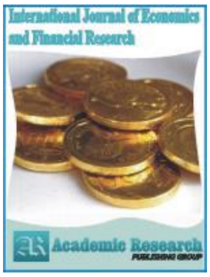



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# Forecasting Iron Price by Hybrid Intelligent System


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**Abstract:** Novel hybrid intelligent framework is introduces by integration of GMDH neural networks with Web-based Text Mining (WTM) and GA and Rule-based Exert System (RES) in this paper for forecast iron price. Our research reveals that by employing hybrid intelligent framework for iron price forecasting, there is better forecasting results respect to the GMDH neural networks. Therefore significance of this study is to survey a hybrid intelligent framework for iron price forecasting.



**Keywords:** Iron price forecasting; Group Method of Data Handling (GMDH) neural networks; Hybrid Intelligent System; Rule–based Expert System (RES); Web-based Text Mining (WTM).


## Contents



## 1. Introduction

In Iran, iron is used in manufacture and housing and it's price is so important, because rises in price of iron can cause to increase house price in Iran.

Iron price is formed by demand and supply forces but influenced by some factors such as iron products inventory levels, political situation and stock markets activities. So the use of iron price as an economic indicator drew the attention of many economists. Neural networks, the genetic algorithm and their integration are used for engineering decision systems, techniques. These systems are used in economics.

Cheng and Titterington (1994) revealed a new neural networks. They showed that in comparison with statistical techniques neural networks provide a higher degree of robustness. Kuo and Reitsch (1995) revealed that neural networks provide meaningful predictions, when independent variables are missing. Therefore neural networks tended view regression analysis in independent variables at presence of obscurity. Then well-trained network is expected to provide robust predictions. Wong and Yakup (1998) surveyed applications of neural network in finance and business.

Sarfaraz and Afsar (2005) have done another paper by neuro-fuzzy networks for gold price forecasting in Iran. Gencay (1996) used technical analysis rules as inputs for neural networks, and nonlinear models with powerful pattern recognition properties for foreign exchange markets. Gencay (1998a) and Gencay (1999) and Gencay and Stengos (1998) for both foreign exchange rates revealed simple technical rules improved results of forecast for current returns.

In this paper a moving average daily Iron price from 2009 to 2013 is used to forecast the iron price and a GMDH neural networks model, using WTM and RES techniques are used for iron price forecasting. This paper showed that the hybrid intelligent framework improves the iron price forecasting.

In this paper, in section 2 a general discussion of WTM, RES and GMDH neural networks modeling is introduced. Empirical results and concluding reviews are presented and in Section 3 and Section 4.

# 2. The Hybrid Intelligent System for Iron Price Forecasting

In this paper we employed a hybrid intelligent system that can forecast iron price in the volatile metal market. Hybrid intelligent system consists of GMDH based time series forecasting module, RES module, bases and bases management module and WTM module.

## 2.1. Web-based Text Mining (WTM) Module[1]

The iron market is an unstable market with high volatility, and iron prices are often affected by many related factors. These related factors must be taken in to consideration to improve forecasting accuracy. Therefore we should collect related information from the Internet and analyze its effects on the iron price. However, to collect the related knowledge from Internet is too hard and time waste. But WTM is one of the most effective techniques for collecting this information. (Rajman and Besanon, 1998).

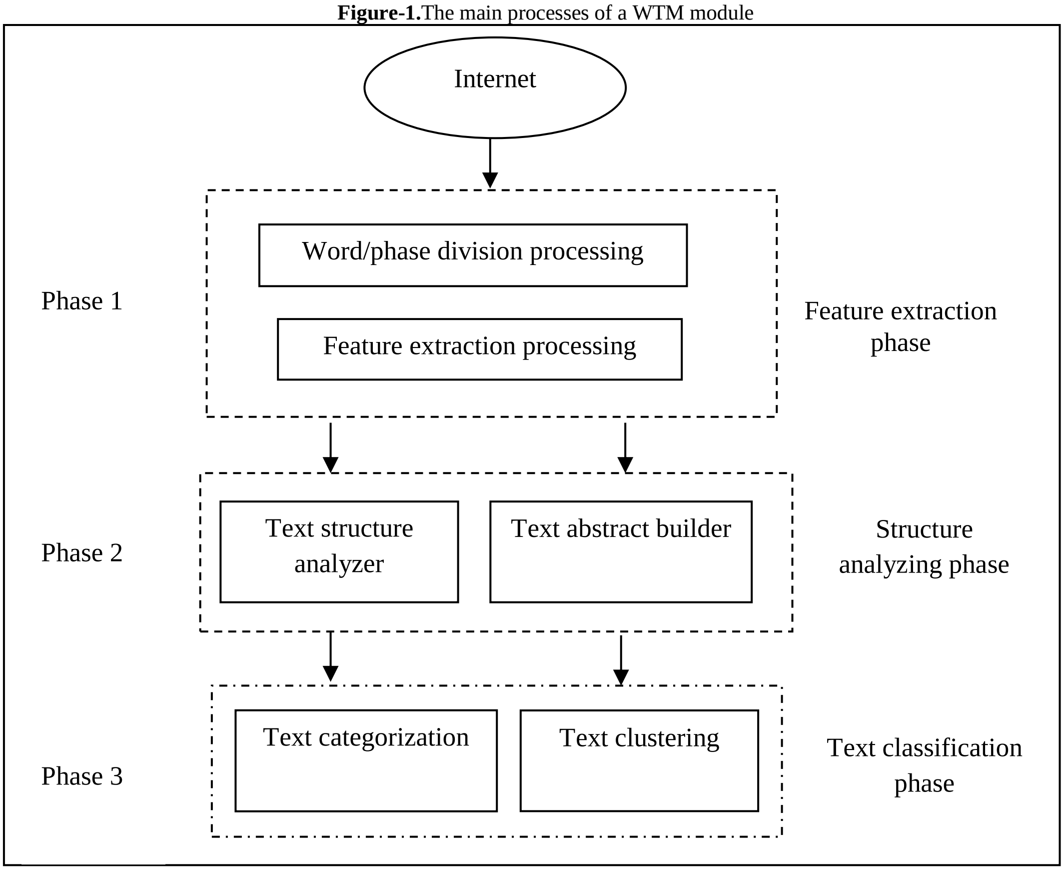
The main goal of the WTM module, in this study, is collected related information affecting iron price variability from Internet and to provide useful information for the RES forecasting module. The main process of the WTM is presented in Figure1.

As Figure 1, WTM process can be divided into three phases:

**1) Feature Extraction Phase:**

The Internet contains an enormous and widely distributed information base and the amount of information increases. In the information base, some conditions can be obtained by using a search engine. However, the collected text sets are mainly represented by web pages.

**Figure-1.**The main processes of a WTM module




**2) Structure Analyzing Phase:**

Text abstracts can be generated using a text abstract builder based on the results of text structure analyzer. Web texts contain both pure texts and hyperlinks which reflect relationships in different web pages. Therefore it is necessary to analyze the text structure. We can judge relationships in different documents by analyzing linkage of web texts. Finding new knowledge is so important. Therefore we can obtain similar and interconnected material in different web texts, thus efficiency of information retrieval is increased.

[1]Varahrami (2014).

**3) Text Classification Phase Create:**

In data mining, Classification is one of the most important tasks. Main goal of classification is to make retrieval or query speed faster and make the retrieval more efficient and more precise than before. (Wang *et al.*, 2004)

## 2.2. Rule-based Expert System (RES)[2]

In this paper KB is represented by all types of rules from knowledge engineers. The main work of an RES module is collected and extracted rules or knowledge category from the KB. Our expert system module is used to extract some rules to judge variability in the iron price by summarizing relationships between iron price fluctuation and irregular key factors affecting iron price volatility. We use from useful price volatility mechanism to predict iron price movements; one has to first observe historical price patterns that occur frequently in the iron market.

In this paper, the relationships between the iron price variability and the factors affecting iron price are examined. (Bauer and Liepins, 1992)

If there are strong connections between price movements and price influencing factors, then factors are selected from the historical price patterns and a KB for predicting iron price variability can be constructed. Therefore, some world events such as wars can have an immediate impact on the iron price. Then to represent irregular patterns in a more organized and systematic way, price patterns are classified into individual patterns and combination patterns.

Individual patterns have simple conditions and attributes are used in defining combination patterns. In this paper, the pattern can be considered to represent a rule because the conditions of a pattern can be seen as conditions of a rule. Figures 2 and 3 show how individual patterns and combination patterns. As figure 2. If important events are matched with the IF condition of a particular pattern, then pattern is identified by the conditions, and the EXPLANATION part gives information about what the pattern really means. Individual pattern has its own meaning and can be an important role in predicting iron price volatility. As figure 3, combination patterns integrate several conditions or patterns to explain a certain sophisticated phenomenon, (Wang *et al.*, 2004)

**Figure 2.** The syntax of individual pattern.

```
PATTERN pattern name
IF condition A
(AND condition B)
(OR condition C)
. . .
THEN PATTERN = pattern name
EXPLANATION = statement A
```

**Figure 3 .**The syntax of a combination pattern.

```
PATTERN pattern name
IF pattern A
(AND pattern B)
(OR pattern C)
(AND condition A)
(OR condition B)
. . .
THEN PATTERN = pattern name
```

## 2.3. GMDH Neural Networks[3]

GMDH neural networks are based on concept of pattern recognition. GMDH neural networks are highly flexible, semi parametric models, have been used in many scientific fields such as engineering**.**

Neural networks represent an alternative to standard regression techniques and are useful for dealing with non-linear multivariate relationships, for economists.

By applying GMDH algorithm there can be represented a set of neurons in which different pairs of them in each and thus produce new neurons in the next layer. The formal definition of identification problem is to find a function f^ that can be approximately used instead of actual one, f, 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 observation of multi-input-single-output data pairs:

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

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:

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

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

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

---

[2] Varahrami (2014).

[3] Abishami *et al.* (2010a).

General connection between inputs and output variables can express by a complicated discrete form of the Volterra functional series, which is known as the Kolmogorov–Gabor (Farlow, 1984; Iba *et al.*, 1996; Ivakhnenko, 1971; Nariman-zadeh *et al.*, 2002; Sanchez *et al.*, 1997). :

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

Full form of mathematical description can be represented by a system of partial quadratic polynomials consisting of only two neurons in the form of:

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

Therefore, such partial quadratic description is 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 by regression techniques (Farlow, 1984; Nariman-zadeh *et al.*, 2002) so that difference between actual output, y, and the calculated, y^, for each pair of xi, xj as input variables is minimized. In Eq. (5) coefficients are obtained in a least-squares sense. In this way, the coefficients of each quadratic function Gi are obtained to fit the output that is:

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

In form of the GMDH algorithm, all two independent variables out of total n input variables are taken in order to construct the regression polynomial in the form of Eq. (5). $\binom{n}{2} = \frac{n(n-1)}{2}$ 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 $\in$ (1, 2, . . . ,n). In other words, it is now possible to construct M data triples in the form:

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

Using quadratic sub-expression for each row of M data triples, the following matrix equation can be readily obtained as:

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

Where $\mathbf{a}$ 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 $Y = \{y_1, y_2, y_3, \ldots, y_M\}^T$ is the vector of output's value from observation:

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

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

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

We should note that this procedure is repeated for each neuron of next hidden layer according to the connectivity topology of the network. Recently, for each neuron searching its optimal set of connection with the preceding layer, genetic algorithms have been used in a feed forward GMDH-type neural network (Nariman-zadeh *et al.*, 2002).

### 2.4. Bases and Bases Management Module[4]

Bases management module is an important part of our new approach because other modules have a strong connection with this one.

KB, in the bases management module, is the aggregation of domain materials and rules from knowledge engineers. Furthermore, KB rules are formulated by extracting information from the DB historical data. KB is component determining quality of the new approach. In addition, KB is organized and qualified determines strength over the iron prediction. Databases are collected from real iron prices and iron price predict results from the GMDH forecasting module. It can be used to fine-tune the knowledge in order to adapt to a dynamic situation. 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. Therefore in the based management module, knowledge management and verification (KMV) can add new rules to the KB, 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 KB that represent the domain expert's heuristics and experience. Using the knowledge acquisition tool, domain experts specify their rules for the KB in the format "IF · · · THEN · · ·". The knowledge acquisition automatically converts the rules into an inner encoded form. After new rules have been added, the knowledge base verifier checks for any inconsistency, incompleteness that might have arisen as a result of adding the rules (Wang *et al.*, 2004)

## 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

In this paper, daily iron price covering January 1, 2009 through December 31, 2013 separately, are used and with iron prices, iron contracts obtained from Metal Price[5]. We utilize neural networks with two hidden layers and a direct connection between the lagged moving average and prices. As input variables to the neural networks, 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[6] are used. The iron daily price data used in this study.

It is necessary to introduce a forecasting evaluation criterion to evaluate the prediction performance. In this study, two main evaluation criteria, root mean square error (RMSE) and direction statistics (Dstat) are introduced. The RMSE is calculated as: (Berger, 1985; Casella and Lehmann, 1999; Degroot, 1980; Mood *et al.*, 1974).

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

$e_i$ denotes the difference between forecasted and realized values and n is the number of evaluation periods. A change in trend is more important in iron price forecasting, than precision level of goodness of fit from the viewpoint of practical applications is serious. Then we introduce Dstat. Its 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. As the effects on iron price of irregular events can be measured in the rational range, then the interval forecasting results can be obtained.

Irregular events and their effects are examined and explored. WTM is used to find the irregular events and RES is to measure degree of impact of these irregular events.

**Table-1.** The factor classification

| Factors | Examples |
|---|---|
| Speculation | 2009: in future market |
| Dollar s value decline | 2009-2013: average decline is 20% |
| Increasing global iron demand | 2009-2010: demand of iron increase in housing |
| Increasing metal price | 2011-2013 |
| Increasing investment in metal | 2009 -2013 |

[4]Abishami *et al.* (2010b).

[5] **MetalPrices.com**

[6] 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 (1996).

**Table-2.**The typical rules in the knowledge bases

| Rule NO | Condition | Direction movements | The movements (%) |
|---|---|---|---|
| 1 | Speculation | Increase | 12 |
| 2 | Dollar s value decline | Increase | 35.94 |
| 3 | Increasing global iron demand | Increase | 11 |
| 4 | Increasing metal price | Increase | 3 |
| 5 | Increasing investment in metal | Increase | 6.2 |

According to the previous description of WTM, we can find some irregular events that affect the iron price from Internet. Some main factors are concluded by analyzing past events in Table 1.

Table 2 showed the forecasting rules according to the extraction of historical events affecting the iron price. A range of price movements can be given by the expert system module, when certain irregular events happen. By help of this information, by using the WTM and RES modules, we can judge the effect of irregular future events on the iron price. KB rules should be adjusted with time and events in order to keep the expert system robust.

### 3.2. A Simulation Study

A simulation experiment for proposed the hybrid intelligent system for iron price forecasting is used. Therefore, we reveal that forecasting rules from expert system and moving average iron 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.*, 2008) which designed with this target: reducing error in modeling and forecasting that simultaneously increase exactitude of forecasting and the stability of process of measurement the scale of variables effects in various patterns. The evaluation criteria are RMSE and Dstat.

Table 3 shows results of the simulated experiment. We can see that the hybrid intelligent system outperforms the individual GMDH method in terms of either RMSE or Dstat. Values of Dstat of our hybrid intelligent forecasting method for each evaluation period exceed 70%, it indicated that proposed hybrid intelligent forecasting approach has good performance for the iron price forecasting.

In the case of individual GMDH method, the RMSE indicator, third sub-period 2011 performs the best. While in the case of the hybrid intelligent method, the results of 2013 outperform those of the other evaluation period. The main reason is that many important events affecting iron price volatility happened in this year and information of those important events could be obtained by the WTM technique.

Indicator Dstat is more important than the indicator RMSE, from practitioner's point of view. Because the former can reflect movement trend of iron 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 2013 is much better than 2009, 2010.2011 and 2012 as shown in Table 3.

**Table-3.** The forecasting results of iron price for period of Jan. 2009 - Dec. 2013

| Evaluation Method | Full Period (2009-2013) | Sub Period I 2009 | Sub Period II 2010 | Sub Period III 2011 | Sub Period IV 2012 | Sub Period V 2013 |
|---|---|---|---|---|---|---|
| **GMDH:** | | | | | | |
| RMSE | 3.475 | 3.461 | 3.212 | 3.023 | 3.187 | 3.206 |
| Dstat (%) | 60.15 | 57.24 | 59.35 | 62.33 | 64.42 | 66.18 |
| **Hybrid Intelligent:** | | | | | | |
| RMSE | 2.572 | 2.834 | 2.765 | 2.526 | 2.045 | 1.912 |
| Dstat (%) | 82.29 | 74.77 | 77.97 | 80.53 | 88.36 | 94.25 |

As Table 3, a smaller RMSE does not necessarily mean higher Dstat. For example, for individual GMDH method, RMSE for 2010 is slightly smaller than for full-period 2009-2013, while the Dstat for period of 2009-2013 is larger than 2010. However, overall prediction performance of the proposed hybrid intelligent approach is sgood because the RMSE for each evaluation period is smaller than 3.00 and the Dstat for each evaluation period exceeds 70%. This indicates that if traders use the proposed approach to forecast iron price, there are some profit opportunities. (Wang *et al.*, 2004)

## 4. Conclusions

In our survey, we find some irregular events that affect iron price and we reveal rules according to events affecting iron price and we used from a hybrid intelligent framework integrating WTM and RES with GMDH neural networks for iron price forecasting.

We showed that during the crisis period, when we observed the effects of irregular and infrequent events on iron price by WTM and RES, better forecasting results respect to the GMDH neural networks are accrued. In our sample, in 2013 different important events happen, in this year GMDH neural networks can not reveal effects of these events on forecasting iron price and forecast's results of this methodology are not so well.

Therefore, hybrid intelligent forecasting model can be used as an effective tool for iron price forecasting and can improve forecasting accuracy.

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