Sensitivity Analysis of Economic Variables using Neuro-Fuzzy Approach

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Abstract— Sensitivity analysis (SA) is a vital task for decision making in economic management. In this paper, a novel fuzzy sensitivity analyzer (FSA) is proposed to analyze the sensitivity of economic variables. The proposed FSA algorithm consists of an adaptive neuro-fuzzy inference system (ANFIS) that is adjusted for forecasting economic time series. Based on the output of ANFIS, FSA can determine the importance degree of parameters. In the numerical studies, the proposed method is applied for the sensitivity analysis of oil and gold time series. According to the results, FSA indicates that oil price is highly dependent upon the inflation rate, dollar index and market index while OPEC production level and gold price have less impact. Furthermore, in the gold price modeling, the highest sensitivity is obtained from silver price while demand for gold is more a function of market index and inflation rate. The proposed method can be used in many SA applications.

Index Terms— Fuzzy forecast, economic time series, sensitivity analysis, soft computing, economic management.

1. INTRODUCTION

An economic time series is a sequence of successive measurements of an economic activity obtained at regular time intervals (hourly, daily, weekly, monthly, quarterly or annually). It can include price sequence of a commodity or sequence of an economic index e.g. oil price, gold price and market index. In this framework, there is a critical issue considered by researchers and economic analyzers and related to the sensitivity analysis (SA) of variables and determination of their importance [1]. SA determines the relationship between the economic parameters and can help economic managers with decision making in economic problems. In the literature, there are two approaches for SA methods including local and global methods [2-6]. Local or one-factor-at-a-time methods are limited to examining the effects of variations in input parameters in the vicinity of their nominal values. Global SA methods define the contribution of
individual input parameters, including their sets, and provide more comprehensive information on the computational model regarding changes in input parameters throughout their domain [2, 4, 5, 6, 7, 8]. Some mathematics-based SA methods have been proposed in this regards. For example, cosine amplitude method (CAM) has been applied by [9] in order to find the most sensitive parameters. Although, CAM and other mathematics-based SA methods applied in [11-15] can be used for economic time series, they cannot consider the behavioral similarities of parameters. They do not consider the interactions among the parameters [7]. So they cannot be a proper method in the case of economic variables. On the other side, learning-based SA methods [9, 10] can learn the interactions among the economic parameters and consequently they can better assess the influence of parameters on the output of an economic model. For example, in [10], an artificial neural network (ANN) has been applied for SA. In contrast to mathematical methods, ANNs can learn the nonlinear behaviour and hence they can show better results in SA. In [3], [12] and [13], [47] fuzzy-based multiple criteria decision-making (MCDM) models have been reviewed and the effective of a sensitivity analysis on the fuzzy MCDM systems has been shown. In this paper, we aim to propose a novel learning-based SA method using ANFIS. ANFIS has been successfully applied in various applications from prediction [18-22] to estimation [21-23] and enjoys from more number of learning parameters compared with ANNs and it may show more accurate results [21]. To the best of our knowledge, fuzzy approaches have not yet been examined in the SA of economic variables and we aim to introduce it and apply the resulting model in SA problems of oil and gold price and demand [18-23]. However, the proposed method is general and can be used in various applications [18-23] such as product cost estimation [20, 24] and stock price prediction [25-27].

The paper is organized as follows, a short review on ANFIS is presented in Section 2. The fuzzy SA (FSA) is proposed in Section 3. Then it is evaluated in Section 4 and conclusions are drawn in Section 5.

2. ANFIS

The architecture of Sugeno-type ANFIS [31, 32] presented in Fig. 1 includes the following five layers; fuzzifier, production, normalized, defuzzy, and output layer. Through these layers the output of ANFIS is determined. Fig. 1 shows 2 inputs single-output architecture as an example. Fig. 2 shows its inference mechanism. This example includes two linguistic rules as follows:

Rule 1: If \(x \) is \( A_1 \) and \( y \) is \( B_1 \) then \( z_1 = p_1 x + q_1 y + r_1 \)

Rule 2: If \(x \) is \( A_2 \) and \( y \) is \( B_2 \) then \( z_2 = p_2 x + q_2 y + r_2 \)

where \( p_1, p_2, q_1, q_2, r_1, \) and \( r_2 \), are linear parameters whereas \( A_1, A_2, B_1, \) and \( B_2 \) are nonlinear and called membership functions. The final output of ANFIS is formed by using following Eq. (1):
\[ Z = \frac{w_1 z_1 + w_2 z_2}{w_1 + w_2} \] (1)

In this sample ANFIS architecture the learning parameters including \( p_1, p_2, q_1, q_2, r_1, r_2 \) and \( A_1, A_2, B_1, B_2 \) should be adjusted. This adjustment is done by using input-target examples, error backpropagation and LMSE algorithm. In Sugeno model, the subtractive clustering method can be applied [30-34]. More description can be found in [28-29] and [30-33].

Fig. 1. Two inputs single-output architecture of ANFIS [31-34]

Fig. 2. Fuzzy reasoning of ANFIS presented in Fig. 1 [31-34]

3. THE PROPOSED FUZZY SENSITIVITY ANALYZER

In this section, we propose a novel method based on ANFIS to identify the most sensitive factors affecting price and demand.

In contrast to mathematical methods, proposed methods named fuzzy SA (FSA) consider the behavioral similarity of variables. FSA is based on the behaviour learning and can extract the most affecting independent parameters from input variables.

Let \( EV \) be the set of economic parameters under consideration (Tables 1 and 2).

\[ EV_i = \{\text{Inf}_i, \text{Int}_i, \text{Opl}_i, \text{Gol}_i, \text{Sil}_i, \text{Dji}_i, \text{Din}_i\} \] (2)

where \( i \) is index of sample number. If a variable such as \( \text{Int} \) is removed from \( EV \), then we have a new set likes \( EV_{\text{-Int},i} \) that is as follows

\[ EV_{\text{-Int},i} = \{\text{Inf}_i, \text{Opl}_i, \text{Gol}_i, \text{Sil}_i, \text{Dji}_i, \text{Din}_i\} \] (3)

By using this definition, the proposed FSA is as follows;
Algorithm 1. Fuzzy sensitivity analyzer

**Inputs:** a trained ANFIS model, $EV_i$

**Output:** Sensitivity Values of $EV_i$ elements

**The adjustable weights:** AMFIS linear and non-linear weights.

- For $j$ = each variable of $EV$
  - For $i = 1$ ... # of samples
    - Train ANFIS using $EV_{j,i}$ and Target($i$)
    - Output($i$) = ANFIS($EV_{j,i}$)
    - Error($i$) = Output($i$) - Target($i$)
    - $ErrorEV(j) = \text{sum}(Error)/\text{# of sample}$
  - For $j$ = each variable of $EV$
    - Sensivity($j$) = $ErrorEV(j)/\text{sum}(ErrorEV)$

In the algorithm, function $\text{sum}(x)$ returns the sum of values of the array $x$. In Algorithm 1, $EV_i$ should be defined for every economic time series. Table 1 shows them and Table 2 provides more information about these economic variables. Thus the inputs and outputs of ANFIS for training in Algorithm 1 must be considered as presented in Table 1. For example, for demand SA, the inputs include Inf, Int, Opl, Gol, Sil, Dj, Din and Op at ith period and output of the model is Od (U.S. crude oil imports from OPEC) and Gd (Global gold demand).

Table 1. A set of parameters under consideration in Algorithm 1.

| Table 2. Economic variables under consideration [37], [38] |

4. Numerical Results

Oil and gold markets play critical roles in other large commodity markets and their SA are very important [38-43]. In this section we use oil and gold time series to assess the proposed FSA. According to the algorithm 1, the result of the FSA is dependent on the prediction results of ANFIS model on these time series. The prediction results of ANFIS for proce and demand functions of gold and oil are presented in Figs. 3-6 and the final result of FSA is presented in Fig. 7. The prediction results have been compared with an optimum ANN in Tables 3 and 4. According to the comparative results, ANFIS can provide more accurate prediction. In this experiment, the inputs and outputs of ANFIS is determined according to the Table 1. For example, in oil/gold demand prediction, inputs include Inf, Int, Opl, Gol, Sil, Dj, Din and Op at ith period, and the output of the model is Od (U.S. crude oil imports from OPEC) and Gd (Global gold
demand). Also two or more previous values of output can be considered as input variables. In Table 2, For oil demand learning, monthly datasets have been downloaded from http://tonto.eia.gov. And for gold demand learning, the quarterly datasets have been obtained from the source presented in Table 2. Fig. 3 is the curves of estimated values of oil demand versus monthly observations from 2002 till 2012 and in the steady state. A correlation \( \text{COR} = 0.22298 \) is obtained from the ANFIS model. Additionally results show that the \( \text{RMSE} = 181.9693 \pm 0 \) obtained from ANFIS simulation which is lower than \( 236.6038 + 113.0307 \) obtained from ANN. Tables 3 and 4 summarize the comparative results.

The gold demand prediction results are shown in Figs. 4 and 5. Fig. 4 shows the observed and predicted demand and related error between 4th quarter of year 2001 and 4th quarter in year 2012. The \( \text{COR} = 0.78801 \) is obtained from ANFIS based model in steady state. In subtractive clustering we used here, \( \text{radii} = [0.5 0.5 0.5 0.5 0.5 0.5 0.5 .50 .49 0.5 0.5] \).

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**Fig. 3.** Online predicted oil demand values (top) and related error (bottom) from start point in Sep. 2001 obtained using ANFIS.

**Table 3.** The average error, RMSE and correlation comparisons between optimum ANN and in demand function estimation.

**Fig. 4.** Online predicted gold demand values (top) and related error (bottom) from start point in Sep. 2001 obtained using ANFIS.

**Fig. 5.** Actual versus desired output of gold demand, between Q’4 2001 and Q’4 2012 obtained from ANFIS model.

**Table 4** Comparative results of price prediction between ANN and ANFIS with proposed variables set.
Fig. 6. Predicted gold prices (top) and related error (bottom) from start point in Sep. 2001 obtained using ANFIS.

Fig. 6 shows the target and predicted gold price and related error obtained from proposed input variables presented in Table 2. Fig. 6 presents the results of prediction from the start point at Dec-2001. As illustrated in Fig. 6, last 24 months are used for testing the system. The predicted curve illustrated in Fig. 6, is divided into the three segments; the first is the training region that is between months [Sep-2001 Nov-2009]. And the second is the validating region that is between months (Nov-2009 Dec-2010) and the thirds is testing region where the prediction results are validated and it’s between [Dec-2010 Dec-2012]. Fig. 6 shows the target and predicted gold price and related error obtained from proposed input variables presented in Table 2. As illustrated in Table 2, in gold prediction, the best COR = 0.97211 is obtained from the model. According to the more experiments, if ANFIS does not apply the previous values of time series then the error is increased while the proposed input sets provide error = 255.4686±0 in gold forecasting that is much lower than 354.5491±95.17189 obtained from optimum ANN. According to the Student-t test, these results are statistically significant.

Fig. 7. Sensitivity analysis of economic variables obtained from the proposed FSA

To assess the proposed FSA, the trained ANFIS model with parameters provided in Table 1 is applied in Algorithm 1. Fig. 7 shows the final results of SA. The sensitivity value of a variable shows the relationship between the variable and output. For example, in oil price prediction, If the oil price has no relation with a variable like x, then the sensitivity(x) = 0, i.e. x does not affect directly on the oil price or it’s not independent and highly correlated with another input variable. The largest value of sensitivity shows that variable is most sensitive factor affecting oil prices.

The importance of parameters on the oil price, oil demand, gold price and gold demand are shown in Fig. 7. According to the Fig.7, the most effective parameters on the oil price are inflation rate and market index. Fig. 7 presents the sensitivity average and the confidence interval obtained from proposed FSA with various learning parameters such as number of rules in ANFIS. It’s obvious that according to the confidence interval, the results of market index and inflation rate were statistically significant. The results indicated in Fig. 7 are based on student’s t-test with 95% confidence. Fig. 7 shows that the sensitivity average 0.21 and
0.20 obtained from FSA for inflation rate and dollar index respectively. Furthermore, the highest sensitivity were obtained from inflation rate and dollar index in oil demand modeling. These results are statistically significant with respect to the OPEC oil production level, interest rate and silver price but it’s not statistically significant with respect to the gold price and oil price. Gold price model is highly dependent upon the silver price. So our model testifies the results reported by Yazdani et al. (2012) [9] about gold and silver dependency.

5. CONCLUSION

The FSA is proposed here to analyze the sensitivity of economic parameters (source code may be accessible from www.bitools.ir). The proposed FSA applies an ANFIS model in order to predict the economic time series. It has been shown that ANFIS is an appropriate model for senility analysis of price and demand. Furthermore, Numerical studies present the following conclusions. Firstly, according to the results of fuzzy SA, the importance of the inflation rate is higher than OPEC oil production level, market index, USD index, gold price, interest rate, silver Price in one month ahead prediction of oil price and demand. The proposed FSA indicates that oil price is highly dependent upon the inflation rate, dollar index and market index while OPEC production level and gold price have less impact. Secondly, in the gold price modeling, the highest sensitivity is obtained from silver price while demand for gold is more a function of market index and inflation rate. Demand for gold is more a function of market index and inflation rate. Some results, obtained here are new and some other confirmed the results of previous studies especially in dependency of gold and silver price. These results show the proposed learning-based method is highly reliable for testing on other applications. FSA shows a high performance in price and demand modeling and can be used in various applications such as sensitivity analysis of environmental models, in MADM, in renewable energy analysis, etc. Additionally, the excellent results of ANFIS in SA show it can be a proper model for similarity analysis methods [44-47] such as those for economic data.

However the proposed FSA has some weakness. It cannot directly measure the interactions between the parameters. These interactions are very important and can lead to a global SA result. For future developments, factorial design [4] and interactions of parameters with each other should be considered. The factorial design enables the measurement of interactions between each different group of factors [4] and these interactions are very important and may affect the SA results.

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Table 1. A set of parameters under consideration in Algorithm 1.

| Application               | Target | $EV_i$                                      |
|---------------------------|--------|--------------------------------------------|
| Oil price                 | Op$_i$ | Inf$_i$, Int$_i$, Opl$_i$, Gp$_i$, Sil$_i$, Dji$_i$, Din$_i$ |
| Gold price                | Gp$_i$ | Inf$_i$, Int$_i$, Opl$_i$, Gp$_i$, Sil$_i$, Dji$_i$, Din$_i$, Op$_i$ |
| Oil demand function       | Od$_i$ | Inf$_i$, Int$_i$, Opl$_i$, Gp$_i$, Sil$_i$, Dji$_i$, Din$_i$, Op$_i$ |
| Gold demand function      | Gd$_i$ | Inf$_i$, Int$_i$, Opl$_i$, Gp$_i$, Sil$_i$, Dji$_i$, Din$_i$, Op$_i$ |

Table 2. Economic variables under consideration [9], [11]

| Input Variable                           | Unit                  | Symbol | Source                                |
|------------------------------------------|-----------------------|--------|---------------------------------------|
| 1) US Inflation rate                     | -                     | Inf$_i$| [http://inflationdata.com](http://inflationdata.com) |
| 2) Interest rate                          | -                     | Int$_i$| [http://www.EconStats.com](http://www.EconStats.com) |
| 3) OPEC oil production level             | Thousand Barrels Per Day | Opl$_i$| [http://tonto.eia.gov](http://tonto.eia.gov) |
| 4) Gold Price                            | $/ounce               | Gp$_i$ | [http://www.gold.org](http://www.gold.org) |
| 5) Silver Price                          | $/ounce               | Sil$_i$| [https://www.silverinstitute.org](https://www.silverinstitute.org) |
| 6) Market Index                          | $                     | Dji$_i$| [http://finance.yahoo.com](http://finance.yahoo.com) |
| 7) U.S. Dollar Index                      | -                     | Din$_i$| [http://research.stlouisfed.org](http://research.stlouisfed.org) |
| 8) Oil price (USA F.O.B. cost of OPEC)   | Dollars per Barrel    | Op$_i$ | [http://tonto.eia.gov](http://tonto.eia.gov) |
| 9) U.S. crude oil imports from OPEC      | Thousand Barrels      | Od$_i$ | [http://tonto.eia.gov](http://tonto.eia.gov) |
| 10) Global gold demand                   | Tones                | Gd$_i$ | [http://www.gold.org](http://www.gold.org) |
### Table 3. The average error, RMSE and correlation comparisons between optimum ANN and in demand function estimation

| Time series         | Model        | RMSE         | RMSE         | Correlation |
|---------------------|--------------|--------------|--------------|-------------|
| Oil Demand          | ANFIS        | 34614±0      | 23757±0      | 0.22298     |
|                     | Optimum ANN  | 31082.11±1860.656 | 23982.22±8781.989 | 0.20403    |
| Gold Demand         | ANFIS        | 13.4329±0    | 181.9693±0   | 0.78801     |
|                     | Optimum ANN  | 146.81±44.54263 | 236.6038±113.0307 | 0.32314    |

### Table 4 Comparative results of price prediction between ANN and ANFIS with proposed variables set

| Time series | Model     | TrainingSet RMSE | TestSet RMSE | Best Correlation |
|-------------|-----------|------------------|--------------|------------------|
| Gold        | ANFIS     | 131.7283±0       | 255.4686±0   | 0.97211          |
|             | Optimum ANN | 205.4037±229.2613 | 354.5491±95.17189 | 0.96091        |