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# Survey of a Rule Based Expert System for Gas Price Forecasting

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**Abstract:** The difficulty in gas price forecasting has attracted much attention of academic researchers and business practitioners. Various methods have been tried to solve the problem of forecasting gas prices however, all of the existing models of prediction cannot meet practical needs. In this paper, a novel hybrid intelligent framework is developed by applying a systematic integration of GMDH neural networks with GA and Rule-based Exert System (RES) employs for gas price forecasting. In this paper we use a new method for extract the rules. Our research reveals that during the recent financial crisis period by employing hybrid intelligent framework for gas price forecasting, we obtain better forecasting results compared to the GMDH neural networks and results will be so better when we employ hybrid intelligent system with GARCH (1, 1) for gas price volatility forecasting.

**Key words:** Gas price forecasting · Group Method of Data Handling (GMDH) neural networks · Genetic Algorithm (GA) · Hybrid Intelligent System · Rule–based Expert System (RES) · GARCH (1, 1) method

## INTRODUCTION

Problems of complex objects modeling such as analysis and prediction of stock market, gas price and other such variables cannot be solved by deductive logical-mathematical methods with needed accuracy with a suitable number of hidden units. Neural networks get their intelligence from learning process and then this intelligence makes them have the capability of auto-adaptability, association and memory to perform certain tasks. Gas price is primarily formed by supply and demand forces but is also influenced by factors such as gas products inventory levels, stock markets activities, foreign exchange rates and political context.

In time series analysis, a review of the methodological linkage between statistical techniques and neural networks is given by Cheng and Titterington [1]. In comparison with statistical techniques, neural networks make less restrictive assumptions on the underlying distributions and provide a higher degree of robustness. Kuo and Reitsch [2] showed that neural networks provide meaningful predictions when independent variables were correlated or missing. It is also known that neural networks tended to outperform the conventional regression analysis at the presence of ambiguity in independent variables. It is not surprising to learn that neural networks are superior to traditional approaches in terms of parsimony of parameterization. In addition, a network structure is trained by using part of the data and then tested by using the rest of the data. A well-trained network is therefore expected to provide robust predictions. A thorough literature review of neural network applications in finance and business are provided by Wong *et al*. [3]. Nasr *et al*. [4] used artificial neural network (ANN) approach to gasoline consumption (GC) forecasting in Lebanon. Ambrishami *et al*. [5] used GMDH neural network based on Genetic Algorithm to model and forecast the price of Gasoline by using two approaches; Deductive Method and Technical Analysis. The results of deductive method indicate that the accuracy of prediction could reach up to 96% and in technical analysis could reach up to 99%. Mehrara *et al*. [6] used a GMDH neural network model with moving average crossover inputs to predict price in the crude oil futures market. The predictions of price are used to construct buy and sell signals for traders. Compared to those of benchmark models, cumulative returns, year-to-year returns, returns over a market cycle and sharpe ratios all favor the GMDH model by a large factor. The significant profitability of the GMDH model casts doubt on the efficiency of the oil futures market. Brito Buarque [7] used methods of multiple linear regression and artificial neural networks for the

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prediction of gasoline properties from information of composition obtained by gas chromatography, as well as a methodology for prediction of properties using a hybrid method composed of neural networks and group contribution. Gencay [8] use foreign exchange markets to pioneer the use of technical analysis rules as inputs for neural networks, which are flexible, nonlinear models with powerful pattern recognition properties. In a series of articles, Gencay [9] and Gencay [10] and Gencay *et al*. [11] show that simple technical rules result in significant forecast improvements for current returns over a random walk model for both foreign exchange rates and stock indices.

In this paper, we employ moving average daily gas prices from 2004 to 2008 for forecasting the gas price and which are then modeled by developed a GMDH neural networks model. In addition, the effects of irregular and infrequent events on gasoline price are explored by using RES techniques and volatility is based on GARCH (1, 1). Over all, we observed that the hybrid intelligent framework improve the forecasting results of gas price.

This paper is organized as follows. Section 2 provides a general discussion of RES and GMDH neural networks modeling. In Section 3, empirical results are presented and Section 4 offers concluding reviews.

**The Hybrid Intelligent System for Forecasting:** A superior approach is employed to develop a hybrid intelligent system that can implement gas price forecasting in the volatile gas market. The hybrid intelligent system for gas price forecasting consists of GMDH based time series forecasting module, RES module witch rules extract from regression.

In Section 2.1 RES is reviewed. Section 2.2 covers GMDH neural network.

**Rule-based Expert System (RES):** A rule-based expert system has five components: the knowledge base, the database, the inference engine, the explanation facilities and the user interface.

The knowledge base contains the domain knowledge useful for problem solving. In a rule-based expert system, the knowledge is represented as a set of rules. Each rule specifies a relation, recommendation, directive, strategy or heuristic and has the IF (condition) THEN (action) structure. When the condition part of a rule is satisfied, the rule is said to fire and the action part is executed. The database includes a set of facts used to match against the IF (condition) parts of rules stored in the knowledge base. The inference engine carries out the reasoning whereby the expert system reaches a solution. It links the rules given in the knowledge base with the facts provided in the database. The explanation facilities enable the user to ask the expert system how a particular conclusion is reached and why a specific fact is needed. An expert system must be able to explain its reasoning and justify its advice, analysis or conclusion. The user interface is the means of communication between a user seeking a solution to the problem and an expert system. The communication should be as meaningful and friendly as possible. These five components are essential for any rule-based expert system. (Negnevitsky, [12])

The key to an expert system is the construction of its knowledge base (KB). In this study, KB is represented by all types of rules from knowledge engineers who collect and summarize related knowledge and information as well as from history and from domain experts. The main work of an RES module is to collect and extract the rules or knowledge category from the KB. Our expert system module is required to extract some rules to judge abnormal variability in the gas price by summarizing and concluding relationships between gas price fluctuation and irregular key factors affecting gas price volatility. To formulate a useful price volatility mechanism to predict gasoline price movements one has to first observe historical price patterns that occur frequently in the gas market. (Yu *et al*. [13]).

In this paper, the terms “patterns”, “factors” or “events” will be used interchangeably. The relationships between the gas price variability and the factors affecting gas price are examined.

Finally, if there are strong connections between price influencing factors and price movements, then the factors are elicited from the historical price patterns examined and a KB for predicting gas price variability can be constructed. As previously mentioned, world events such as wars can have an immediate impact on the gas price. Furthermore, these factors can exert either an individual or composite effect. In order to represent the irregular patterns in a more organized and systematic way, the price patterns are classified into individual patterns and combination patterns. Individual patterns that have relatively simple conditions and attributes are used in defining combination patterns. In this study, the pattern itself can be considered to be the representation of a rule because the conditions of a pattern can be seen as conditions of a rule in the rule representation. Figures 1 and 2 show how individual patterns and combination patterns are defined and constructed.

```
PATTERN pattern - name
IF condition F
(AND condition M)
(OR condition N)
. . .
THEN PATTERN = pattern name
EXPLANATION = statement F
```

Fig. 1: The syntax of individual pattern.

```
PATTERN pattern - name
IF pattern F
(AND pattern M)
(OR pattern N)
(AND condition F)
(OR condition M)
. . .
THEN PATTERN = pattern name
```

Fig. 2: The syntax of a combination Pattern.

The syntax of an individual pattern uses reserved words such as PATTERN, IF and, OR and EXPLANATION, as illustrated in Figure 1. If certain important events are matched with the IF condition of a particular pattern, then the pattern is identified by the conditions and the EXPLANATION part gives the information about what the pattern really means. The individual pattern itself has its own meaning and can be an important clue in predicting gas price volatility. Likewise, the combination patterns integrate several conditions or patterns to explain a certain sophisticated phenomenon, as illustrated in Figure 2. (Wang *et al*. [3]).

**GMDH neural networks:** GMDH neural networks are based on the concept of pattern recognition and in that sense such networks are a refinement of traditional methods of technical analysis. They are highly flexible, semi parametric models and have been applied in many scientific fields, including biology, medicine and engineering.

For economists, neural networks represent an alternative to standard regression techniques and are particularly useful for dealing with non-linear unvaried or multivariate relationships.

By applying GMDH algorithm a model can be represented as set of neurons in which different pairs of them in each layer are connected through a quadratic polynomial and thus produce new neurons in the next layer. Such representation can be used in modeling to map inputs to outputs. The formal definition of the identification problem is to find a function f^ that can be approximately used instead of actual one, f, in order to predict output y^ for a given input vector X = (x1, x2, x3,... xn) as close as possible to its actual output y. Therefore, given M observations of multi-input-single-output data pairs so that:

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) \quad i=1, 2, \ldots, M \tag{1}$$

It is now possible to train a GMDH-type neural network to predict the output values y^i for any given input vector X = (xi1, xi2, xi3,... xin), that is:

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) \quad i=1,2,\ldots, M \tag{2}$$

The problem is now to determine a GMDH-type neural network so that the square of difference between the actual output and the predicted one is minimized, in the form of:

$$\sum_{i=1}^{M} [\hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) - y_i]^2 \rightarrow \min \tag{3}$$

General connection between inputs and output variables can be expressed by a complicated discrete form of the Volterra functional series that is:

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \ldots \quad n=1, 2,.., N \tag{4}$$

This is known as the Kolmogorov–Gabor (Farlow, [14]; Iba *et al*. [15]; Ivakhnenko, [16]; Nariman-Zadeh *et al*. [17]; Sanchez *et al*. [18]). The full form of mathematical description can be represented by a system of partial quadratic polynomials consisting of only two variables (neurons) in the form of:

$$\hat{y} = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \quad i=1,\&,M, j=1, 2,..,N \tag{5}$$

In this way, such partial quadratic description is recursively used in a network of connected neurons to build the general mathematical relation of inputs and output variables given in Eq. (4). The coefficients $\alpha_i$ in Eq. (5) are calculated using regression techniques (Farlow, 1984; Nariman-Zadeh *et al*., 2003) so that the difference between actual output, y and the calculated one, y^, for each pair of xi, xj as input variables is minimized. Indeed, it can be seen that a tree of polynomials is constructed using the quadratic form given in Eq. (5) whose coefficients are obtained in a least-squares sense.

In this way, the coefficients of each quadratic function Gi are obtained to optimaly fit the output in the whole set of input–output data pairs, that is:

$$E = \frac{\sum_{i=1}^{M} (y_i - G_i)^2}{M} \rightarrow \min \tag{6}$$

In the basic form of the GMDH algorithm, all the possibilities of two independent variables out of total n input variables are taken in order to construct the regression polynomial in the form of Eq. (5) that best fits the dependent observations (yi,i = 1,2,...,M) in a least-squares sense. Consequently, $\binom{n}{2} = \frac{n(n-1)}{M}$ neurons will be built up in the first hidden layer of the feed forward network from the observations {(yi, xip, xiq); (i = 1,2...,M)} for different p, q $\in$ {1, 2,...,n}. In other words, it is now possible to construct M data triples {(yi, xip, xiq); (i = 1, 2..., M)} from observation using such p, q $\in$ {1, 2,..., n} in the form:

$$\left[\begin{array}{cc|c} x_{1p} & x_{1q} & y_1 \\ x_{2p} & x_{2q} & y_2 \\ \hline x_{Mp} & x_{Mq} & y_M \end{array}\right] \tag{7}$$

Using the quadratic sub-expression in the form of Eq. (5) for each row of M data triples, the following matrix equation can be readily obtained as:

$$A\boldsymbol{a} = Y \tag{8}$$

Where **a** is the vector of unknown coefficients of the quadratic polynomial in Eq. (5)

$$\mathbf{a} = \{a_0, a_1, a_2, a_3, a_4, a_5\} \tag{9}$$

And $Y = \{y_1, y_2, y_3, ..., y_M\}^T$ is the vector of output's value from observation. It can be seen that:

$$A = \left[\begin{array}{cccccc} 1 & x_{1p} & x_{1q} & x_{1p}x_{1q} & x_{1p}^2 & x_{1q}^2 \\ 1 & x_{2p} & x_{2q} & x_{2p}x_{2q} & x_{2p}^2 & x_{2q}^2 \\ \hline 1 & x_{Mp} & x_{Mq} & x_{Mp}x_{Mq} & x_{Mp}^2 & x_{Mq}^2 \end{array}\right] \tag{10}$$

The least-squares technique from multiple-regression analysis leads to the solution of the normal equations ac shown in Eq. (11):

$$\mathbf{a} = (A^T A)^{-1} A^T Y \tag{11}$$

This determines the vector of the best coefficients of the quadratic Eq. (5) for the whole set of M data triples. It should be noted that this procedure is repeated for each neuron of the next hidden layer according to the connectivity topology of the network. However, such a solution directly from normal equations is rather susceptible to round off errors and, more importantly, to the singularity of these equations. Recently, genetic algorithms have been used in a feed forward GMDH-type neural network for each neuron searching its optimal set of connection with the preceding layer (Nariman-zadeh *et al*. [17]). Jamali *et al*. [19] have proposed a hybrid use of genetic algorithm for a simplified structure GMDH-type neural network in which the connections of neurons are restricted to adjacent layers. In this paper using GA for finding GMDH-type neural networks for modeling the Pareto optimized data.

**Empirical Results:** In this Section, we first describe the data used in this research in Section 3.1 and then define some evaluation criteria for prediction purposes. Afterwards, the empirical results and explanations are presented in Section 3.2.

**Data Description:** We employ daily Henry Hub Gulf Coast Natural gas spot price covering the period from January 1, 2004 through to December 31, 2008, based on gas contracts obtained from EIA. We use daily data of Natural Gas Futures Contract 1 (Dollars per Million BTU), WTI Spot Price FOB (Dollars per Barrel) and Crude Oil Future Contract 1 (Dollars per Barrel) for regression.

For tractability, we utilize neural networks with two hidden layers and a direct connection between the lagged moving average crossovers and prices.

2 lags of the 5[$MA_5$, $MA_5$(-1), $MA_5$(-2)], 50 [$MA_{50}$, $MA_{50}$(-1), $MA_{50}$(-2)], day moving average crossover[1], as input variables to the neural networks. The gas price data used in this study are daily Henry Hub Gulf Coast Natural gas spot price obtained from EIA (Energy Information Administration). We use the daily data from January 2004

[1]Such models are all based on rules using moving averages of recent prices. A typical moving average is simply the sum of the closing prices for the last *n* number of days divided by *n*, where *n* may be from 1 to 200 days the rules for using these tools are very similar and usually involve making a decision when a short-term average crosses over a long-term average. For example, the rule may be to buy when the 5-day moving average exceeds the 50-day moving average and to sell when the 5-day average is below the 50-day average. (Gencay *et al*. 1996)

to July 2007 as the in sample data sets for training and validation purposes and the remainder as the out of sample data sets for testing purposes and volatility is based on GARCH (1, 1).

In order to evaluate the prediction performance, it is necessary to introduce a forecasting evaluation criterion. In this study, two main evaluation criteria, root mean square error (RMSE) and direction statistics (Dstat) are introduced. The RMSE is calculated as: (Caslla and Lehmann, [20]).

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}e_i^2} \tag{12}$$

Where $e_i$ denotes the difference between forecasted and realized values and n is the number of evaluation periods. In the gas price forecasting, a change in trend is more important than precision level of goodness of fit from the viewpoint of practical applications. As a result, we introduce directional change statistics, Dstat. Its computational equation can be expressed as:

$$\text{Dstat}=\frac{1}{n}\sum_{i=1}^{n}|e_i| \tag{13}$$

Where $ei = 1$ if $(yi+1 - yi)$ $(\hat{y}_{i+1}-yi) = 0$ and $ei = 0$ otherwise. (Wang *et al*. [3]).

In addition, as the effects on gas price of irregular events can be measured in the rational range, then the interval forecasting results can be obtained.

Subsequently, irregular events and their effects are examined and explored. We find the irregular events and RES is utilized to measure the degree of impact of these irregular events.

We find some irregular events that affect the gas price from the Internet[1]. Some main factors are concluded by analyzing past events, as shown in Table 1.

Then for extract rules, we regress gas price on factors that affect it. There for I regress gas price as a dependent variable on oil price, crude oil futures price, natural gas futures price, global demand for gas, global demand for crude oil and dummy variable for environmental policy, taxes placed on gas price and OPEC cut production.

Table 1: The factor classification

| Year | Month | Day | Important events affecting gas price |
|---|---|---|---|
| 2005 | 6 | 2 | Environmental policy |
| 2005 | 9 | 24 | |
| 2006 | 5 | 8-15 | Taxes placed on gas price. |
| 2006 | 12 | 14 | Demand for Crude oil futures contracts increase |
| 2007 | 1 | 22-26<br>29-31 | OPEC cut production affected crude oil price. |
| 2007 | 2 | 12-16<br>20-23 | Increasing global gas demand |
| 2007 | 10 | 15-20<br>24-29 | Demand for natural gas futures contracts increase |
| 2007 | 12 | 26 | OPEC cut production affected crude oil price. |
| 2008 | 2 | 5 | Environmental policy |
| 2008 | 4 | 15 | Demand for Natural gas futures contracts increase |
| 2008 | 5 | 3 | Global demand of gas increased and affected gas price. |
| 2008 | 5 | 5-12<br>14-19<br>20-26 | Global demand of gas increased and affected gas price and global demand of crude oil increased and affected oil price. |
| 2008 | 6 | 2-9<br>11-16<br>24-30 | Crud oil price increased and affected gas price |
| 2008 | 6 | 6-9<br>11-13<br>25-30 | Global demand of gas increased and affected gas price. |
| 2008 | 7 | 1-3<br>10-14<br>29-31 | Demand for Natural gas futures contracts increase |
| 2008 | 9 | 8-15 | Demand for crude oil future contracts increase |
| 2008 | 10 | 16 | OPEC cut production affected crude oil price. |
| 2008 | 12 | 3,18 | Demand for Natural gas futures contracts increases |

[2]www.bloomberg.com www.wtrg.com/prices.htm.
www.washingtontimaes.com www.engdahl.oilgeopolitics.net
www.iirenergy.com

Table 2. OLS results

| Variables | Coefficient |
|---|---|
| Crude oil price | 0.3 |
| Crude oil futures price | 0.12 |
| Natural gas futures price | 0.23 |
| Environmental policy | 0.06 |
| Taxes placed on gas price | 0.26 |
| OPEC cut production | 0.17 |
| Global demand for crude oil | 0.09 |
| Global demand for gas | 0.16 |

Table 3: The typical rules

| Rule NO | Condition | Direction movements | The movements (%) |
|---|---|---|---|
| 1 | Increasing crude oil price | Increase | 30 |
| 2 | Taxes placed on gas price | Increase | 26 |
| 3 | OPEC design to cut production | Increase | 17 |
| 4 | Increasing global gas demand | Increase | 16 |
| 5 | Increasing global crude oil demand | Increase | 9 |
| 6 | Environmental policy | Increase | 6 |
| 7 | Increasing Crude oil futures price(increasing Demand for Crude oil futures contracts increase) | Increase | 12 |
| 8 | Natural gas futures price(increasing Demand for gas futures contracts) | Increase | 23 |

Table 4: The forecasting results of gas price for period of Jan. 2004 - Dec. 2008

| Evaluation Method | full period (2004-2008) | sub –period I 2004 | sub –period II 2005 | sub –period III 2006 | sub– period IV 2007 | sub-periodV 2008 |
|---|---|---|---|---|---|---|
| GMDH: | | | | | | |
| RMSE | 3.513 | 3.501 | 3.019 | 3.194 | 3.213 | 3.197 |
| *Dstat* (%) | 58.74 | 54.47 | 60.04 | 63.08 | 65.15 | 67.29 |
| Hybrid intelligent: | | | | | | |
| RMSE | 2.726 | 3.091 | 2.828 | 2.930 | 2.556 | 2.302 |
| *Dstat* (%) | 72.58 | 66.75 | 77.63 | 78.55 | 80.42 | 87.62 |
| GMDH & GARCH (1, 1): | | | | | | |
| RMSE | 3.329 | 3.283 | 2.917 | 3.116 | 3.150 | 3.106 |
| *Dstat* (%) | 68.33 | 59.12 | 68.24 | 70.38 | 73.62 | 74.91 |
| Hybrid intelligent with GARCH (1, 1): | | | | | | |
| RMSE | 2.514 | 2.894 | 2.783 | 2.674 | 2.181 | 1.915 |
| *Dstat* (%) | 80.72 | 76.85 | 82.65 | 85.21 | 89.43 | 93.33 |

We regress these variables with OLS and shown results in Table 2.

Table 2 presents in details the main judgmental or forecasting rules in this study according to the extraction of historical events affecting the gas price and contracts obtained from EIA (Energy Information Administration). In this table we are shown every events that affect gas price, these events are collected from sites. Therefore from Table 2 we can build rules, for example (Table 3) when crude oil price increases 1 percentage then gas price increases 30 percentages.

With the help of this information, one can judge the effect of irregular future events on the gas price by using the RES module. The rules should be adjusted with time and events in order to keep the expert system robust. We are shown rules in blow table and enter these rules to GMDH neural network and build an intelligent system for forecasting.

**A Simulation Study:** We employ a simulation experiment for proposed the hybrid intelligent system for gas price forecasting. In the simulation study, we reveal that

forecasting rules from expert system and moving average gas price are modeled by using GMDH neural networks. We used the Muti-Objective Optimization Program (Atashkari *et al*.[21]) and Pareto based multi-objective optimization (Amanifard *et al*. [22]) that was designed with this target: reducing error in modeling and forecasting that simultaneously increase the exactitude of forecasting and the stability of process for measurement the scale of variables effects in different patterns. Accordingly, the evaluation criteria are the root mean square error (RMSE) and direction change statistics (Dstat). For a comparison, the full evaluation period is divided into five sub-periods in terms of chronology. In addition, the individual GMDH forecasting method is used as a benchmark model in this research. The corresponding results are summarized in Table 4.

It observed that the hybrid intelligent with GARCH (1, 1) outperforms the other methods, in terms of either RMSE or Dstat. Notably, the values of Dstat of our hybrid intelligent forecasting method for each evaluation period exceed 70%, indicating that the proposed hybrid intelligent forecasting approach has good performance for the gas price forecasting considering the complexity of the gas market.

Focusing on the RMSE indicator, in the case of individual GMDH method, the second sub-period 2005 performs the best, followed by 2004, 2006, 2007 and 2008. While in the case of the hybrid intelligent method, the results of 2008 outperform those of the other evaluation period. The main reason is that many important events affecting gas price volatility happened. The information of those important events could be obtained.

From a practitioners' point of view, the Dstat indicator is more important than the RMSE. This is because the former c an reflect the movement trend of gas price and can help traders to make good trading decisions. For the test case of our hybrid intelligent approach and from the view of Dstat, the performance of 2008 is much better than 2004, 2005, 2006 and 2007, as shown in Table 4.

From Table 4, we observe that a smaller RMSE does not necessarily mean a higher Dstat value. For example, for the test case of the individual GMDH method, the RMSE for 2004 is slightly smaller than full-period period of 2004-2008, while the Dstat for 2004-2008 is larger than that for 2004. However, the overall prediction performance of the proposed hybrid intelligent approach is satisfactory because the RMSE for each evaluation period is smaller than 3.00 and the Dstat for each evaluation period exceeds 70%. Thus, the forecasting results of hybrid intelligent method are better than GMDH & GARCH (1, 1) method, but forecasting the gas price based on the hybrid intelligent with GARCH (1,1) is more accurate and this indicates that there are some profitable opportunities if traders use the proposed approach to forecast gas price.

## CONCLUSIONS

In this paper, we find some irregular events that affect the gas price and reveal rules according to events affecting gas price and a hybrid intelligent framework integrating RES with GMDH neural networks is employed for gas price forecasting.

We observed that during the crisis period, when we investigate the effects of irregular and infrequent events on gas price by regression and RES, we obtain better forecasting results compared to the GMDH neural networks and results will be so better when we employ hybrid intelligent system with GARCH (1, 1) for gas price volatility forecasting.

Overall, the obtained results reveals in 2008, when different important events took place, GMDH neural networks can not reveal effects of these events on gas price forecasting and forecast's results of this methodology are not so well.

Hence, the novel hybrid intelligent forecasting model can be employed as an effective tool for gas price forecasting and can improve forecasting accuracy. We can use from this method for forecasting the price of other commodities such as crude oil, gasoline metal price and price of other commodities.

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