degrees of business cycles from the Council of Economic Planning and Development. These intervals can be regarded as TFNs. Fig. 3 shows the monthly Taiwanese business index from October 1990 to November 2010. The monthly data were divided into three sets: the training set (October 1990 to December 2008), the validation set (January 2009 to December 2009), and the testing set (from January 2010 to November 2010). Moreover, Fig. 3 also shows IFSs of business cycles index in October 2008. The training data were used to design the forecasting model, and the testing data were employed to measure the forecasting performance of the different forecasting models. In addition, the root mean square error (*RMSE*) and mean absolute percentage error (*MAPE*) were used to measure the forecasting accuracy of the two models. (23) to (24) illustrate the expression of *RMSE*, *MAPE* respectively.

$$RMSE = \left\{ \frac{1}{M} \sum_{t=1}^M (Y_{Ct} - Y_C(x_t))^2 \right\}^{0.5} \quad (23)$$

$$MAPE(\%) = \frac{100}{M} \sum_{t=1}^M \left| \frac{Y_{Ct} - Y_C(x_t)}{Y_{Ct}} \right| \quad (24)$$

where M is the number of forecasting periods; Y_{Ct} is the actual value, and $Y_C(x_t)$ is the forecasting value at period t .

TABLE I. THE INDEX OF BUSINESS CYCLES IN TAIWAN

Lights	Intervals of business cycle	Meanings of business activities
Red	[38, 45]	Excellent
Yellow-Red	[32, 37]	Good
Green	[23, 31]	Medium
Yellow-Blue	[17, 22]	Retrieving
Blue	[9, 16]	Not good

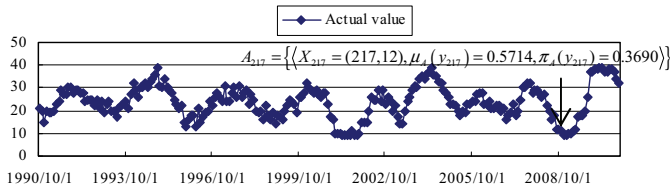


Figure 3. Illustration of actual values from October 1990 to November 2010

Table II illustrates the actual values and experimental results of the IFLS-SVR model from January 2010 to November 2010. In addition, Table II shows the optimal parameters of the proposed IFLS-SVR model. Fig. 4 makes a point-to-point comparison of actual values and predicted values of IFLS-SVR. Fig. 4 shows that the IFLS-SVR model can efficiently capture the trend of data. From observing the Fig. 4 we can find that the LS-SVR and SVR have lower forecasting values from January 2010 to November 2010. This may be because that LS-SVR and

SVR have over fitting phenomenon in the forecasting index of business cycles. The forecasting values are similarity the validation set by using LS-SVR and SVR technologies. The Table III shows and ranks the performances of three models. Again, the IFLS-SVR outperforms others models in terms of forecasting accuracy.

Finally, the Wilcoxon signed rank test was implemented to test the forecasting result. The test results, presented in Table IV, show significant differences among the IFLS-SVR, the LS-SVR and SVR models, indicating the forecasting result of IFLS-SVR is better than those of the traditional LS-SVR and SVR approaches based on *MAPE* and *RMSE*.

TABLE II. COMPARISON OF THE FORECASTING RESULTS AND PARAMETERS

Date	Actual value	IFLS-SVR ($C/\sigma=100.74/0.01$)	LS-SVR ($C/\sigma=317.39/0.19$)	SVR ($C/\sigma=35.84/0.22/0.88$)
2010/1/1	38	41.7312	19.1038	8.4093
2010/2/1	38	41.1553	18.9448	8.7809
2010/3/1	39	39.4172	18.7833	9.2896
2010/4/1	39	36.9449	18.6193	10.651
2010/5/1	37	34.2029	18.4530	12.9979
2010/6/1	37	31.5830	18.2843	15.211
2010/7/1	38	29.3428	18.1133	16.2752
2010/8/1	38	27.5961	17.9400	16.4975
2010/9/1	37	26.3409	17.7645	16.1791
2010/10/1	34	25.5041	17.5868	14.6248
2010/11/1	32	24.9845	17.4070	10.8380

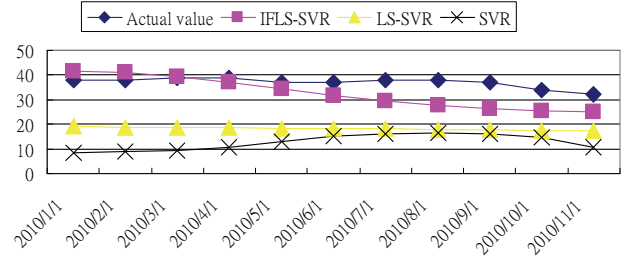


Figure 4. Illustration of actual values and forecasting values of three models

TABLE III. FORECASTING PERFORMANCES OF THREE MODELS

	IFLS-SVR	LS-SVR	SVR
MAPE(%)	15.6856	50.515	65.5035
RMSE	6.6308	18.8022	24.6016
Rank	(1)	(2)	(3)

TABLE IV. WILCOXON SIGNED RANK TEST FOR THE FORECASTING RESULTS

	LS-SVR	SVR
IFLS-SVR	-2.93(0.003) *	-2.93 (0.003) *
SVR	-2.93 (0.003) *	

Cell: standardize value(p value).

*significant different at $\alpha=0.05$.

V. CONCLUSIONS

Due to the recent global economic recession, analysis of business cycles is increasingly crucial. This study develops a novel IFLS-SVR model to exploit the unique strength of the intuitionistic fuzzy set theory and the LS-SVR technique, in order to predict long-term business cycles in Taiwan.

Simulation results indicate that the IFLS-SVR model offers a promising alternative in business cycles in uncertain circumstances. The superior performance of the IFLS-SVR model can be ascribed to two causes. First, the LS-SVR can efficiently capture trends of nonlinear data. Second, the IFLS-SVR model can provide creditable predictions for long-term Taiwanese business cycle predictions. For future work, forecasting other types of uncertain time series data by the IFLS-SVR model is a challenging issue for study. Future studies can also consider using data preprocessing techniques to improve the forecasting accuracy of the IFLS-SVR model.

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