A System for Fuel Distribution in Nigeria Based on Statistical Computer Machine Intelligence Learning Algorithm

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ABSTRACT

The current problem of fuel scarcity in Nigeria and the drawbacks associated with it bearing in mind the undesirable effects it has on the economy, transport sector and the small and medium scale enterprises cannot be overemphasized. In this paper, we present the situation of PMS distribution in the Nigerian state using a monitoring tool based on machine intelligence and human-like statistical learning system, the numerical deviant learning algorithm (n-DLA). Specifically, this algorithm is a variant of a cortical-like algorithm based on artificial (machine) intelligence technique. Experiments with this algorithm showed that price hike cannot be avoided in the months that follow due to abnormal distribution of product unless a drastic action is taken by the operators to avert the situation. This approach can be a useful tool in predicting in advance the month that may have a high likelihood of a hike in the pump price of PMS in addition to its distribution.

Key words: Artificial Intelligence, deviant learning, predictive monitoring, nonlinear representation, PMS distribution

INTRODUCTION

Currently, Nigeria is a fuel dependent economy particularly for her immediate energy demands. Fuel is an essential product that plays a vital role (at least for now) in the operation of modern society. Unfortunately, the primary fuel product, Premium motor spirit (PMS), can become very scarce and exorbitant making it difficult for the populace to operate and enjoy their lives.

In a previous paper, we presented a technique for monitoring price of PMS also popularly referred to as ‘ Petrol’ or ‘ Gasoline’ . Petrol is a product of national interest and is indeed a well-sourced for commodity. It is a combustible fuel well suited for automobiles and petrol engines. The PMS pump price fluctuation can be defined as a price volatility problem (PVP) as discussed in (Osegi & Anireh, 2016a). The PVP is the result of the variability in PMS pump price and associated influence by Government and petroleum regulatory agencies including the market forces. It has been noted that the distribution of PMS across the Nigeria borders is increasing at an alarming rate and this may likely indicate a diversion of essential commodity due to competitive demand across the West African sub-region (see the work by Obasanjo & Nwankwo, 2014). In addition, there is the case of pipeline vandalism across the country such as reported in a recent study (Aminu & Olawoore, 2014). One consequence of this situation is the prevalent scarcity and consequential hike in prices and this is due to the ineffective distribution/diversion of this essential product within the major cities in the Nigerian state (Ehinomen & Adeleke; Obasanjo & Nwankwo, 2014).

In recent times, PMS has been so very scarce and exorbitant irrespective of the efforts put in place by the present

President Buhari– led administration. In particular, with the effect of subsidy removal, it was hoped that a stable PMS price and distribution will ensue and thus would have made this algorithm unnecessary. Unfortunately, this is not the case as observed from data made available from the Nigerian Bureau of Statistics (NBS) and by independent research study, (Alaba & Agbalajobi, 2014). In retrospect, it was observed that it is still not possible for the PMS pump price to go down well enough for it to be affordable by the citizenry.

In this study we use a cortical-like algorithm called the Deviant Learning Algorithm (DLA) to monitor and learn a distribution-price mapping of PMS in Nigeria using monthly available PMS price-distribution data. Informed by this knowledge, we use the DLA to make future predictions of PMS distribution for the subsequent month. In particular, we noted that this area is still needs more in terms of research and has not been given any enough considerable attention as is presented here.

This paper is organized as follows.

In Section 2 we present related works in the field of PMS price and distribution. Section 3 presents materials and methods used in the experiments while in Section 4 we give our results and some discussions. Finally, we give our conclusions in Section 5.

RELATED WORKS

PMS price demand and distribution have not been a well-researched topic though it is an active area for possible innovations.

In Omisakin et al (2012) the use of co-integrated structural breaks was applied for the modeling of gasoline demand. Time series modeling was used in their research including various co-integration techniques and price-income parameterization. Their model showed long/short-term inelasticity in price and income estimates while a price-income interaction model showed that the responsiveness of consumers to a price variation will increase as income increases through time.

Abdullahi (2014) used structural time series model (STSM) to estimate the demand function of 5 petroleum products. They reported an inelasticity and stochastic demand characteristic for both price and income variables of the STSM. Furthermore, in Abdullahi et al (2016), STSM was used to forecast demand for gasoline and diesel under three scenarios: reference case, low and high demand scenarios.

Kolawole et al (2017) investigated determinants of six energy types in Sub-Saharan Africa. They used Energy demand models and discovered that PMS (petrol) among other energy types are influenced by income, degree of urbanization, economic structure and population.

Zhang et al., (2020) In the early 21st century limited 2D seismic data were considered to pinpoint the drilling locations based on subsurface mapping. Since it is riddled with risk the chance of success was 1:7. With time more data was acquired in each of the lease curved out for exploration. This large volume of data was termed as big data which was stored in Terabytes of memory space with the advancement in acquisition, processing and interpretation of seismic and well data. These big data was analysed using the machine learning concept. The objective behind use of big data and applicability of machine learning is to improve the signal to noise ratio during acquisition and processing. The clean data obtained were used to interpret 2D, 3D and 4D seismic using various robust algorithms. Mapping of various subsurface horizons accurately helped an interpreter to prepare subsurface volume maps and transform it into amplitude, porosity and saturation maps by integrating it with well logging. Inversion techniques were utilised to understand data parameters from the subsurface models.

Anirbid et. al (2021) in their article titled Application of machine learning and artificial intelligence in oil and gas industry provided a comprehensive review of machine learning anc AI applications on the upstream oil and gas sector. They described various machine learning algorithms used in oil and gas industry and outlined the key upstream activities where machine learning can be applied as exploitation, reservoir engineering, drilling and production optimization. In these areas where machine learning can be applied, it helps improve signal- to- noise ratio in seismic data acquisition and processing, integrates data from seismic, well logs, core analysis for reservoir modelling and field development planning among other things.

Pavlos, S 2020 reviewed 41 research papers on computational intelligence (CI) methods for optimizing local energy markets (LEMs) at the power distribution level. LEMs aim to facilitate integration of distributed energy resources (DERs) like solar, wind, batteries etc. Most common LEM models considered sellers as distributed generators, buyers as loads, mediators as aggregators. Common DER types were solar and wind. Common objective was minimizing total operating cost. Most used CI methods were particle swarm optimization, genetic algorithms, and multi-agent systems. These were applied to schedule DERs and determine energy transactions in LEMs. Future research areas identified include developing regulatory frameworks for LEMs, defining roles of market players, coordination between transmission and distribution system operators, communication networks and software platforms for trading. Other areas are distribution infrastructure investments, profitability analysis of LEMs, addressing scalability, data privacy, developing advanced models considering multiple objectives and constraints. Cross-disciplinary teams involving different domains like CS, engineering, economics are needed for LEM research. A gradual transition from existing markets to LEM-enabled frameworks is suggested. In summary, the article reviews computational methods used in research on local energy markets and identifies key open challenges and future research directions in this area.

Through the use of long-run regression estimates, Nwosu & Ajibola (2013) showed gasoline price to have a strong determining impact on the output growth of the Nigerian economy.

In research and industry, tools that are based on cortical-like intelligence and that are online capable i.e. tools that are capable of learning to predict incoming data continually, can be an advantage. A software application algorithm based on such tools has already been developed in (Osegi & Anireh, 2016b) for the monitoring of PMS price; however, due to its inherent complexity and use of symbolic or character-wise transformation, such software algorithms are too complex to implement, time consuming and may not accurately represent the desired input-output representational mapping. There is therefore an urgent need to improve the state-of-the-art in predictive forecasts particularly as it pertains the monitoring of certain physical phenomena like the distribution of PMS.

MATERIALS AND METHOD

For the experiments in this paper, we have used the monthly PMS price and distribution for the months of March 2016 to December 2016; data for this study was obtained from the Nigerian National Bureau of Statistics (NBS) and the Nigerian National Petroleum Corporation (NNPC) respectively. The PMS data reports the average monthly prices of PMS paid by households across the 36 states of the federation including the Federal Capital territory (FCT); it also reports the distribution of PMS to the various states of the Federation the FCT included. For this research study we have considered only the data for Rivers State. Software programming and simulation experiments are performed using the MATLAB software environment.

Dataset and Application Software Program

The input data consists of two key attributes; the PMS distribution in liters and PMS price in Naira; other attributes are the month and year and are used for labeling purposes. The dataset was sourced from the Petroleum Products Pricing Regulatory Agency (PPPRA) in Nigeria. For the research study, the dataset for analysis have been transformed using a max-normalization routine where the input data is scaled between a range of 0 and 1; the transformed data are then referred to here as signals.

The programming software used is MATLAB deployed on an Intel i-core3 processor with 4GB RAM space. A software program based on the Deviant Learning Algorithm (DLA) developed earlier in (Osegi and Anireh, 2016b) is fine-tuned for numerical predictions and can be obtained from the MATHWORKS MATLAB central code repository. It is important to note that this software program have been optimized for speed and ease in implementation which makes it easier to replicate in any other language.

Methodology

The methodology is based on an iterative routine using statistical machine intelligence and the algorithm is based

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on a numerical version of the DLA for intelligent predictions. The DLA is inspired by experiments of the Mismatch Negativity (MMN) effect which is in turn influenced by memory traces in the auditory cortex (Naatanen et al, 1978; Naatanen et al, 2007). The procedure involves data normalization, data training and predictions. These are the justifications for using the DLA algorithm:

a) It is based on a proven concept of statistical intelligence exhibited in the auditory cortex, making it a biologically inspired approach.

b) It represents the state-of-the-art in statistical machine intelligence and can provide fast online numerical solutions.

c) The character-wise transformation used in their previous work (Osegi & Anireh, 2016b) was complex and time-consuming. The numerical DLA (n-DLA) variant used in this study is optimized for speed and ease of implementation.

d) The algorithm can learn a distribution-price mapping and make future predictions of PMS distribution based on previous data.

The core algorithm for performing simulations with the DLA is as follows:

1. Transform inputs data to a scale of 0 and 1 by performing a max-normalization operation
2. Define the iteration number
3. Train the DLA on the normalized inputs using n-DLA functional class
4. Compute a deviant-mean
5. Compute prediction errors
6. Compute predictions
7. Update the predictions with the deviant mean by additive connectionist mapping
8. Repeat steps ii to vii until the desired performance expectation/or convergence is met

RESULT AND DISCUSSIONS

Experiments performed using the above method and data are interpreted in terms of the normalized encoded signal (NES) which is a technique presented here for descriptive analysis. The purpose of the simulation experiments is to use the distribution data of PMS in advance to predict the its distribution in the next month given the PMS price and distribution for previous months. The simulation experiments were divided into two parts. The first part uses 5 observations where the PMS price and distribution in Rivers State is presented to the algorithm for the first five months (from March 2016 to July 2016); the second part consists of 10 observations with duration from March 2016 to December 2016. The results of the actual/predicted PMS distribution for the first and second parts are given in Figures 1 and 2 respectively.

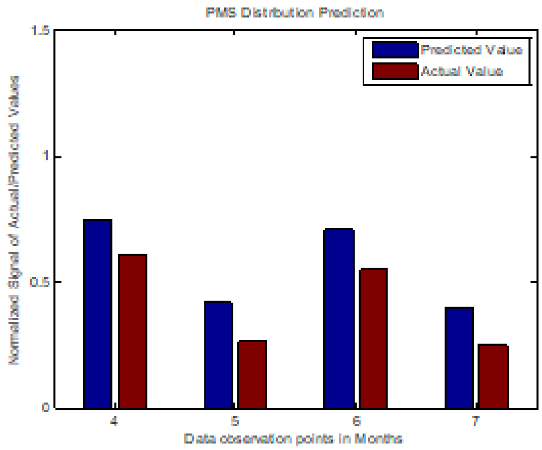

Fig. 1 Predicted versus actual PMS distribution for the Months of April (4) through July (7); first and second bars are the predicted and actual values respectively.

For the months of March to July 2016 (see Fig. 1), the DLA will predict a decrease of PMS distribution at the 5th month (May, 2016) and an increase at 6th month (June, 2016); this is followed by a decrease in the 7th month (July, 2016). The interesting point here is that the same scenario is exhibited by the true (actual) PMS distribution indicating that the predicted PMS distribution for the location under study is indeed a suitable nonlinear representation of the actual value with an exhibition trend.

In Fig.2, the results of PMS distribution predictions are shown. The results are generally confirmatory to the previous results and show that PMS distribution will exhibit nonlinearities with a trend as in the previous case; however, there is a discrepancy in the prediction for the 10th month which explains away the PMS distribution for that month.

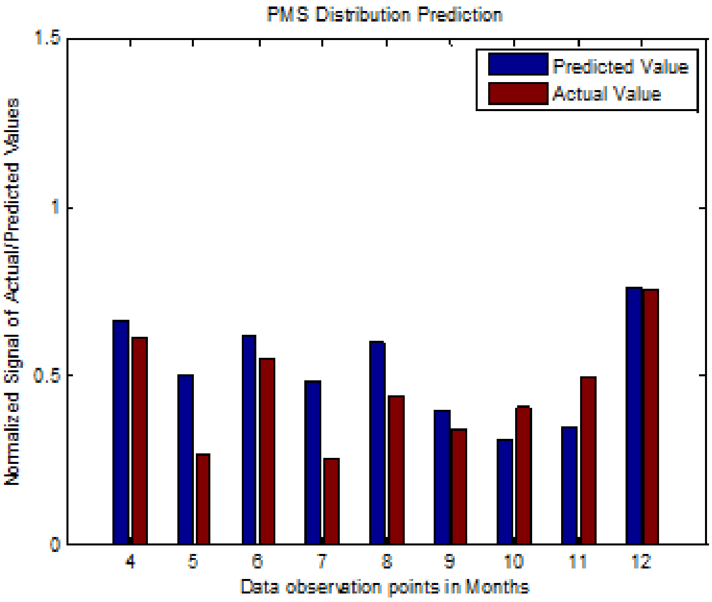

Fig. 2 Predicted versus actual PMS distribution for the Months of April (4) through December (12); first and second bars are the predicted and actual values respectively.

CONCLUSION, RECOMMENDATIONS AND FUTURE WORK

The effective distribution of PMS plays a key role in its pricing as insufficient supply/or diversions of this essential product can lead to artificial scarcity and hike in price. This research presents a variant of a novel algorithm, n-DLA, which is based on cortical processing in the auditory cortex. The algorithm is able to forecast in advance, the probable PMS distribution in Rivers State of Nigeria. The results using the proposed have shown that the study location exhibits a non-linear PMS distribution. The results of experiments indicate a trend; it is important to energy marketers and regulatory agencies and more importantly to academics interested in the dynamics of energy resource supply and demand.

The n-DLA is the first algorithm utilizing a proven concept of statistical intelligence exhibited in the auditory cortex. It represents the state-of-the-art in the field of statistical machine intelligence and is the future in the area of attaining very fast online numerical solutions to varying degrees of problems.

The use of n-DLA tool for monitoring purposes can be extended to other domains. Currently, it is being upgraded for diverse prediction tasks in the oil, gas and other related sectors such as in power systems and energy.

REFERENCES

1. Abdullahi, A. B. (2014). Modeling petroleum product demand in Nigeria using Structural Time Series Model (STSM) approach. *International Journal of Energy Economics and Policy*, *4*(3), 427.
2. Abdullahi, A. B. (2016). Imperatives for Modelling and Forecasting Petroleum Products Demand for Nigeria. *Journal of Research in Business, Economics and Management*, *6*(4), 998-1011.

3. Alaba, O. C., & Agbalajobi, S. A. (2014). Evaluation of private refineries and depots in distribution of petroleum products in Nigeria. *International Journal of Engineering and Technology*, *4*(2).
4. Aminu, S. A., & Olawore, O. P. (2014). Empirical investigation of challenges of distribution of premium motor spirit (PMS) in Federal Capital Territory (FCT), Abuja and environs, Nigeria. *International Journal of Management Science & Humanities*, *2*(2), 17-59.
5. Ehinomen, C., & Adeleke, A. (2012). An assessment of the distribution of petroleum products in Nigeria. *E3 Journal of Business Management and Economics*, *3*(6), 232-241.
6. Nigeria Bureau of Statistics (2016). Premium Motor Spirit (Petrol) Price Watch. http://www.nigerianstat.gov.ng
7. Nwosa, P. I., & Ajibola, A. A. (2013). The effect of gasoline price on economic sectors in Nigeria. *International Journal of Energy Economics and Policy*, *3*(1), 99.
8. Näätänen, R., Gaillard, A. W., & Mäntysalo, S. (1978). Early selective-attention effect on evoked potential reinterpreted. *Acta psychologica*, *42*(4), 313-329.
9. Näätänen, R., Paavilainen, P., Rinne, T., & Alho, K. (2007). The mismatch negativity (MMN) in basic research of central auditory processing: a review. *Clinical neurophysiology*, *118*(12), 2544-2590.
10. Osegi, N., & Anireh, V (2016a). Monitoring Premium Motor Spirit Price In Nigeria: A Novel Artificial Intelligence Approach. Nigerian Journal of Oil And Gas Technology, 1(2), 52-57.
11. Osegi, E. N., & Anireh, V. I. E (2016b). Deviant Learning Algorithm: Learning Sparse Mismatch Representations through Time and Space. Working Paper. 2016. <hal-01359723v2>
12. Omisakin, O. A., Oyinlola, A. M., & Adeniyi, O. A. (2011). Modeling Gasoline Demand with Structural Breaks: New Evidence from Nigeria. *International Journal of Energy Economics and Policy*, *2*(1), 1-9.
13. Obasanjo, O. T., & Nwankwo, O. C. (2014). Distribution Constraints of Petroleum Products by Road Transport from Pipeline and Products Marketing Company (PPMC) Kaduna. *Journal of Logistics Management*, *3*(2), 21-27.
14. Kolawole, A., Adesola, S., & De Vita, G. (2017). A Disaggregated Analysis of Energy Demand in Sub-Saharan Africa. *International Journal of Energy Economics and Policy*, *7*(2).
15. Castineira, D., Toronyi, R., and Saleri, N., (2018) Machine Learning and Natural Language Processing for Automated Analysis of Drilling and Completion Data. Society of Petroleum Engineers. https://10.2118/192280-MS.
16. Zhang, J., Yin, X., Zhang, G., Gu, Y., Fan, X., 2020. Prediction method of physical parameters based on linearized rock physics inversion. Petrol. Explor. Dev. 47 (1), 59e67. https://doi.org/10.1016/S18763804(20)60005-2.
17. Anirbid, S., Kriti Y., Kamakshi, R., Namrata, B., Hemangi, O (2021). Application of machine learning and artificial intelligence in oil and gas industry. Science direct; Petroleum Research 6 (2021) 379e391.
18. Pavlos S. Georgilakis (2020). Review of Computational Intelligence Methods for Local Energy Markets at the Power Distribution Level to Facilitate the Integration of Distributed Energy Resources: State-of-the art and Future Research. Energies 2020, 13, 186; doi:10.3390/en13010186 www.mdpi.com/journal/energies.
19. Zendehboudi, A.; Baseer, M.A.; Saidur, R. (2018) Application of support vector machine models for forecasting solar and wind energy resources: A review. J. Clean. Prod. 2018, 199, 272–285. [CrossRef]
20. Olivella-Rosell, P.; Lloret-Gallego, P.; Munne-Collado, I.; Villafafila Robles, R.; Sumper, A.; Ottessen, S.O.;Rajasekharan, J.; Bremdal, B.A. (2018) Local flexibility market design for aggregators providing multiple flexibility services at distribution network level. Energies 2018, 11, 822. [CrossRef]
21. Saxena, K.; Abhyankar, A.R. (2019) Agent based bilateral transactive market for emerging distribution system considering imbalances. Sustain. Energy Grids Netw. 2019, 18, 100203. [CrossRef]