The Multiagent Model for Predicting the Behaviour and Short-term Forecasting of Retail Prices of Petroleum Products

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Keywords: Multi-agent Models, Oligopolistic Market, Neuron Net, Retail Prices, Petroleum Products, Short–term Forecasting.

Abstract: In this study, we develop a multi-agent system model for the purpose of predicting the behaviour of petroleum product prices using short-term forecasting. Having analysed the issue, we found that the ability of multi-agent models to describe the behaviour of individual market agents along with with the oligopolistic nature of the market makes it possible to describe a long-term cooperation of agents. But the accuracy of short-term price predictions for the multi-agent model is insufficient. According to our hypothesis, this is caused primarily due to the nature of the agent's heuristic algorithm as well as taking the price indices as the sole input. The accuracy of the price forecast for the multi-agent model in the short term is somewhat inferior to co-integration models and forecasting models based on neural networks that use historical price data of petroleum products. In this paper we have studied a hybrid model containing a certain set of agents, their price reaction is based on the neural network training process for each agent. With this approach it is possible to consider not just the price data from the past, but also such factors as potential threats and market destabilisation. Result comparison between the price obtained through our short-term forecast model and real data shows the former's advantage over pure multi-agent models, co-integration models and over models forecasting based on neural networks.

1 INTRODUCTION

Assessment of the current situation and forecasting price changes remains being a relevant theme in market research. Previous studies made in recent years regarding the petroleum product market in different countries clearly show a significant margin of error transience of price. High dependence on the fuel market of the world oil market impact on retail prices, and their volatility in recent years has a clear upward trend. This all led to the existing situation, in which forecasted retail prices show significant deviations from the actual data.

Factor analysis has shown that the main sources of market balance disturbances tend to be of external nature, especially when it comes to prices of oil its derivatives around the world and exchange rates. However, based on the interpretation of Engle-Granger, it has been proved that the price is fixed depending on each particular combination of input factors. This in turn permits using error correction models to forecast retail prices. At the same time, it is typical of the petroleum product market to experience price hikes – sudden changes in retail price of petroleum products due to shifts in external factors.

Such price hikes are unpredictable, thus resulting in destabilization of the petroleum product, which then leads to negative consequences for the economy and sometimes may even trigger social unrest. The co-integration theory is not designated for such cases; all the while it is effective in predicting the trends of gasoline prices at times when the impact of external factors is relatively small. The situation is even more complicated by the oligopolistic nature of the retail market. These two circumstances: fluctuations in wholesale prices and the oligopolistic nature of the market price give birth to an anomaly known as price asymmetry. Thus creating the necessity to not merely predict prices for a given period, but to somehow anticipate fuel price hikes, in an effort to control the situation. In this paper we glance at the system of predicting and forecasting prices of petroleum products, based on the factors related to the data monitoring information system

Galchynsky, L. and Svydenko, A.
The Multiagent Model for Predicting the Behaviour and Short-term Forecasting of Retail Prices of Petroleum Products.
DOI: 10.5220/0006361706320637
In *Proceedings of the 19th International Conference on Enterprise Information Systems (ICEIS 2017) - Volume 1*, pages 632-637
ISBN: 978-989-758-247-9

that could potentially be a threat, destabilizing the market price for petroleum products.

2 RELATED WORKS

The theme of forecasting the price of petroleum products is important for markets around the world. In the past decades this topic was focused on by many researchers in numerous countries around the world (Lewis, 2003; Sadorsky, 2006; Perdiguero García, 2010). In (Galczynski, 2014) have been analyzed the comparative capabilities of different statistical techniques and neural networks that use historical data values of retail prices in terms of the accuracy of short-term forecasting of the product oil prices.

Many aspects of using the multi-agent approach to competition in oligopolistic markets were studied by (Tsvetovat and Carley, 2002; Happenstall et al., 2004; Levin et al., 2009; Ramezani et al., 2011; Galchynsky et al., 2011).

Also a number of studies focusing on using neural networks for short-term forecasting of commodity market prices have been conducted by (Hinton et al., 2012), (Wan. et al., 2013),(He et al., 2015).

3 MODEL

Previous studies proved the possibility of constructing agent-based models for the petroleum product. However, having analyzed their use, a fair number of deficiencies start to surface, such as the lack of accurate short-term price forecasts. In our opinion this is due to the heuristic nature of describing agent behavior, which is linked to the current retail prices.

Nonetheless, it is well known that the behavior of market players, putting wholesale prices and price competition aside, is affected by various economic indicators of the network. At any given time period the agent calculates a simplified set of economic indicators: cost of sales per unit, current margin of the retail network and where their own selling prices stand compared to those of their competitors. In addition to price indicators, an important factor in making a decision to change prices for petroleum products, thus resulting in market stress, is additional non-price related information on various threats that may appear on the market. For the Ukrainian petroleum product these threats can be grouped into the following classes:

- changes in excise duty for manufacturing and importing petroleum products;
- changes in excise duty for retail sales of petroleum products;
- changes in petroleum prices;
- significant fluctuations of petroleum product prices in Europe and wholesale prices in Ukraine;
- rate hikes for rail transport and pipeline transport;
- changes in the legislative framework and/or introduction of new taxes;
- other threats that are potentially able to disrupt the normal cycle of raw material supply.

Based on this list we can see that information about threats can be obtained both through numerical values, and via various textual information reported by the media and other sources. Depending on these groups of factors, one must first predict price behavior, and only then should a forecast be constructed.

Unlike previous agent-type models of the petroleum product market, this model includes only one type of agents - retail petrol station chains. The model does not implement complex communication mechanisms between agents, but the agents do share information about their prices with other agents. The only action that the agent is capable of is to change the price.

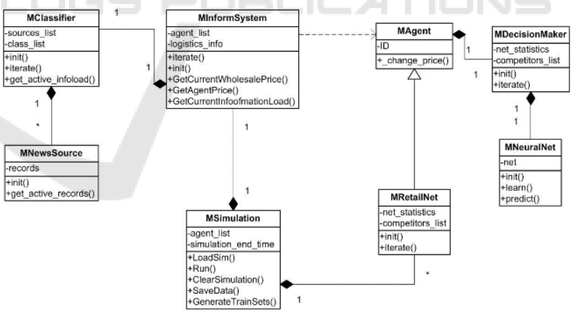

Figure 1: Model Structure.

The agent's behavior is based on results of the calculation of the neural network. In every time period the agent performs the following actions:

- gathers information on prices of other agents;
- receives information on wholesale prices and the list of threats;
- decides on a price change.

Figure 1 shows the structure of the object model, in fact for the real market, in this case the Ukrainian petroleum product this amounts to 6 agents. The current number of networks is dictated primarily by the national character of their actions and relationships with other agents. Other agents have an insignificant market share, that being said, the networks are led by market leaders. Therefore, increasing the number of agents will simply lead to a significant increase in complexity, without providing any significant improvement in forecast accuracy. Per contra one must note that agent-based models should also directly or indirectly consider the other party of the market relations – the consumers. In the latter case, the impact of consumers is considered indirectly, mainly due to the lack of reliable data on the dynamics of fuel consumption by individual market players.

One of the conditions for proper functioning of the neural network the stationarity of the input and output data. However, studies show that retail prices in the petroleum product are far from stationary. This makes it impossible to use absolute price value for input prices of the neural network. Having analyzed the growth of retail prices thus as seen in Table 1 the increment of the retail price is of the first order, hence allowing us price surges as inputs for the neural network.

Table 1: Assessment of stationarity of the retail prices and their increments.

Temporal series	Dickey-Fuller	p-value
Retail prices for gasoline A-95 in the period 2010-2014	2,211	0,49
Growth rate of retail gasoline prices in the period 2010-2014	-7.921	0,01

It is also important to consider lags related to purchasing and selling the products. If we ignore lag compensation this will lead to inconsistencies between the value of net costs relative to the that of the selling price. To compensate for the lag in calculating the margin, we use the following current lag cost determination algorithm:

Choose date t_0 with a stable wholesale price

```
t = t0
lag[t] = L_typ
while t < t_cur
    lag[t] = f_LAG((t-lag[t-1])..t)
    if lag[t] - lag[t-1] > 1
        lag[t] = lag[t-1] + 1
    t = t + 1
end
```

The following algorithm is used to determine lag, calculated separately for each network at a certain period of time using the formula below:

$$f\_LAG = \min\left(L_{typ}; \frac{a}{\left(100 \cdot \left(P_t - P_{t-lag}\right)\right)^{\gamma}}\right)$$

where P_{t-lag} – is the price at the beginning of the period, P_t – is the price at the end of the period, L_{typ} – is the default lag value for stable market conditions. Indicators *a* and γ are evaluated separately for each of the agents on the , based on the analysis of the price surges and behaviour of the market entities.

The cost is not only used for calculating the margin, but is also used in a rule that limits the behavior of the network: the selling price cannot be lower than the cost of production. Under standard conditions this rule is practically never used, but at times of significant volatility of incoming data it generally minimizes risk of experiencing situations with delay in model response for the surges of inputted data.

All incoming threat-related information is assigned not only a class, but also a threat rank, which corresponds to the threat level for the market. In this study we have identified the following threat ranks:

- -2 – a significant impact on the market towards a drop in prices;
- -1 – a moderate impact on the market towards a drop in prices;
- 0 – no impact on the market is observed;
- 1 – a moderate impact on the market towards a hike in prices;
- 2 – a significant impact on the market towards a hike in prices.

Taking into account the price formulation factors shown above, Figure 2 depicts the structure of the neural network and the interpretation of the input. It was found that the best form of neural networks for solving this problem is a multilayer perceptron with 4 hidden layers. At the core of this network is a fully-connected multilayer perceptron (layers 2-6). The first layer has the activation ReLU (Rectified Linear Unit) function and is intended to form linear combinations of input. During the learning process it generates indicators, based on which the retail network acquires a behavioral classification. Unlike the linear activation function, ReLU can reduce the number of neurons per layer thanks to its non-linear nature. Output has no activation function, but is rather used as a multiplexer of the perceptron's output layer of price growth for the next time period. Such network structure is dictated primarily by the specificity of the input and output data.

About categorized under threat of impact forces form the index of informational load. This index is the sum of ranks of active threats at a time. This approach takes into account both direct and indirect impacts on the market with the formation of the retail price.

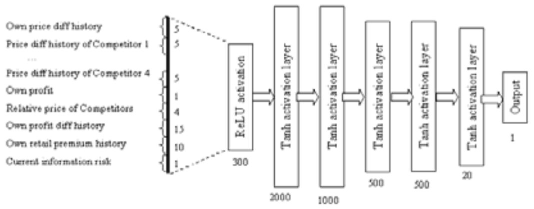

Figure 2: The structure of the neural network.

4 LEARNING NETWORKS

Each agent's neural network is trained separately. To generate a set of input data we used a mock launch of the agent model without the use of neural networks. All values used for input to the neural network will be calculated for each agent based on real statistic data. Information on threats is formulated beyond the agent model – in the threat identifying system for the petroleum product, where the corresponding information gathering, classification and threat ranking are carried out.

To train the network we used daily prices of retail chains, daily wholesale price on the Ukrainian border and the total value of the active threats broken down by day.

Training and testing was conducted based on the data collected from the following 2 periods:

- January 2010 to June 2012 with verification on data from July to December 2012 - a period of normal market conditions

- June 2013 to May 2014 with verification on data from June 2014 onwards - a period of significant price volatility.

The main challenge in using neural networks for economics-related tasks is the inhomogeneity of data, thus over-educating the network. In an effort to avoid such a scenario this model uses the Dropout method.

5 EXPERIMENTAL RESULTS

The figure seen below depicts a comparison of price forecast graphs calculated using the agent forecast model and the real data for the period from 2010 to 2012.

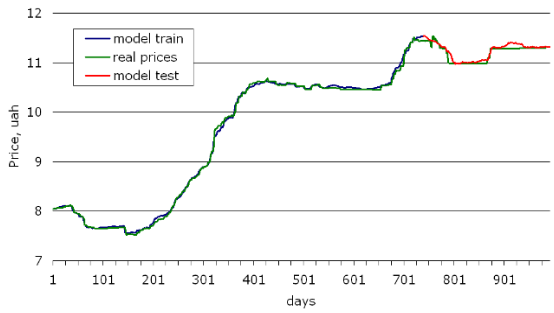

Figure 3: Comparison of price forecasts for the described model with real data for 2010-2012.

Shares of zeroing for our network are presented in Table 2. Regularization was never carried out for the last layer, since it serves solely to formulate linear combinations of output data. For other layers the ratio depends on the number of neurons in adjacent layers.

Table 2: Regularization ratios for the Dropout method.

Number of layer	1	2	3	4	5	6	7
dropout ratio	0.5	0,5	0.5	0.3	0.3	0.3	-

To build and train a network we have used our own software written in C++ based on the FANN library. To train the system we used a packet method of error backpropagation with a stochastic method of gradient descent. Due to the significant size of neural networks, the training algorithms were modified to work in a multi-stream mode on video display cards by utilizing CUDA.

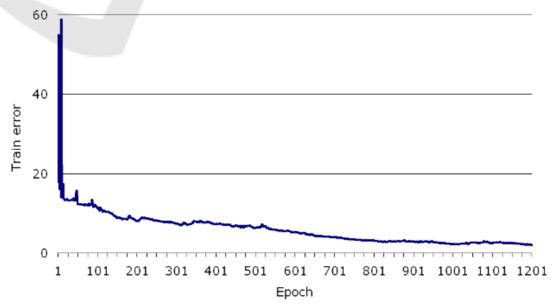

Figure 4: Error margin dynamics during the training process of the neural network.

It should be noted that when one constructs a forecast for wholesale prices, the forecast horizon remains unchanged. This is a certain simplification dictated due to a wholesale price forecast requiring a forecast of the exchange rate. The latter would be quite challenging to acquire at times of market instability. Therefore the precision of the forecast may be improved by using forecast values from input data of the agent model.

We have made comparisons with real data and other short-term forecast models in an effort to assess the potential of the model's forecasting capabilities.

Figure 5 shows an error comparison between the agent model and the co-integration model under normal market conditions. In this situation, the agent model shows the best result with an error rate of 1.1% for the forecasted two week period compared to 1.8% for the co-integration model.

Short-term prediction accuracy measured by the absolute standard deviation calculated from real data within the prediction interval.

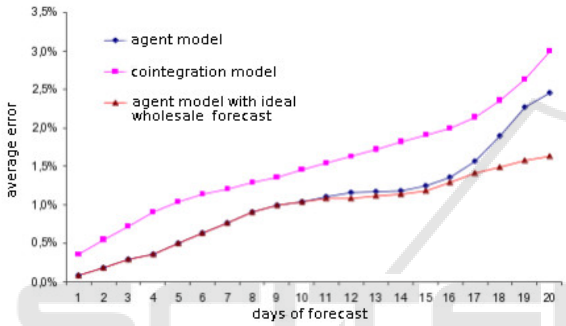

Figure 5: Comparison of prediction accuracy between the agent model and the co-integration model under normal market conditions.

We have also assessed the error margin if there had been an "ideal" model capable of predicting the behavior of wholesale prices, which are part of the input data for the agent model. The results show that by using third-party agent models the forecast model can be increased to nearly 3 weeks, while maintaining a reasonable result.

Figure 6 shows a comparison of average forecasting errors for a period of considerable volatility in market prices. As we can see, the co-integration model displays a higher accuracy rate for periods up to 1 week, while forecasts for periods over 7 days are more accurate when using the neural network model. In any case, the main cause of disturbances for this period was the exchange rate. The accuracy of the model granted with an ideal wholesale forecast model was not conducted due to absence of exchange rate forecasting models for an unstable economic climate.

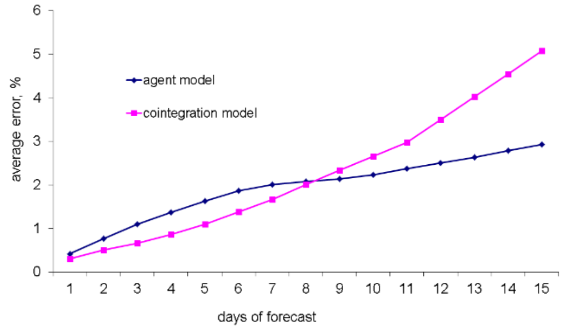

Figure 6: Comparison of prediction accuracy between the agent model and the co-integration model, in the case of significant market price volatility.

6 CONCLUSIONS

Results show that the combination of agent-based models and neural networks in which the neural network serves as a tool/method of price reactions for each of the agents in response to the actions of the competition allows for the best results when it comes to predicting retail prices of petroleum products compared to those taken separately from a pricing forecast model based on separate multi-agent model rules and a single neural network. This hybrid model improves the solution of this nontrivial problem primarily due to the consideration of the petroleum product's particular features as an oligopolistic competitive environment and incorporation of particular information, which is used by retailers to formulate their prices. As a result of combining several approaches to data formulation: using information including threats as input parameters and using parallel computing to accelerate the training process of the neural network, we were able to build a model capable of predicting the short-term behavior of retail prices and considering the pricing dynamics of each market participant.

This hybrid model doesn't just build a forecast based on the historical data for the previous time periods, but it also considers the ever-changing market behavior. We were able to lower the forecast uncertainty levels below what was possible with statistical methods. This paper shows the results the first proposed hybrid model for oligopolistic oil product market based on multi-agent approach, in which the algorithm is based on behavior calculation agent by neural network. This allows to get a better short-term prognosis with substantial volatility of oil product prices than predictions based on historical data.

ACKNOWLEDGEMENTS

The authors express their gratitude to the management of consulting and analysis firm "Psyche" for providing detailed data on the retail prices of petroleum products on the Ukrainian market.

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