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Modified s-S Inventory Model Using Artificial Neural Network

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Abstract— The use of Artifical Neural Network (ANN) in modifying and improving the output of existing scientific and economic models has been pragmatic in recent time. In this study, we modify the traditional s-S stochastic inventory model by adding the ANN predicted customers demand at lead time to the re-order quantity. The ANN was designed and implemented using Visual Basic 6.0 programming tools and Microsoft Access as the database. Data collected from petrol mega station were standardized to fit the [0,1] ANN sigmoid transfer function domain. Backpropagation algorithm was used in training the Network. At every re-order point the expected period (days) of arrival of goods was inputted into the system and the quantity of goods to be demanded (D_p) by the customers before the arrival of new stock was predicted and added to the s-S re-order quantity. The correlation coefficient of 0.97 and 0.58 were obtained for the modified s-S and traditional s-S inventory models respectively. The modified s-S model was found to be 97% efficient in preventing stock out of petrol in a distribution depot.

Index Terms— Artificial neural network, Backpropagation algorithm, Sigmoid transfer function, Stochastic inventory model.

1 INTRODUCTION

Inventories could be viewed as goods or materials, kept for sales, usage or processing. Virtually every segment of the economy relies on some form of inventory for their operations. The ubiquitous nature of inventory has motivated this study with a view of harnessing methods and technology for effective monitoring of inventory levels to ensure continuous availability of goods with stochastic demand.

Many researchers have worked on inventory models, as in [1], [3], [2], [5], [7]. Gallego [3] opined that in continuous review (Q, R) policy, the inventory manager continuously monitors the inventory position and places an order of size Q whenever the inventory position falls to or below the reorder point R. Tajbakhsh [7] observed that the continuous review *(Q,R)* policy is appropriate when inventory levels are reviewed continuously. Feng *et al* [2] opined that in the case of periodic review, a slight alteration of the continous review policy is required, two levels, $s < S$, *are* defined and the starting inventory at the beginning of a period is set to u such that *If* $u \leq s$, an order of $S - u$ is placed otherwise no order is made.

Artificial Neural Network (ANN) as presented in [6],[8], [9] has been developed as generalizations of mathematical models of biological nervous systems. They have the advantageous capabilities of learning from training data, recalling memorized information, and generalizing to the unseen patterns.

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A popular supervised training algorithm is the back propagation. It uses the historical data to adjust the network's weight and thresholds so as to minimize the error in its predictions on the training set. If the network is properly trained, it has the ability to learn and model the unknown function that relates the input variables to the output variables, and can subsequently be used to make predictions where the output is not known.

2 MATERIALS AND METHODS

Back Propagation Multilayer Perceptron Neural Network (BPMLNN) with supervised training technique proposed in [8] is applied in this research. The Proposed network comprises three layers. The size of the input, hidden and output layers are 6,3,1 respectively.

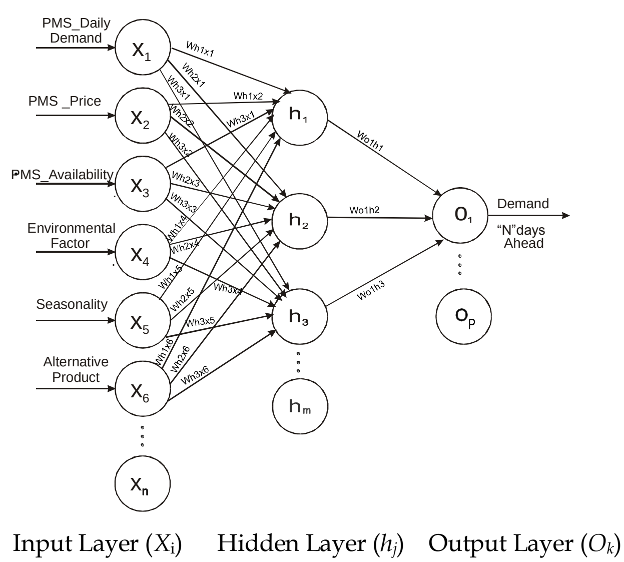

Fig. 1: Artificial neural network schema for petrol demand Prediction.

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The size of the input layer corresponds to the number of data attributes that could influence the aggregate demand of Petrol, "N"days into the future as shown in fig.1. The ANN architecture of fig. 1, was trained with a supervised multilayer back propagation training process proposed in [8]. The hidden layer nodes and output layer nodes were computed by equations 1 and 2 respectively.

$$h_j = f\left(\left(\sum_{j=1}^{m}\sum_{i=1}^{n} W_{ji}x_i\right)+\theta_j\right) \qquad (1)$$

$$o_k = f\left(\left(\sum_{j=1}^{m} w_{kj}h_j\right)+\theta_k\right) \qquad (2)$$

Where: h_j, O_k are hidden and output nodes respectively W_{ji}, W_{kj} are the weights connecting hidden and input layer, Output and hidden layers respectively. x_i is the random variable of the input layer, θ_j and θ_k are the bias value at the hidden and output layer node. Errors at the hidden layer and output layers are computed by equations 3 and 4 respectively

$$e_j = h_j(1-h_j)(w_{kj}e_k) \qquad (3)$$

$$e_k = (d_k - o_k)(o_k)(1-o_k) \qquad (4)$$

If the error is greater than a certain predefined value, (0.001) in this case, it is propagated back into the network by means of adjustment of the weights connecting the output to the hidden layers and those connecting the hidden layers to the input layers. Output and hidden layer weights are adjusted by equations 5 and 6 respectively

$$w_{ji}(n+1) = w_{ji}(n) + \beta e_j x_i + \alpha \sum \Delta w_{ji} \qquad (5)$$

$$w_{kj}(n+1) = w_{kj}(n) + \beta e_k h_j + \alpha \sum \Delta w_{kj} \qquad (6)$$

Where: n is step in the training cycle, $w_{kj}(n)$ is the weights between the output and hidden node at cycle (n), $w_{ji}(n)$ is the weights between the hidden and input node at cycle (n), d_k and o_k are the desired and computed output respectively, e_j and e_k are hidden and output layer error components , α is the momentum parameter, β is the Learning rate parameter , $\sum \Delta w_{ji}$ is the cumulative change in weights of the hidden and input node, $\sum \Delta w_{kj}$ is the cumulative change in weights of the output and the hidden node. The desired output d_k is computed by equation 7

$$d_k = \sum_{i=1}^{N} x_i \qquad (7)$$

A total of 161 data set for petrol data set were collected from Pipelines and Product Marketing Company (PPMC) Depot, Port Harcourt. After the computation of the desired output (60 days-ahead-demand), using equation 7, 59 data set were discarded for lack of insufficient data to accumulate next 60 days desired demand. 102 data set were therefore available for the research. The 102 available data set were divided into three parts: training, validation and testing data set in the ratio of 8:1:1 respectively. The Data were stored in MS-Access 2007, and was operated upon by ANN computer program designed using Visual Basic 6.0, running on Windows Vista operating System on a pentium IV computer system.

3 RESULTS AND DISCUSSION

The proposed inventory model with effect of varying demand of product at lead time is organised such that the probability of stockout at lead time is greater than zero. This could be achieved by increasing the volume of reorder point by volume of safety stock for the next order if the volume at previous reorder point could not sufficiently serve the customers at lead time. Where : Lead time is the time taken for the products to arrive at the depot and safety stock is inventory held to protect against stockout.

In s-S inventory model, two levels, $s < S$, *are* defined and the starting inventory at the beginning of a period is set to u. The order quantity is given by equation 8

$$\text{Order Quantity} = \begin{cases} S-u & \text{if} \quad u \le s \\ 0, & \text{otherwise} \end{cases} \qquad (8)$$

Where: S is the maximum storage capacity; s is the predefined inventory level u is the starting inventory at the beginning of a period. We modify the *s-S* inventory model as follows:

$$\text{Order Quantity} = \begin{cases} (S-u)+D_p & \text{if} \quad u \le s \\ 0, & \text{otherwise} \end{cases} \qquad (9)$$

Where: D_p is the predicted demand at lead time obtained as follows:

From the Artificial Neural Network (ANN) model, the desired demand of petrol d_k , N days into the future is given as:

$$d_k = \sum_{i=1}^{N} x_i \qquad (10)$$

where x_i is the daily demand of petrol.

When the Sum of Squared Error (SSE) from the ANN model tends to zero, the desired output d_k can be predicted by the computed output O_k given by:

$$O_k = f\left(\left(\sum_{j=1}^{m} w_{kj} h_j\right) + \theta_k\right) \qquad (11)$$

where f is the sigmoid transfer function expressed as:

$$f(x) = \frac{1}{(1 + e^{-x})} \qquad (12)$$

We set y to be the number of days before the arrival of new stock from the *s-S* inventory model, and thus compute the predicted demand D_p as follows:

$$D_p = \frac{y(O_k)}{N} \qquad (13)$$

Where: y is expected delivery period

O_k is the computed demand, N days into the future obtained from the ANN model and applied in fig.2.

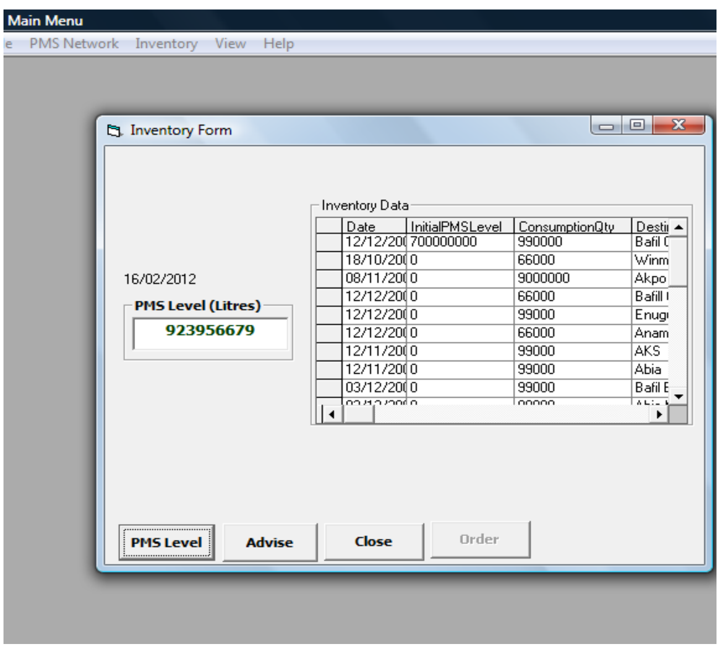

Fig. 2 : Petrol Inventory Form

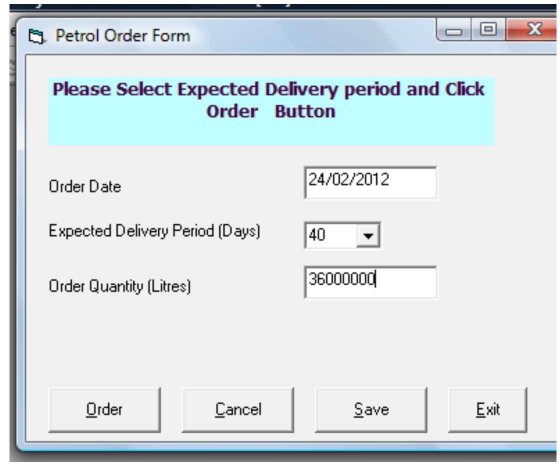

Fig 3 : Order Quantity Form.

From Fig. 3, the order qunatity of product is computed using the modified s-S model of equation 9. The user inputs the expected delivery period and clicks the Ok button for automatic computation of the order quantity .

Table 1 : Comparison between the traditional *s-S* and Modified *s-S* Inventory Reorder Quantities.

SN	Expected Delivery period (days)	s-S Reorder Qty (Litres)	Modified s-S Reorder Qty (Litres)
1	1	3000000	3000000
2	5	3200000	4166000
3	10	3600000	8333000
4	15	3000000	12500000
5	20	3800000	20000000
6	25	3000000	20833000
7	30	4000000	25000000
8	35	4000000	30000000
9	40	3000000	36000000
10	45	5000000	37500000

Source: Field Experiment and simulation with computer program, 2012

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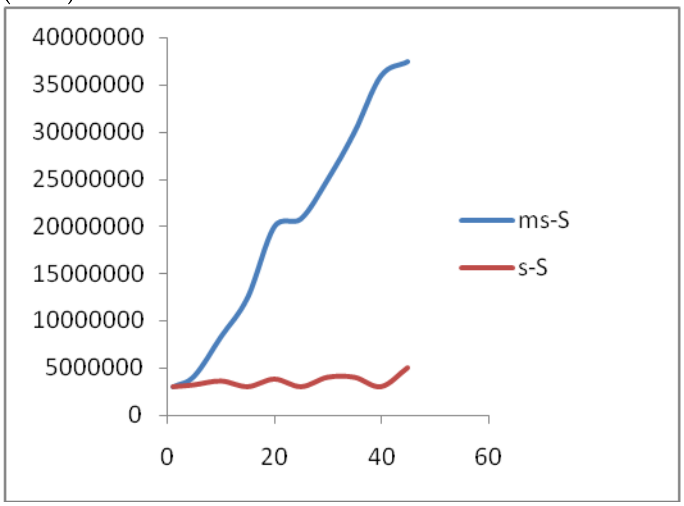
Re-Order Qty
(litres)



Expected delivery period (days)

Fig. 4 : Graph of Reorder Quantities of *s-S* and *ms-S* models

From the graph of fig.4, both traditional *s-S* and modified *s-S* (*ms-S*) models suggest the same re-order quantity when the expected days of delivery is less than or equals to one (1) day. As the expected delivery day increases, *ms-S* model scales proportionally by increasing the re-order quantity whereas the s-S model maintains almost a constant re-order quantity. The ability of *ms-S* to predict the demand of products at lead time and scale re-order quantity proportionally to expected delivery period could prevent product stock-out at the depot. Computing the correlation coefficient between the expected period of delivery and the *ms-S* model gives 0.97 whereas *s-S* model gives 0.58, the results show that ms-S model is more efficient in preventing product stockout at the depot.

4 CONCLUSION

Traditional s-S inventory model has been modified in this work using Artificial Neural Network (ANN). The modified s-S (*ms-S*) model has been found to be 97% efficient in scaling the re-order quantity of petrol with specified delivery period at the depot compared to the 58% efficiency rendered by the traditional *s-S* model. We recommend the combination of neural network and fuzzy logic computing tools for modification of the *s-S* inventory model in future research.

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REFERENCES

[1] M. Dror and M. Ball "Inventory/routing: Reduction from an Annual to a Short Period Problem," *Naval Research Logistics Quarterly*, 34(6):891-905, 1987.

[2] Q. Feng, G. Gallego, S. Sethi, H. Yan, H. Zhang "Periodic Review Inventory Model with Three Consecutive Delivery Modes and Forecast Updates," *Journal of Optimization Theory and Applications*, 124 (1): 137-155, 2005.

[3] G. Gallego, " A minmax distribution free procedure for the (*Q*, *R*) Inventory model," *Columbia University, New York, USA . Elsevier: Operations Research Letters*, *11(1)* : 55–60, 1992 .

[4] J. J. Hopefield, " Neural Networks and Physical Systems with emergent Collective Computational Properties," *Proceedings of the National Academy of Sciences of the USA*, 79:2554-2588, 1982.

[5] R. R. Lindeke, "Inventory Control Models: Uncertainty of Demand, Production and Operations Management," *IEEE* 3265, 2007.

[6] O. U. Obot., O.C Akinyokun and S.S.Udoh, "Application of Neuro–Fuzzy Expert System for Diagnosis of Hypertension," *Journal of Nigeria Computer Society (NCS),* 15(2):131-147, 2008.

[7] M. Tajbakhsh ," On the distribution free continuous-review inventory model with a service level constraint," *Department of Industrial Engineering, Dalhousie University, Elsevier: Computers & Industrial Engineering* ,59(4): 1022–1024, 2010.

[8] S.S. Udoh and O. Olabode, " Artificial Neural Network for the Prediction of the Demand of Petrol using Periodic Review, s-S, model in a Distribution Network," *Journal of Applied Mathematical and Computational Sciences (AMCOS)*, 1(2): 151-164, 2010.

[9] S. S. Udoh, " Prediction of the Demand of Petrol at the Depot," *An M. Tech Research, Department of Computer Science, Federal University of Technology, Akure.* Pp 100-120, 2009. (Master of Technology Thesis)