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Research Note

Sensitivity analysis of economic variables using neuro-fuzzy approach

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Abstract. Sensitivity Analysis (SA) is an essential requirement 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 to carry out 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 are of low impact. Furthermore, in the gold price modeling, the highest sensitivity is obtained from silver price, while demand for gold is a function of market index and inflation rate. The proposed method can be used in many SA applications.

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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 a sequence of economic indexes, e.g., oil price, gold price, and market index. In this framework, researchers and economic analyzers consider a critical issue of the Sensitivity Analysis (SA) of variables and the determination of their importance [1]. SA determines the relationship between economic parameters and can help economic managers with decision-making in economic problems. In the literature, there are two approaches for SA methods: 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 [2,4–8]. Some mathematically based SA methods have been proposed in this regard. For example, Yazdani-Chamzini et al. [9] applied the Cosine Amplitude Method (CAM) to find the most sensitive parameters. Although CAM and other mathematically based SA methods applied in the referenced studies [10–14] can be used for economic time series [15], they cannot consider the behavioral similarities of parameters. They do not consider the interactions among the parameters [7]. Therefore, they

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cannot be a proper method in the case of economic variables. On the other hand, learning-based SA methods [9,16] can learn the interactions among economic parameters and, consequently, can better assess the influence of parameters on the output of an economic model. For example, Valdivia and Arturo [16] applied an Artificial Neural Network (ANN) for SA. In contrast to mathematical methods, ANNs can learn the nonlinear behavior and, hence, show better results in SA. In a number of referenced studies [3,11,12,17], fuzzy-based Multiple Criteria Decision-Making (MCDM) models were reviewed, and the effectiveness of an SA with respect to the fuzzy MCDM systems was shown. This paper aims to propose a novel learning-based SA method using Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS is successfully applied in various applications from prediction [18–23] to estimation [22–24] and features a large number of learning parameters compared with ANNs; it may show more accurate results [22]. To the best of our knowledge, fuzzy approaches have not yet been examined in the SA of economic variables; now, they are introduced in this study, and the resulting model will be applied to the SA problems of oil and gold price and demand [19–24]. The proposed method is generalizable and can be used in various applications [19–24] such as product cost estimation [21,25] and stock price prediction [26–28].

The paper is organized as follows. A short review of 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 [32,33] presented in Figure 1 includes the following five layers: fuzzifier, production, normalized, defuzzification, and output layer. Through these layers, the output of ANFIS is determined. Figure 1 shows a two-input single-output architecture as an example. Figure 2 shows its inference mechanism. This example includes two linguistic rules as follows:

$$Rule1: \ If\ (x \text{ is } A_1) \text{ and } (y \text{ is } B_1),$$

$$\text{then } z_1 = p_1x + q_1y + r_1,$$

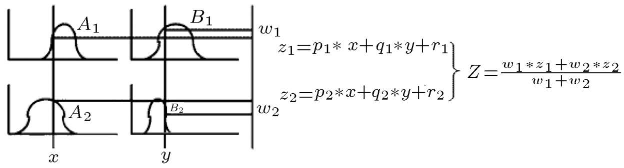

Figure 2. Fuzzy reasoning of Adaptive Neuro-Fuzzy Inference System (ANFIS) presented in Figure 1 [32–35].

$$Rule2: \ If\ (x \text{ is } A_2) \text{ and } (y \text{ is } B_2),$$

$$\text{then } z_2 = p_2x + q_2y + r_2,$$

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 through Eq. (1):

$$Z = \frac{w_1z_1 + w_2z_2}{w_1 + w_2}. \tag{1}$$

In this sample, ANFIS architecture of 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 [31–35]. More descriptions can be found in [29,30–34,36,37].

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

In contrast to mathematical methods, the proposed method, namely Fuzzy SA (FSA), considers the behavioral similarity of variables. FSA is based on the behavior learning and can extract the most affecting independent parameters from input variables.

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

$$EV_i = \{Inf_i, Int_i, Opl_i, Gol_i, Sil_i, Dji_i, Din_i\}, \tag{2}$$

where i is the index of sample number. If a variable such as *Int* is removed from EV, then we have a new set like $EV_{-Int,i}$, which is as follows:

$$EV_{-Int,i} = \{Inf_i, Opl_i, Gol_i, Sil_i, Dji_i, Din_i\}. \tag{3}$$

By using this definition, the proposed FSA is as follows:

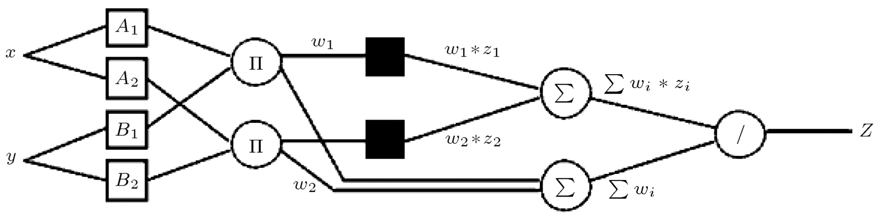

Figure 1. Two-input single-output architecture of Adaptive Neuro-Fuzzy Inference System (ANFIS) [32–35].

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

Application	Target	EV_i
Oil price	Op_i	$Infi$, Int_i Opl_i, Gp_i, Sil_i, Dji_i, Din_i
Gold price	Gp_i	$Infi$, Int_i Opl_i, Op_i, Sil_i, Dji_i, Din_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 [38,39].

	Input variable	Unit	Symbol	Source
1	US inflation rate	—	Inf	http://inflationdata.com
2	Interest rate	—	Int	http://www.EconStats.com
3	OPEC oil production level	Thousand barrels per day	Opl	http://tonto.eia.gov
4	Gold price	$/ounce	Gp	http://www.gold.org
5	Silver price	$/ounce	Sil	https://www.silverinstitute.org
6	Market index	$	Dji	http://finance.yahoo.com
7	U.S. dollar index	—	Din	http://research.stlouisfed.org
8	Oil price (USA F.O.B. cost of OPEC)	Dollars per barrel	Op	http://tonto.eia.gov
9	U.S. crude oil imports from OPEC	Thousand barrels	Od	http://tonto.eia.gov
10	Global gold demand	Tones	Gd	http://www.gold.org

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

Algorithm 1. Fuzzy sensitivity analyzer.

In the algorithm, function $sum(x)$ 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, Dji, Din, and Op in the ith period and the output of the model is Od (U.S. crude oil imports from OPEC) and Gd (Global gold demand).

3. Numerical results

Oil and gold markets play critical roles in other large commodity markets, and their SA is very important [39–44]. In this section, oil and gold time series is used to assess the proposed FSA. According to Algorithm 1, the result of the FSA is dependent on the prediction results of ANFIS model in the time series. The prediction results of ANFIS for price and demand functions of gold and oil are presented in Figures 3–6, and the final result of FSA is presented in Figure 7. The prediction results are compared with an optimum ANN in Tables 3 and 4. According to the comparative results, ANFIS can make more accurate predictions. In this experiment, the inputs and outputs of ANFIS are determined, as shown in Table 1. For example, in the case of oil/gold demand prediction, inputs include Inf, Int, Opl, Gol, Sil, Dji, Din, and Op in the ith period, and the outputs of the model are Od (U.S. crude oil imports from OPEC) and Gd (Global gold demand). Moreover, two or more previous values of the outputs can be considered as input variables. In Table 2, for oil demand learning, monthly datasets were downloaded from http://tonto.eia.gov. In addition, for gold demand learning, the quarterly datasets were obtained from a source presented in Table 2. Figure 3 shows the curves of estimated values of oil demand versus monthly observations from 2002 till 2012 and in the steady state. A correlation COR = 0.22298 is obtained by the ANFIS model. Additionally, results show that RMSE = 181.9693 ± 0 obtained by ANFIS simulation is lower than 236.6038+113.0307, obtained by ANN. Tables 3 and 4 summarize the comparative results.

The gold demand prediction results are shown in

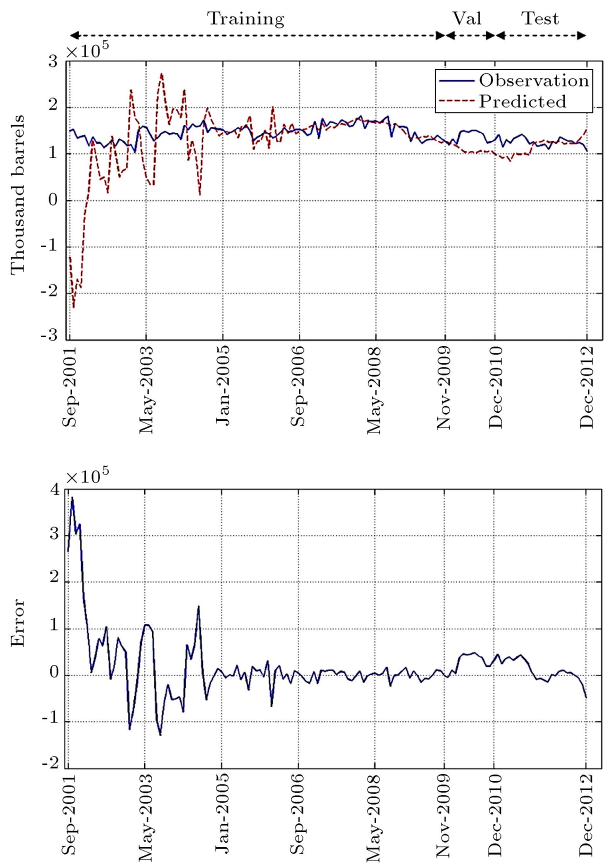

Figure 3. Online predicted oil demand values (top) and related error (bottom) from the start point in Sep. 2001 obtained using Adaptive Neuro-Fuzzy Inference System (ANFIS).

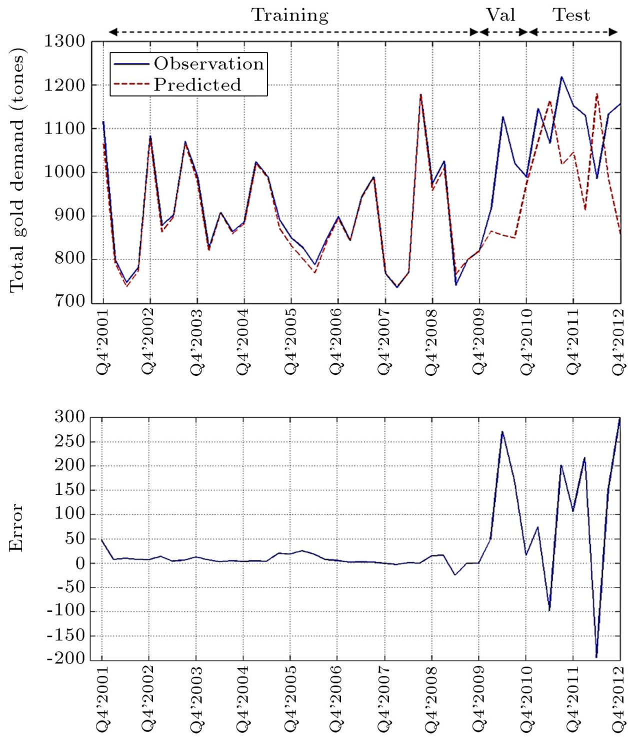

Figure 4. Online predicted gold demand values (top) and related error (bottom) from the start point in Sep. 2001 (Q4' 2001) obtained using Adaptive Neuro-Fuzzy Inference System (ANFIS).

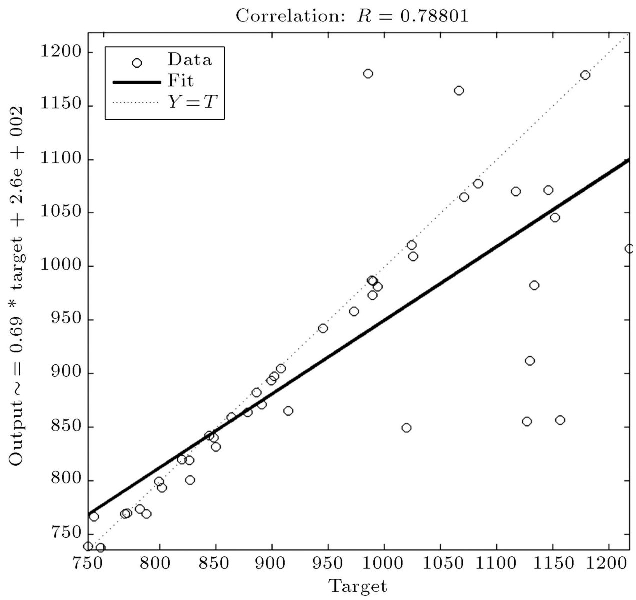

Figure 5. Actual versus desired outputs of gold demand between Q$'$4 2001 and Q$'$4 2012 obtained by the Adaptive Neuro-Fuzzy Inference System (ANFIS) model.

Figures 4 and 5. Figure 4 shows the observed and predicted demand and related error between the 4th quarter of 2001 and the 4th quarter of 2012. The COR = 0.78801 is obtained by the ANFIS-based model in the steady state. In subtractive clustering, radii = [0.5 0.5 0.5 0.5 0.5 0.5 0.5 .50 .49 0.5 0.5] were used.

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

To assess the proposed FSA, the trained ANFIS

Table 3. The average error, RMSE, and correlation comparisons between optimum Artificial Neural Network (ANN) and 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 Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) and the proposed variables set.

Time series	Model	Training set RMSE	Test set 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

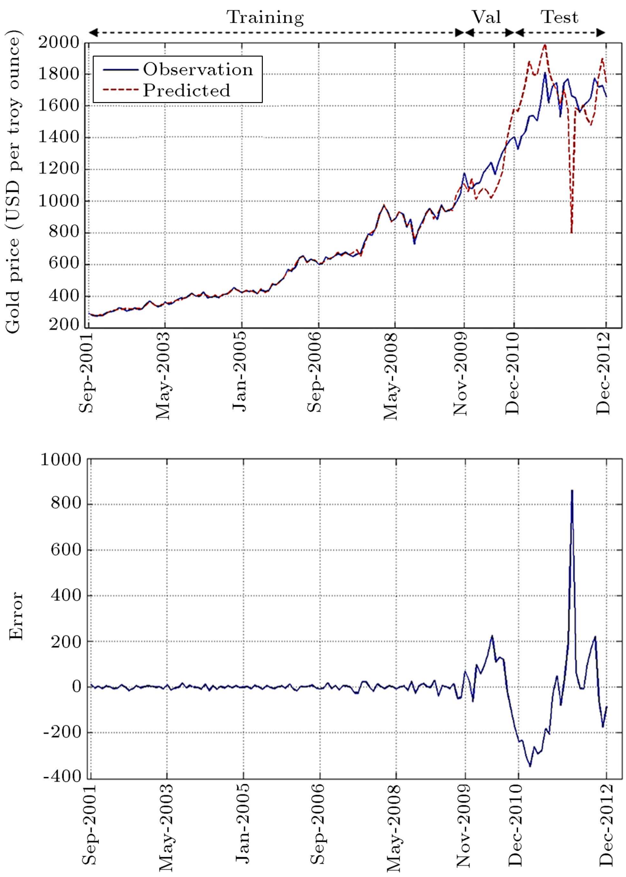

Figure 6. Predicted gold prices (top) and related error (bottom) from the start point in Sep. 2001 obtained using Adaptive Neuro-Fuzzy Inference System (ANFIS).

model with the parameters provided in Table 1 is applied in Algorithm 1. Figure 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 predictions, If the oil price has no relation with a variable like x, then the sensitivity (x) $= 0$, i.e., x, does not affect directly the oil price, or it is not independent and highly correlated with another input variable. The largest value of sensitivity shows that the variable is the most sensitive factor affecting oil prices.

The importance of parameters on the oil price, oil demand, gold price, and gold demand is shown in Figure 7. According to Figure 7, the most effective parameters for the oil price include inflation rate and market index. Figure 7 presents the sensitivity average and the confidence interval obtained by the proposed FSA with various learning parameters such as the number of rules in ANFIS. It is obvious that, according to the confidence interval, the results of market index and inflation rate are statistically significant. The results indicated in Figure 7 are based on students' t-test with 95% confidence. Figure 7 shows that the sensitivity average values of 0.21 and 0.20 are obtained by FSA for inflation rate and dollar index, respectively. Furthermore, the highest sensitivity is obtained for 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; however, they are not statistically significant with respect to the gold price and oil price. Gold price model is highly dependent upon the silver price. Therefore, the proposed model verifies the results reported by Yazdani-Chamzini et al. (2012) [9] about gold and silver dependency.

4. Conclusion

The FSA was proposed here to analyze the sensitivity of economic parameters (source code may be accessible from www.bitools.ir). The proposed FSA applied an ANFIS model in order to predict the economic time series. It was shown that ANFIS was an appropriate model for senility analysis of price and demand.

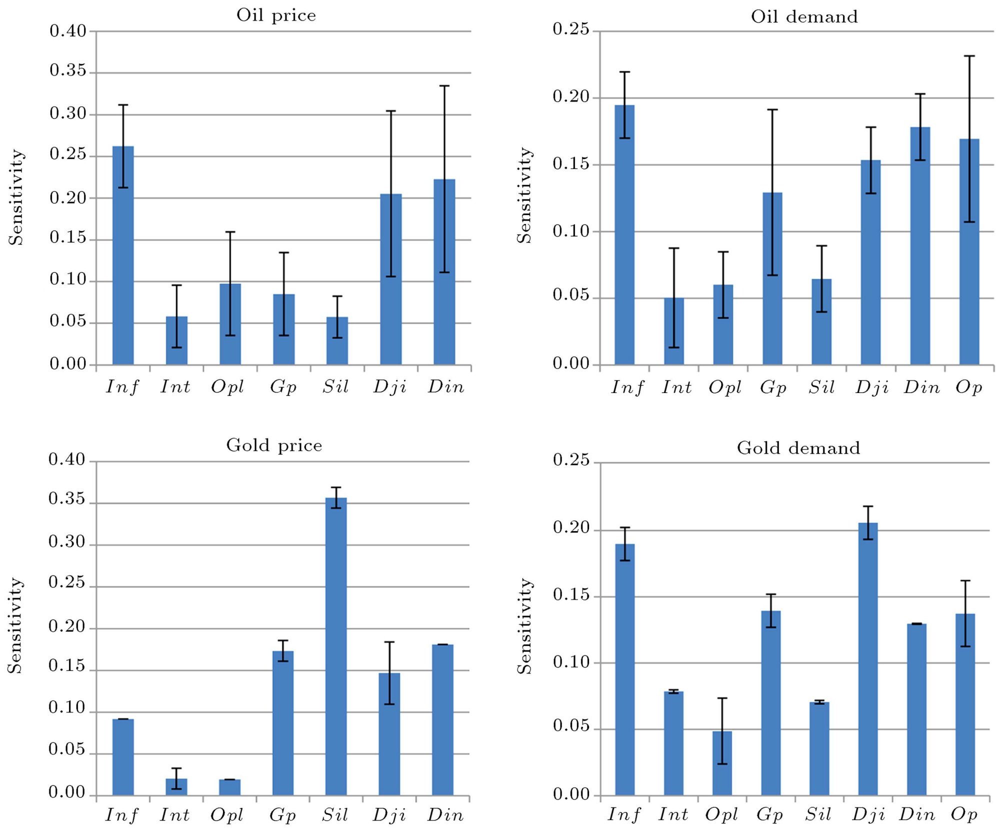

Figure 7. Sensitivity analysis of economic variables obtained by the proposed Fuzzy Sensitivity Analyzer (FSA).

Furthermore, numerical studies presented the following conclusions. Firstly, according to the results of fuzzy SA, the importance of the inflation rate was higher than OPEC oil production level, market index, USD index, gold price, interest rate, silver price in one month ahead of the 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 was obtained from silver price while demand for gold was a function of market index and inflation rate. Demand for gold was a function of market index and inflation rate. Some results obtained here are new, and some others confirm the results of previous studies, especially the dependency of gold and silver price. These results showed that the proposed learning-based method was highly reliable for testing on other applications. FSA showed a high performance in price and demand modeling and could be used in various applications such as sensitivity analysis of environmental models, MADM, renewable energy analysis, etc. Additionally, the excellent results of ANFIS in SA showed that it could be a proper model for similarity analysis methods [17,45–47] such as those for economic data.

However, the proposed FSA is susceptible to some weaknesses. It cannot directly measure the interactions between the parameters. These interactions are very important and can lead to globally applicable SA results. 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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