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Building a Decision Support System for Crude Oil Price Prediction using Bayesian Networks

Nuka Nwiabu[a*], Mirabel Amadi [b]

[a]Computer Science Department, Rivers State University, Port Harcourt, Nigeria.
[b] Computer Science Department, Rivers State University, Port Harcourt, Nigeria.
[a]nwiabu.nuka@ust.edu.ng
[b]mimypride@gmail.com

Abstract

Decision Support Systems are computer based systems that are aimed at assisting decision-makers in taking productive, agile, innovative and reputable decisions. This work presents a Decision Support System using Bayesian Network to predict crude oil price .Bayesian Network technology and its application in predicting crude oil price is presented. Price data obtained from the Central Bank of Nigeria was classed into High and Low cases to denote the upward and downward price movement in which information was revealed. The input data were used in this model to train the network and to validate its generalization ability in other to deliver the best prediction forecast. A linguistic prediction model which utilized the Bayesian Network whose aim was to integrate linguistic information into a quantitative prediction model was established. The results obtained from the linguistic model demonstrate that linguistic information adds value to oil price prediction.

Keywords: Bayesian Networks (BNs); Crude oil price; decision support system (DSS)

1. Introduction

Making decisions concerning complex systems, such as management of organisational operations, industrial processes, investment portfolios, the command and control of military units, or the control of nuclear power plants often strains our cognitive capabilities [1]. Even though individual interactions among system`s variables may be well understood, predicting how the system will react to an external manipulation such as a policy decision is often difficult [2]. In many situations the quality of decisions are important, aiding the deficiencies of human judgment and decision making has been a major focus of science throughout history [3]. More recently, these methods, often enhanced by a variety of techniques originating from information science, cognitive psychology, and artificial intelligence, have been implemented in the form of computer programs, either as stand-alone tools or as integrated computing environments for complex decision making. Such environments are often given the common name of Decision Support Systems (DSS) [2].Decision Support Systems (DSS) is an umbrella term applied to any computerized system used in aiding and making decisions in an organization [4]. Different technologies have been used in building a DSS such as Fussy, Neural Bayesian networks etc. Classically, the process of designing a DSS has been classified into three categories: Structured, Unstructured, and Semi-Structured [4]. Structured DSSs are those that involve a straightforward decision-making process where standard procedures exist to make the required decision; for example, processing a new order in an online store. While, Unstructured DSS is where the problem of coming up with a decision is often complex, fuzzy, or has no standard solutions, for example, buying new software for processing documents in a firm. Finally, semi-structured DSS are in-between cases, where part of the decision-making process can be structured but others cannot. An example is selecting the best car insurance. With respect to the application that has driven the design of a DSS, DSSs are classified into model-driven, data-driven, communication-driven, document-driven, and knowledge-driven [5]. The overall aim of this thesis falls within the domain of Model-driven DSSs. Proper application of decision-making tools increase productivity, efficiency, and effectiveness and gives many businesses a competitive advantage over their competitors, allowing them to make optimal choices for technological processes and their parameters, planning business operations, logistics, or investments [2].

1.1 Bayesian Networks (BNs)

BNs enable causally reasoning with domain concepts in a visually appealing and more intuitive fashion compared to many other ML techniques [6], and they can be used to address the Crude Oil price questions. They encode uncertain domain knowledge in a natural manner. A BN consists of a directed acyclic graph (DAG), and an underlying joint probability distribution, which together provide a mathematically sound and compact way to encode uncertainty in a given domain. From the outset, marketing informatics has been the main driver in the development of BNs [7]. This is partly due to their ability to intuitively encapsulate the causal links between the predicting factors that are stored in marketing/business datasets [8].

BNs are suitable tools for probabilistic inference that can aid Crude oil decision making, since (1) their graphical nature enables the information they contain to be easily understood by a marketing/business expert [9]. (2) They can formally incorporate prior knowledge while learning the structure and parameters of the network [10]. (3) they facilitate parameter estimation due to their compact representation of the joint probability space (4) they not only allow observational inference but also causal interventions [6] (5) they can be used to query any given node in the network and are therefore substantially more versatile compared to classifiers built based on specific outcome variables; and (6) they perform well in making predictions with incomplete data, since the predictor variables are used to estimate not only the query variable but also one another [11].

1.2 Factors Affecting the Crude Oil Price Market

Crude Oil prices in the market are greatly determined by commodities traders' activities [12]. Prices are determined by the way commodities traders observe possible factors related to the market in order to develop a bid. The market factors that draw the attention from traders are -The current supply, Oil reserves, and the current demand. It is also noted that crude oil prices are not only determined by the expectations and activities of the commodities trader's but they are also affected by other important and related factors like crisis, OPEC, disasters etc. These factors have fed the steady, sometimes drastic fluctuations of oil prices in recent years. [13]Has suggested that the major aspects affecting the oil market are the demands, supplies, population, geopolitical risks and economic issues:However, due to lack of availability of data in a desired way, the scope of this work is confined to the input variables of demand and supply.

1.3 Limitation of Study

There are lots of parameters that affects the crude oil price market, but getting data on all these parameters seemed surprisingly difficult. Thus this research is limited to the economic variables of Demand and Supply.

1.4 Literature Review

The review of the related scholarly views focuses on the structure of decisions and the benefits derived from the DSS. Important themes are derived and some research results of DSS have emerged in the literature [14] proposed a novel decision support system (DSS) named OPEC-DSS to support OPEC's decisions on oil production level. Their system (OPEC-DSS) was based on two important factors in oil prices; the first was OPEC oil production level (OPEC-PL) and the second, USA oil imports level (USA-IL). Their system (OPEC-DSS) supports the analysers and decision-makers in three following issues: (1) OPEC-DSS can propose the optimum decisions on OPEC-PL and USA-IL. (2) It can illustrate the strategies stabilizing the oil prices. (3) OPEC-PL can calculate the optimum OPEC-PL when USA-IL has been determined. They used a 122 monthly samples dataset from Jan 2002 to Feb 2012 for evaluation, obtained from two sources: first the OPEC website and the second is www.iea.gov. Their proposed system was based on Game Theory (GT) and Artificial Neural Network (ANN). In GT model, OPEC plays with USA, as one of the major purchaser, to reach the maximum payoff formed by ANN. In fact the ANN is oil price predictor applied by the game model. The Nash Equilibrium Point(s) (NEPs) of the game is the optimum decisions and the strategies, fixing the oil prices, can be extracted by payoff function. Their experimental results showed that, the model can be used for decision-making in production, imports and exports of crude oil.Their model was an improvement on the work carried out by [15] to precisely investigate the impact of OPEC decisions on changes in oil price, based on GARCH model. In their work, the types of decisions are "no change", "increase" and "cut" and do not include the rate of increase and decrease. Oil prices can be controlled by decisions made about the rate of increase and decrease of production and although OPEC tries to make decisions with highest benefits and best outcomes via the increase of the prices; but on the other hand the stability of prices is vital to economies and it can be influenced by the decisions made by OPEC [16]. Additionally, in face of the decisions of the OPEC, oil importing countries make decisions of their own which best serves their goals. These conflicts of interests result in complications in decision-making which also proves the necessity of a decision support system [17]. Thus a DSS was proposed by [14] to assert the OPEC decisions on increase and decrease rates and illustrate the effect of the decisions on the future prices.

An Intelligent Decision Support Systems for Oil Price Forecasting was built by [18]. Their research studied the application of hybrid algorithms for predicting the prices of crude oil. Brent crude oil price data and hybrid intelligent algorithm (time delay neural network, probabilistic neural network, and fuzzy logic) were used to build the intelligent decision support systems for predicting crude oil prices. Their model was able to predict future crude oil prices from August 2013 to July 2014. Their result showed that future prices can guide decision makers in economic planning and taking effective measures to tackle the negative impact of crude oil price volatility. Energy demand and supply projection can effectively be tackled with accurate forecasts of crude oil prices, which in turn can create stability in the oil market. They concluded that the future crude oil prices predicted by the intelligent decision support systems can be used by both government and international organizations related to crude oil such as the Organization of Petroleum Exporting Countries (OPEC) for policy formulation in the next one year.

2. Methodology

The methodology adopted for this research work is The Quantitative Research Methodology (QRM). The goal is to build a decision support system that will predict crude oil prices, based on monthly data inputted into the system using Bayesian network technology. The overall strategy is, creating a database based on the current and past information embedded in the dataset in predicting crude oil prices solely using Bayesian Network technology. Once this database is created future prices are added and performance is measured. In order to do so effectively, attention was paid to finding optimal Bayesian Network model.The dataset used for the prediction experiments are a period of 111 Months was chosen as a basis to collect the quantitative data for the quantitative prediction model, as daily data are incomplete as a result of the weekend or shut down of the market as an outcome of sudden events [19]. The collected data range from January 2006 to February 2015 and was sourced from The Central Bank of Nigeria website [20].

2.1 Design Considerations

The design methodology considered for this research work is the Object Oriented Design Methodology. This design methodology enables us to identify classes, understand their behaviour and relationships of the different UML models used for this research. Although design guide lines, and some rules of thumb do exists. However, there is no evidence that any of these rules should work for a given problem. Therefore designing Bayesian networks could be a challenging task. Figure 4.1 shows architectural model to design Bayesian network for prediction task.

3. Decision Support Systemusing Bayesian Network

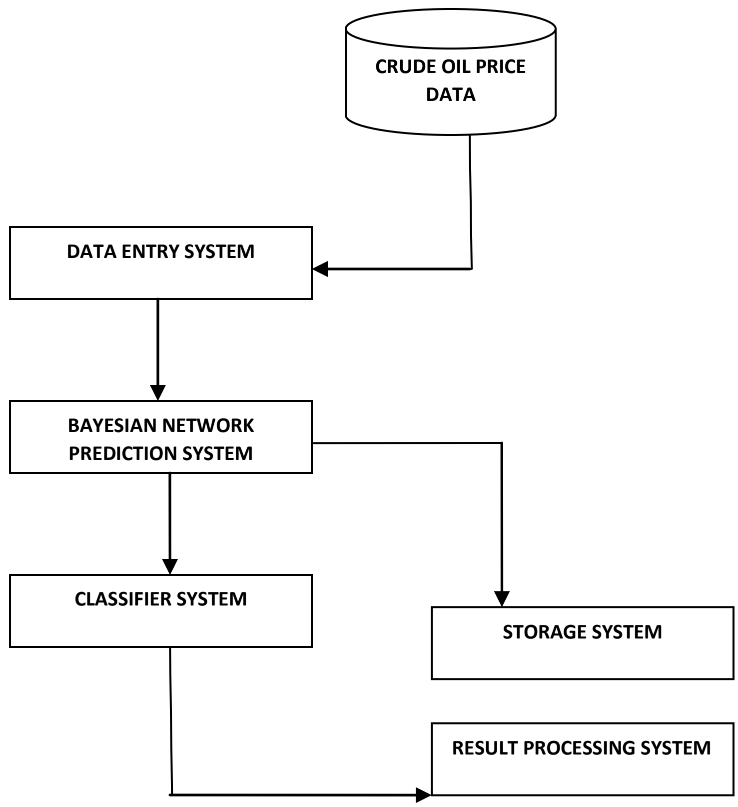

Figure1: Architecture of the Proposed Bayesian Network for Crude Oil Price Prediction

The architectural design of crude oil pricing/prediction discusses the processes that have contributed and an impacted on crude oil pricing/prediction. Figure 4.1 illustrates the data flow diagram; the system is composed of the following five (5) core building blocks.

A. Crude oil price database
B. Data entry system
C. A Bayesian Network prediction system
D. A prediction storage system
E. A classifier system

In addition, the result process system is added for user interactivity. The following core building blocks are discussed under the following sub-sections:

A. Crude Oil Price Database

This serves as a container for the Bayesian Network system variables including the year, month, demand price, supply price, and the actual crude oil sales price (target). However, after an initial analysis and experimentation, it was found that the year/month variables did not impact positively on the learning process (performance) of the Bayesian Network. Thus only the supply, the demand, and the crude oil export price (target) were considered for further experimentations. The supply and demand serve as the core input parameters while the crude oil export price serves as the target.

B. Data Entry System

The data entry system permits the interaction between the user and the Bayesian Network through a convenient user interface. This entry process allows the definition of two key state variables. The first case variable (state 1) defines the state of the supply while the second state variable (state 2) defines the state of the demand.

C. Bayesian Network Prediction System

The Bayesian Network prediction system includes the Bayesian believe algorithms which is based on the Naïve Bayes Theorem, which in turn describes the maximum aperiori or posteriori hypothesis. The Bayesian Network believe algorithms initially triggers the competitions of the target probabilities in line with the class conditional /class relational independence. In this system, the target probabilities are computed using the equation described below:

Input $T_{i\,=}$ target attribute input

$$Ti(transform) = \{Ti > \mu Ti = 1$$

$$0,\ otherwise\} \qquad (1)$$

Where $\mu Ti_{=}$ Mean Threshold Operation (MTO) and is given as:

$$\mu Ti = \frac{\sum Ti}{n} \qquad (2)$$

n is the total number of attributes.

How MTO Works

1. Compute the mean of the target attribute data
2. It uses the mean computed in step 1 to conditionally generate the patterns of 1’ s or 0’s using a threshold operator (<, > or equivalent)

Suppose the following sample dataset;

Table 1: Sample Preprocessed Dataset to Compute MTO (source:www.cbn.gov.ng)

S/n	Supply	Demand	Price
1	2.28	1.83	110.83
2	2.21	1.76	108.84
3	2.22	1.77	110.41
4	2.33	1.88	111.90
5	2.16	1.71	114.60
Total	**11.20**	**8.95**	**556.58**

Let's consider the price as our target attribute, and the Supply and Demand as our input attribute

We compute the target Mean Threshold $(\mu Ti) = \frac{556.58}{5} = 111.32$

To Compute T_i Transform

We compare our result with each attribute (price) in our dataset, in other to get our target class representation in binary form using our threshold operators <, > or its equivalent. If MTO is greater than the attribute price we have a 1 (price is high) but if less than we have a 0 (price is low).

Target Class Representation

Table 2: Target Class Representation

I	Ti Transform
1	1
2	1
3	1
4	0
5	0

Computation of IndividualTargetClass Probability

We compute the individual target class probability using the equation

Probability = <u>Probability of Occurrence of an event</u> (3)

Total Number of Event

Probability of low class is 2/5 = 0.4

Probability of high class is 3/5 = 0.6

Computation of the Supply Attribute

We compute the attribute Mean Threshold (μAi) = $\frac{11.20}{5}$ = 2.24

We compare our result with each attribute (demand) in our dataset, in other to get our attribute class representation in binary form using our threshold operators <, > or its equivalent. If MTO is greater than the attribute price we have a 1 (price is high) but if less than we have a 0 (price is low)

Table 3: Supply Attribute Representation

I	Ai Transform
1	0
2	1
3	1
4	0
5	1

Computation of the Demand Attribute

We compute the attribute Mean Threshold (μAi) = $\frac{8.95}{5}$ = 1.79

We compare our result with each attribute (supply) in our dataset, in other to get our attribute class representation in binary form using our threshold operators <, > or its equivalent. If MTO is greater than the attribute price we have a 1 (price is high) but if less than we have a 0 (price is low)

Table 4: Demand Attribute Representation

I	Ai Transform
1	0
2	1
3	1
4	0
5	1

D. Prediction Storage System

The prediction storage system permits the storage of predictions generated by the Bayesian Network for each Monte Carlo iteration. The generated predictions are stored in a suitable database file for later access.

E. The Classifier System

The classifier system evaluates the performance of the Bayesian Network prediction systems for each Monte Carlos iterations. The performance is evaluated on the basis of the percentage classification accuracy. The percentage accuracies are estimated considering the True-Positive (TP) and the True-Negative (TN) state for each prediction compared to the actual (target). In addition, if the prediction is not a True-Positive (TP), then it is a False-Positive, and if the prediction is not a True-Negative (TN), then it is a False-Negative (FN).

Classifier System can then be computed as:

$$Percentage\ Accuracy = \left(\frac{TP+TN}{TP+TN+FP+FN}\right)100 \quad (4)$$

Where;

TP = Total number of true-positive

TN = Total number of true-negative

FP = Total number of false-positive

FN = Total number of false-negative

4. Oil Price Decision Support System using Bayesian Network

The predictive system is based on the Bayesian network, It has been trained to predict crude oil prices in range of tens (10's) of barrels, from a minimum of ten (10) barrels a day to a maximum of one hundred and twenty (120) barrels a day, showing the prices in US Dollars (USD) for which crude oil is traded internationally. The key default network parameter specifications used is tabulated in Table 5. This show the number of Training Samples, Attribute States (State 1and 2) Number of Trial Runs, Prediction Range and other associated Bayesian Network parameters as used in the system.

Table 5: Key predictive System Network Parameters

System Parameter	Value
Number of Trial Runs	10
Number of Training Samples	100
Prediction Range	120
State 1	0
State 2	0
Percentage Classification	100

5. Results

Table 6: Results when predicting state (Supply) (1) high and (Demand) high (1)

S/n	Number of Training Sequences Considered	Classification Accuracy
1	10	0.40
2	20	0.65
3	30	0.77
4	40	0.83
5	50	0.86
6	60	0.27
7	70	0.36
8	80	0.38
9	90	0.40
10	100	0.44

Results of tests tabulated in Table 6 using the specified network parameters showed that as the input parameters (Supply (State 1) and Demand (State 2)) was adjusted for (1, 1) When State 1and 2 are both High as used for the prediction experiment, showed an upward/ steady increase in the equilibrium output and better performance of the system based on the rated classification accuracy, as shown in Figure 2 below, until the number of training sequence was adjusted for 60, then there was a sudden drop/decrease (system interruption) the equilibrium output due to high supply and low demand of crude oil, but at 70 there was increase up till 100 showing a balance in the system as it was initially before the interruption/change. As the effect of the changein price will depend on the relative size of the changes in both state.

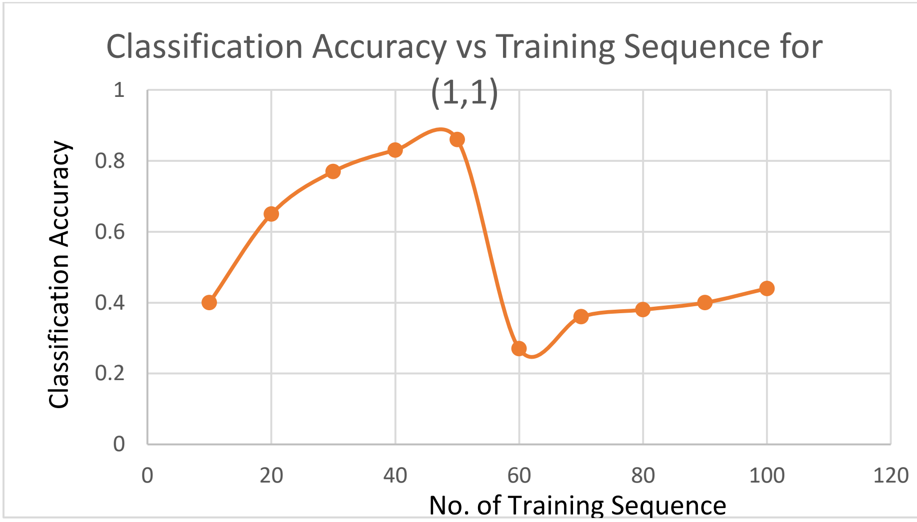

Figure 2: Graph of Classification Accuracy vs. Training Sequence for Supply High and Demand High

Table 7: Results when predicting states (Supply) high (1), (Demand) low (0)

S/n	Number of Training Sequences Considered	Classification Accuracy
1	10	0.40
2	20	0.35
3	30	0.23
4	40	0.18
5	50	0.14
6	60	0.27
7	70	0.36
8	80	0.38
9	90	0.40
10	100	0.44

Results of tests tabulated in Table 7, using the specified network parameters showed that as the input parameters (Supply (State 1) and Demand (State 2)) was adjusted for (1, 0) When State 1 is high and state 2 lowas used for the prediction experiment, the system showed a steady decrease in the price movement (as well as poor performance of the system as rated in the classification accuracy window) as shown in Figure 3belowdue to a higher (excess) supply of crude oil, until the number of training sequence was adjusted for 60, then there was a sudden increase in price showing that the demand for crude oil has increased which in turn triggered the price increase till 100, showing a high performance of the system.

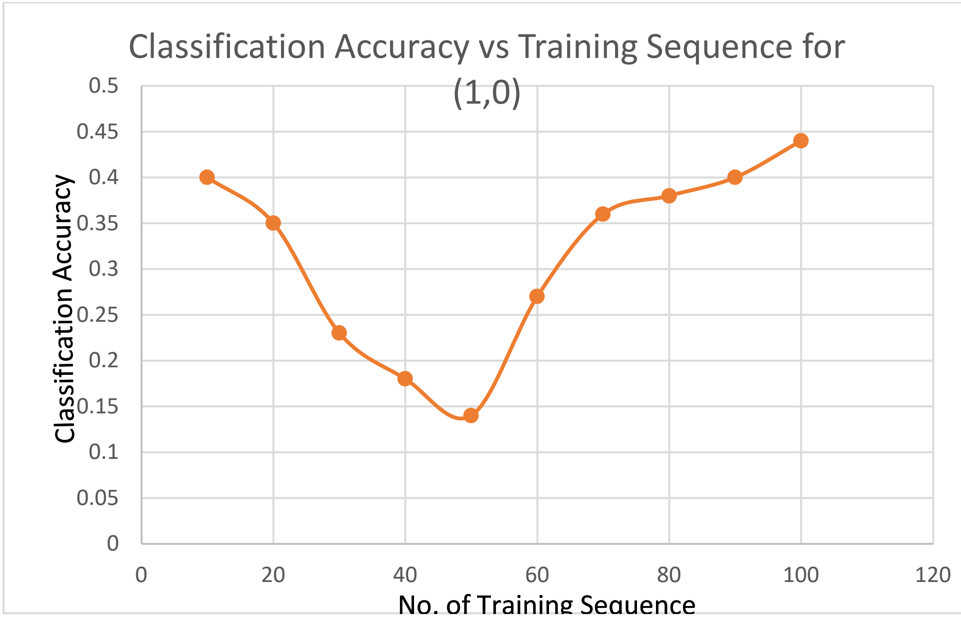

Figure 3: Graph of Classification Accuracy vs. Training Sequence for Supply High and Demand Low

Table 8: Results when predicting states (Supply) Low (0), (Demand) High (1)

S/n	Number of Training Sequences Considered	Classification Accuracy
1	10	0.27
2	20	0.36
3	30	0.38
4	40	0.40
5	50	0.44
6	60	0.40
7	70	0.35
8	80	0.23
9	90	0.18
10	100	0.14

Results of tests tabulated in Table 8 using the specified network parameters showed that as the input parameters (Supply (State 1) and Demand (State 2)) was adjusted for (0, 1) When State 1 is low and state 2 highas used for prediction experiment, the system showed a steady increase in the price movement (as well as high performance of the system as rated in the classification accuracy window) as shown in Figure 4 belowdue to a higher (excess) demand for crude oil, until the number of training sequence was adjusted for 60, then there was a sudden decrease in price showing that the supply of crude oil has increased, which in turn triggered the price decreasetill 100 signifying a poor performance of the system.

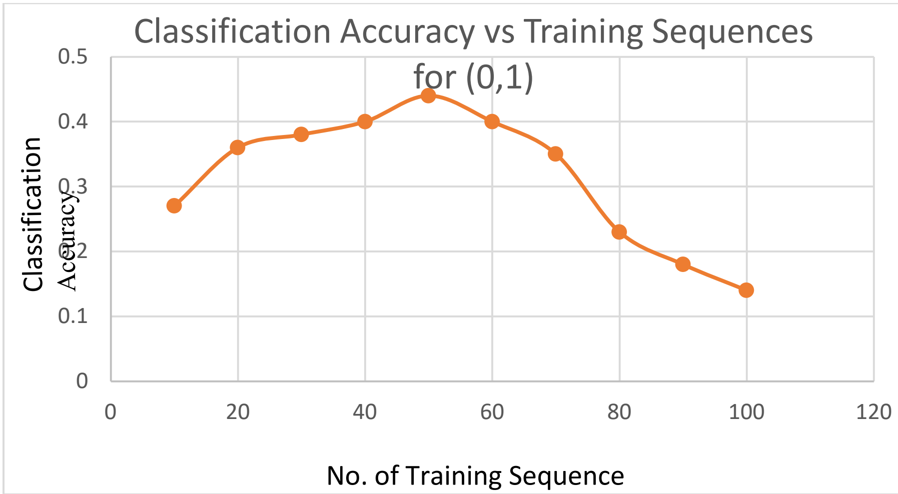

Figure 4: Graph of Classification Accuracy vs. Training Sequence for Supply Low and Demand High

Table 9: Results when predicting states (Supply) Low (0), (Demand) Low (0)

S/n	Number of Training Sequences Considered	Classification Accuracy
1	10	0.44
2	20	0.40
3	30	0.38
4	40	0.36
5	50	0.27
6	60	0.86
7	70	0.83
8	80	0.77
9	90	0.65
10	100	0.40

Results of tests tabulated in Table 9 using the specified network parameters showed that as the input parameters (Supply (State 1) and Demand (State 2)) was adjusted for (0, 0) When State 1 and 2 are both Low as used for the prediction experiment, the systemshowed a steady decrease in the equilibrium output and poor performance of the system based on the rated classification accuracy, as shown in Figure 5 below until the number of training sequence was adjusted for 60, then there was a sudden increase (system interruption) in the equilibrium output due to low supply and high demand of crude oil, but at 70 there was a decrease up till 100 showing a balance in the system as it was initially before the interruption/change. As the effect of the change in price will depend on the relative size of the changes in both state.

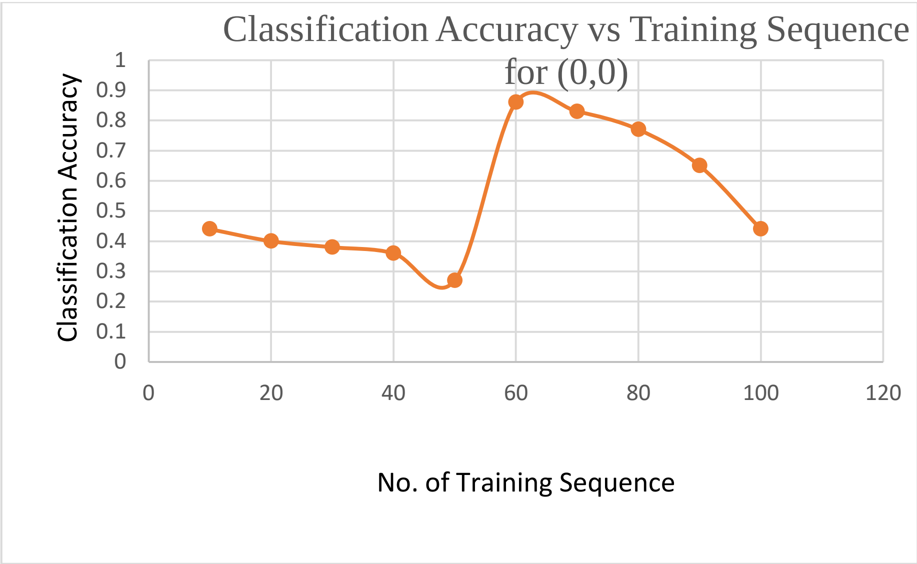

Figure 5: Graph of Classification Accuracy vs. Training Sequence for Supply Low and Demand Low

6. Evaluation

Table 10: Dataset for Crude Oil Price in USD

Number of Training Sequences Considered	Year	Months	Price of Crude Oil in USD
10	2008	March	103.73
20	2008	April	116.73
30	2008	May	126.57
40	2008	June	138.74
50	2008	July	141.86
60	2008	August	115.84
70	2008	September	103.83
80	2008	October	75.31
90	2008	November	54.31
100	2008	December	44.36

As obtained from the dataset gotten from the source mentioned in section 2 above, result showed that between March 2008, the price of crude oil was 103.73 USD per barrel, there was a steady increase in price up to July 2008 (141.86 USD per barrel) because demand for crude oil was high, but by August 2008 which is at point 60 as shown in Figure 6 below there was a sudden drop in price of crude oil (115.84 USD per barrel) showing that the supply of crude oil has increased and all through the price of crude oil dropped till 100.

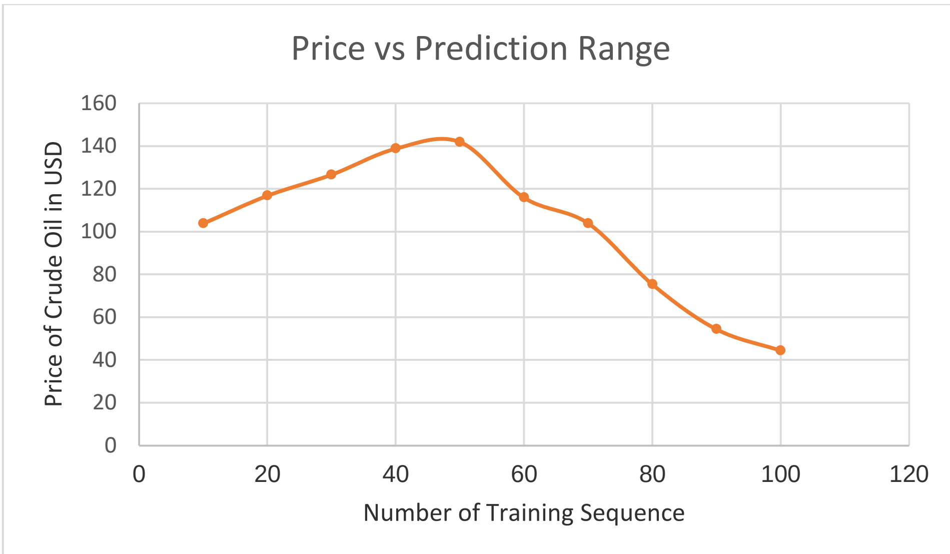

Figure 6: Graph of Price vs. Number of Training Sequences

The system was evaluated based on comparative analysis of the dataset obtained from the source mentioned above and, the Bayesian Network prediction experiment as shown in section 6 (Result Discussion) table 8 and figure 4 above using the specified network parameters for the prediction experiment, both results showed that there was a steady increase in price as demand was high for each of the number of training sequences but at point 60 there was a sudden drop in price of crude oil because the supply of crude oil had increased.

7. Conclusion

The crude oil price market is known for its obscurity and complexity. Due to this high uncertainty aligned to the irregular events in the market, predicting the market's behaviour is a challenging task. Nevertheless, its uncertainty and volatile characteristics attract much attention of researchers. Two fundamental factors (demand and supply) that had played an important role in oil prices were presented. Bayesian Network technology was presented and its application to investigate the prediction of crude oil prices practically. The price data obtained from the credible source discussed above were classed into High and Low cases to denote the upward and downward price movement in which information was revealed. The input data were used in this model to train the network and to validate its generalisation ability in other to deliver the best prediction forecast.A linguistic prediction model which utilised the

Bayesian Network whose aim was to integrate linguistic information into a quantitative prediction model was established. The results obtained from the linguistic model demonstrate that linguistic information adds value to the prediction network. This model also adds credibility to Bayesian Network as a promising prediction tool.

8. Recommendation

The Bayesian Network model is a promising tool in determining crude oil price prediction, in that Nations, such as Nigeria whose economic mainstay is solely determined by projected oil budget of which if there is a fall will make them experience a deficit in their annual budget, thus leading to hardship in the economy. The predictive system will help such nations plan their annual budgets so as to avoid running into a budget deficit.

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