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A Hybrid Intelligent System for Forecasting Gasoline Price

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Abstract

The difficulty in gasoline price forecasting has attracted much attention of academic researchers and business practitioners. Various methods have been tried to solve the problem of forecasting gasoline 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) with Web-based Text Mining (WTM) employs for gasoline price forecasting. Our research reveals that during the recent financial crisis period by employing hybrid intelligent framework for gasoline 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 gasoline price volatility forecasting.

Keywords: Gasoline price forecasting; Web-based Text Mining (WTM); Group Method of Data Handling (GMDH) neural networks; Genetic Algorithm (GA); Hybrid Intelligent System; Rule–based Expert System (RES); GARCH (1, 1) method.

1- Introduction

Problems of complex objects modeling such as analysis and prediction of stock market, gasoline price and other such variables cannot be solved by deductive logical-mathematical methods with needed accuracy with a

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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. Gasoline price is primarily formed by supply and demand forces but is also influenced by factors such as gasoline 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 (1994). 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 (1995) 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. (1998). Nasr et al. (2002) used artificial neural network (ANN) approach to gasoline consumption (GC) forecasting in Lebanon. Ambrishami et al. (2008) 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. (2008) 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 (2009) used methods of multiple linear regression and artificial neural networks for the 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 (1996) 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 (1998a) and Gencay (1999) and Gencay et al. (1998) 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 gasoline prices from 2004 to 2008 for forecasting the gasoline 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 WTM and RES techniques and volatility is based on GARCH (1, 1). Over all, we observed that the hybrid intelligent framework improve the forecasting results of gasoline price.

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

2-The Hybrid Intelligent System for crude oil price forecasting.

A superior approach is employed to develop a hybrid intelligent system that can implement gasoline price forecasting in the volatile gasoline market. The hybrid intelligent system for gasoline price forecasting consists of WTM module, GMDH based time series forecasting module, RES module, bases and bases management module.

In Section 2.1 the WTM and in Section 2.2 RES are reviewed. Section 2.3 covers GMDH neural network. Afterwards Section 2.4 reviews Bases and bases Management Module.

2-1- Web-based text mining (WTM) module

The gasoline market is an unstable market and gasoline prices are often affected by many related factors. In order to improve forecasting accuracy, these related factors must be taken in to consideration. It is therefore necessary to collect related information from the Internet and analyze its effects on the gasoline price. However, it is very difficult to collect the related knowledge from the Internet. With the advancement of computational techniques, WTM is believed to be one of the most effective techniques of collecting this information. (Rajman and Besanon, 1998)

In this study, the main goal of the WTM module is to collect related information affecting gasoline price variability from the Internet and to use this provide the collected useful information for the RES forecasting module. The whole WTM process can be divided in to three phases as follows:

1) Feature extraction phase:

The Internet contains an enormous, hetero-structural and widely distributed information base in which the amount of information increases in a geometric series. In the information base text sets that satisfy some conditions can be obtained by using a search engine. However, the collected text sets are mainly represented by web pages, which are tagged by hypertext makeup language (HTML). Thus collected documents or texts are mostly semi- or non-structural information.

Our task is to extract certain features that represent the text contents from these collected texts for further analysis and application. Here the vector space model (VSM) is introduced to analyze the text content. (Salton et al. 1971)

2) Structure analyzing phase:

In this phase, based on the results of the text structure analyzer, text abstracts can be generated using a text abstract builder. In the text sets, web texts contain both pure texts and all kinds of hyperlinks that reflect relationships in different web pages. It is therefore necessary to analyze the text structure. By analyzing the linkage of web texts, we can judge relationships in different documents. This is useful for finding new knowledge. In the same way, by analyzing the web linkage and the number of hyperlinks, we can obtain similar and interconnected material in different web texts, thus further increasing the efficiency of information retrieval.

3) Text classification phase:

Classification is one of the most important tasks in data mining. The main goal of classification is to make retrieval or query speed faster and make the retrieval more efficient and more precise than before. (Shi, 2002).

2-2- 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, 2005)

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 gasoline price by summarizing and concluding relationships between gasoline price fluctuation and irregular key factors affecting gasoline 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 gasoline market. (Yu et al. 2003)

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

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PATTERN pattern- name
IF condition A
(AND condition B)
(OR condition C)· · ·
THEN PATTERN = pattern name
EXPLANATION = statement A
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Figure 1. The Syntax of Individual. Pattern.

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PATTERN pattern- name
IF pattern A
(AND pattern B)
(OR pattern C)
(AND condition A)
(OR condition B)
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Figure 2 .The Syntax of a Combination Pattern.

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 gasoline price variability can be constructed. As previously mentioned, world events such as wars can have an immediate impact on the gasoline 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. Figures1 and 2 show how individual patterns and combination patterns are defined and constructed. 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 gasoline 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. 2004)

2-3- 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:

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

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:

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

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:

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

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

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

This is known as the Kolmogorov–Gabor (Farlow, 1984; Iba et al. 1996; Ivakhnenko, 1971; Nariman-Zadeh et al. 2002; Sanchez et al. 1997). 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:

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

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 a_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, $\binom{n}{2} = \frac{n(n-1)}{2}$ 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∈ {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 ∈ {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:

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

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 as 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. 2003). Jamali et al. (2006) 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.

2-4- Bases and bases Management Module

The bases management module is an important part of our new approach because the other modules have a strong connection with this one. For example, all three use databases (DB) but in addition the econometrical module and GMDH utilize model bases (MB) while the RES mainly uses knowledge bases (KB). In the bases management module, KB is the aggregation of domain materials and rules from knowledge engineers and domain experts. Furthermore, the KB rules are formulated by extracting information from the DB historical data. KB is the key component determining the quality of the new approach. In addition, how well the KB is organized and qualified determines supportive strength over the gasoline prediction. In the same way, the databases are collected from real gasoline prices and gasoline price prediction results from the GMDH forecasting module. It can be used to fine-tune the knowledge in order to adapt to a dynamic situation. The model bases are the aggregation of algorithms and models from other modules. This component can also support implementation of the GMDH forecasting module and WTM module.

In addition, knowledge management and verification (KMV) in the based management module can add new rules to the KB using a knowledge acquisition tool, edit or adjust existing rules and delete obsolete rules in the KB. KMV can also verify the KB by checking consistency, completeness and redundancy. There are hundreds of rules in the KB that represent the domain expert’s heuristics and experience. Using the knowledge acquisition tool, domain experts specify their rules for the KB and represent their rules in the format “IF · · · THEN · · ·”. The knowledge acquisition toll automatically converts the rules into an inner encoded form. After the new rules have been added, the knowledge base verifier checks for any inconsistency, incompleteness or redundancy that might have arisen as a result of adding the rules. (Yu et al. 2003)

3- 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.

3-1- Data Description

We employ daily gasoline price covering the period from January 1, 2004 through to December 31, 2008, based on gasoline contracts obtained from EIA. 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 gasoline price data used in this study are daily gasoline prices obtained from EIA (Energy Information Administration). We use the daily data from January 2004 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, 1999)

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \qquad (12)$$

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).

Where e_i denotes the difference between forecasted and realized values and n is the number of evaluation periods. In the gasoline 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:

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

Where $ei = 1$ if $(yi+1 - yi)\ (\hat{}yi+1 - yi) \geq 0$, and $ei = 0$ otherwise. (Wang et al. 2004)

In addition, as the effects on gasoline 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. WTM is used to find the irregular events and RES is utilized to measure the degree of impact of these irregular events.

According to the previous description of WTM, we can find some irregular events that affect the gasoline price from the Internet[1]. Some main factors are concluded by analyzing past events, as shown in Table1

Table 1: The factor classification

1- www.bloomberg.com.
www.wtrg.com/prices.htm.
www.washingtontimaes.com.
www.engdahl.oilgeopolitics.net
www.iirenergy.com.

Year	**Month**	**Day**	Important events affecting gasoline price
2005 2005	6 9	2 24	Environmental policy
5	8-15		Taxes placed on gasoline price and taxes increased.
2006	12	14	Storm
2007	1	22-26 29-31	OPEC cut production affected crude oil price.
2007	2	12-16 20-23	Average inventories for gasoline declined and affected gasoline price.
10	15-20	24-29	
2007	12	26	Storm
2008	2	5	OPEC cut production affected crude oil price.
2008	4	15	Environmental policy
2008	5	3	Storm
5	5-12	14-19 20-26	Global demand of gasoline increased and affected gasoline price.
2008	6	2-9 11-16 24-30	Global demand of gasoline increased and affected gasoline price.
2008	6	6-9 11-13 25-30	Crud oil price increased and affected gasoline price
2008	7	1-3 10-14 29-31	Crud oil price increased and affected gasoline price
2008	9	8-15	Average inventories for gasoline declined and affected gasoline price.
2008	10	16	Environmental policy
2008	12	3,18	OPEC cut production affected crude oil price.

Table 2 presents in details the main judgmental or forecasting rules in this study according to the extraction of historical events affecting the gasoline price and contracts obtained from EIA (Energy Information Administration). When certain irregular events happen, a range of price movements can be given by the expert system module. With the help of this information, one can judge the effect of irregular future events on the gasoline price by using the WTM and RES modules. The KB rules should be adjusted with time and events in order to keep the expert system robust.

Table 2: The Typical Rules in the Knowledge Bases

Rule NO	Condition	Direction Movements	The Movements (%)
1	Increasing crude oil price	Increase	29 -38.5
2	Taxes placed on gasoline price	Increase	29 -36
3	OPEC design to cut production	Increase	0.7 -2
4	Increasing global gasoline demand	Increase	1.6 -3
5	Average inventories for gasoline decline	Increase	4.5 -7
6	Environmental policy	Increase	6.2 -10
7	Storm	Increase	31 -42

3-2- A Simulation Study

We employ a simulation experiment for proposed the hybrid intelligent system for gasoline price forecasting. In the simulation study, we reveal that forecasting rules from expert system and moving average gasoline price are modeled by using GMDH neural networks. We used the Muti-Objective Optimization Program (Atashkari et al.2007) and Pareto based multi-objective optimization (Amanifard et al. 2007) 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 3.

Table 3: The forecasting results of gasoline 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	3.516	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	2.728	3.092	2.829	2.931	2.555	2.304
Dstat (%)	72.59	66.74	77.62	78.55	80.41	87.63
GMDH & GARCH (1, 1):						
RMSE	3.329	3.284	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	2.780	2.674	2.182	1.925
Dstat (%)	80.72	76.83	82.63	85.23	89.48	93.33

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 gasoline price forecasting considering the complexity of the gasoline market.

Focusing on the RMSE indicator, in the case of individual GMDH method, the second sub-period_2005 performs the best, followed by2004, 2006 ,2007and 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 gasoline price volatility happened. The information of those important events could be obtained and analyzed by the WTM technique.

From a practitioners' point of view, the Dstat indicator is more important than the RMSE. This is because the former can reflect the movement trend of gasoline 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 3.

From Table 3, 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 gasoline 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 gasoline price.

4- Conclusions

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

We observed that during the crisis period, when we investigate the effects of irregular and infrequent events on gasoline price by WTM 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 gasoline price volatility forecasting.

Overall, the obtained results reveals in 2008, when different important events took place, GMDH neural networks cannot reveal effects of these events on gasoline 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 gasoline price forecasting and can improve forecasting accuracy.

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