www.ijecs.in
International Journal Of Engineering And Computer Science ISSN:2319-7242
Volume 7 Issue 2 February 2018, Page No. 23639-23641
Index Copernicus Value (2015): 58.10, 76.25 (2016) DOI: 10.18535/ijecs/v7i2.19

Prediction of Indian petroleum product prices by using Kalman Filter based Neural Networks

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Abstract:

The experiments are performed over the petroleum product prices data which are downloaded from Indian oil corporation Limited (IOCL) official website. These data are updated on daily basis according to the guidelines from Indian government and the price of international market. Predictions of PP prices are sound interesting as the fluctuations in the PP prices are influencing the stock market prices. We have compared Kalman filter based neural networks (KFNN) with two other well-known neural networks (NNs) training method for the petrol price predictions. Results show that the KFNN training method is converging faster and shows better performance with less error. Therefore KFNN showed effectiveness for PP price predictions.

Keywords: Kalman Filter, Neural Networks, Petroleum products**.**

I. INTRODUCTION

Petroleum product prices predictions are showing the importance for the economy, and politics [1]. The prices of PP can be directly or indirectly influence the stock market of different countries. Different studies are performed for forecasting PP prices [2-7]. Chen et al [2] has compared international oil exchange rate for forecasting PP prices. A genetic algorithm [3] based model is reported for the pattern matching of PP prices. This model predicts the prices based on the price-sheets of the previous years. A soft computing based method [4] is reported for the prediction of PP prices in the western Texas. A wavelet based neural network (NN) [5] is used for daily PP prices changes and performed fitting. A semi supervised learning method is reported to predict monthly PP prices changes. NN and combined compressed sensing based de-noising (CSD) [6] is used to forecast PP prices. Similarly, NN with regression analysis [7] is also reported for PP prices predictions.

PP is the deregulated commodities [1] in many countries including India. Government in India is not responsible for any losses due to Petrol price degradations. But diesel, LPG and kerosene prices are subsidized or directly influenced by the government policies. Kerosene is widely used in rural India for domestic fuel while diesel is used as a fuel for industries and automobiles. Therefore the prices change of diesel and kerosene is strongly monitored by Indian government which is directly affecting the rural and industrial sector. Indian state-run fuel retailers IOCL, Hindustan petroleum (HP), and Bharat petroleum (BP) are revising PP prices twice a month before 16 June 2017. But after this date, a dynamic PP prices scheme is brought by Indian government that the price of petrol and diesel are revising daily at 6 am IST. Smallest change of the international oil price can be passing to retailer to consumer directly by this scheme. Consumer will be more aligned to the market and follow the practice of more advanced markets.

We have introduced Kalman filter based NN (KFNN) [8] for the prediction of Indian petrol prices. We have also compared the results of KFNN with the output of Elman recurrent NN (ERNN) [9] and Recurrent Fuzzy NN (RFNN) [10]. It is observed that KFNN converged fast with less error. Therefore, using KFNN for the weight optimizing of NNs makes fast and accurate PP prices predictions.

1. METHOD

Input X is petrol price data with window size N as

$$X=[x_1,x_2,x_3,\ldots\ldots,x_N] \qquad (1)$$

And the output *Ym* is

$$Ym=\sum_{i=1}^{N} x_i\, w_{i,m} \quad (2)$$

Where, *m* is the node number and $w_{i,m}$ is the weight connecting input *i* to *m*. An activation function *G* is required at the node for the designed feed forward NN as

$$G(Ym)=\frac{1}{1+e^{-aY_m}} \quad (3)$$

Bias value is added to the output node and the error is calculated from the substation of target *t* value from the output value *o*.

In this paper, NN weights are optimized by using Kalman filtering (KF) [8]. KF is a prediction correction model and this model is faster and accurate than the typical gradient decent weight corrections models. KF used measurements over the time with noise and can estimates the unknown variables. It is a linear algorithm and the system states are calculated recursively over the stream of the noisy input data. Extended kalman filter (EKF) [8] is used here as a variant of KF and it has differentiable functions of the state transitions and the observation. This model used smaller dimensions of the matrix that decreased the weight training time [8]. Given *J* neurons present in NN and w_k^j are the weights connecting with them at the time *k*. Weights at *k*+1 time is $w_{k+1}^j = w_k^j + \Omega_k^j$ and the output is $t_k = h(w_k+x_k) + v_k$. Where Ω_k^j and v_k are the Gaussian process and noises which are defined as

$$E(v_k) = E(\Omega_k^j) = 0 \quad (4)$$

$$E((\Omega_k^j) (\Omega_k^j)^{\mathrm{T}}) = (Q_k^j)\delta_{kl} \quad (5)$$

$$E(v_k\, v_l^T) = R_k \delta_{kl} \quad (6)$$

E is the expectation value and δ_{kl} is the delta function. Kalman gain matrix *K* is defined as

$$K_k^j = P_k H_k^j [\textstyle\sum_{\mathrm{i}} (H_{\mathrm{k}}^{\mathrm{i}})^{\mathrm{T}} P_k^i\, H_k^i + R_{\mathrm{k}}]^{-1} \quad (7)$$

$$w_{k+1}^j = w_k^j + K_k^j + \xi_k \quad (8)$$

$$P_{k+1}^j = (\mathrm{I} - K_k^j\, (H_{\mathrm{k}}^{\mathrm{j}})^{\mathrm{T}})\, P_k^j + Q_k^{\;j} \quad (9)$$

Where *I* is an identity matrix, and P_k^j is the approximate error covariance matrix, $H_{\mathrm{k}}^{\mathrm{j}}$ is a Hamiltonian matrix, ξ_k is the error vector, and Q_k^j and R_{k} are Gaussian process and noises. Weights are corrected at the equation 8 and the quality is estimated at the equation 9.

1. Results

Data of PP prices are downloaded from IOCL website (https://www.iocl.com/TotalProductList.aspx) and saved in the text format. These data contain prices for petrol, diesel, kerosene and LPG for the city of Delhi, Kolkata, Mumbai and Chennai dated 04-June-2002 to 29-January-2018. It is observed that the price change per month is higher than the daily basis. Data on the daily basis are used to train KFNN which are developed on Python scripts. The performance of KFNN is compared with ERNNs, and RFNNs. About 380 petrol price data are set for training purpose and 20 petrol price data points for the predictions. Table 1 is showing the average training time and epochs for the three types of NNs. In this table KFNN training method takes less epochs and time than the other NNs. Figure 1 is showing the combined plots for the training of the petrol price data with different NNs. Figure 2 is showing the predictions of PP prices where KFNN is showing better accuracy. Table 2 is showing the mean square error (MSE) [8] for NNs reported in this paper. This parameter is used to check the performance of the reported NNs for PP prices predictions. Kalman filter based NNs has shown the best performance in compare to others.

Table 1: Average training times and epochs for the different types of NNs.

	Types of NNs with back propagation algorithm	**Number of training epochs (average)**	**Training time in second (average)**
1	ERNN	33.01	36.6
2	RFNN	12.05	21.8
3	KFNN	6.001	11.2

Table 2: Average MSE for the different types of NNs.

	Types of ANN with back propagation algorithm	**Mean square error (MSE) (average)**
1	ERNN	0.0189388888889
2	RFNN	0.00268888888889
3	KFNN	0.00050138888888

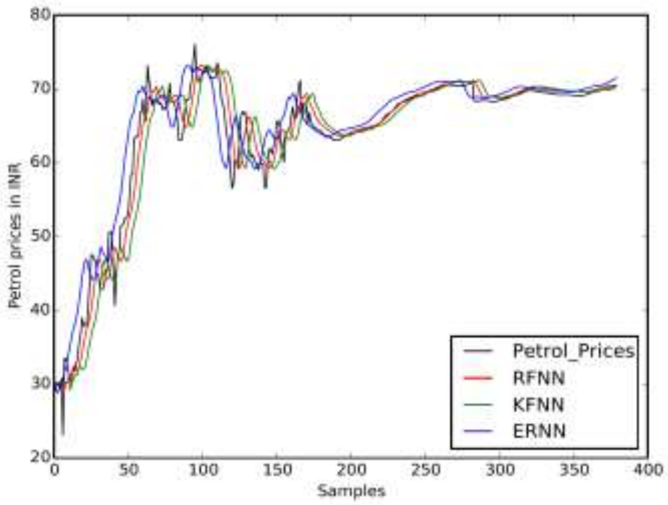

Figure 1: Training of petrol prices with the different NNs.

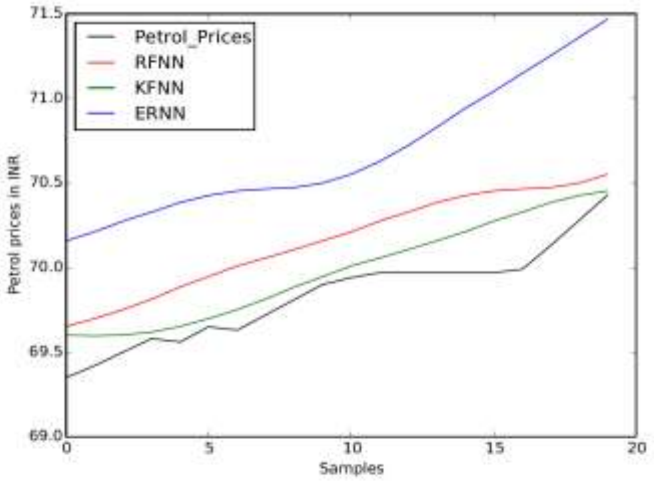

Figure 2: Prediction of the petrol prices with the trained weights obtained from the training of different NNs.

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