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Annual Fuel Demand Forecasting for International Aircraft by Fuzzy Logic

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ABSTRACT

Forecasting is the prediction of future events and conditions and is a key element in service organizations,especially banks, for management decision-making. In preparing a projection of a company's future revenues and expenses, a sales forecast must first be prepared. Whereas expenses can be controlled by management on a day by day basis, sales occur only when outside parties make a proactive purchase decision. Management, by devising a successful marketing strategy, influences the buying decisions of its customers but cannot make the customers buy. Therefore, management must somehow predict or forecast how many units will be sold and at what price and during what time frames. Fuel is a major cost expense for air carriers. A typical airline spends 10% of its operating budget on the purchase of jet fuel, which even exceeds its expenditures on aircraft acquisitions. [1] Thus, it is imperative that fuel consumption be managed as wisely as possible. [8]This study explores the potential of the neurofuzzy computing paradigm to model the annual fuel demand forecasting for international aircraft in India. [8] The neurofuzzy computing technique is a combination of a fuzzy computing approach and an artificial neural network technique. Parameter optimization in the model was performed by a combination of back propagation and least squares error methods. [8] Performance of the neurofuzzy model was comprehensively evaluated with that of independent fuzzy and neural network models developed for the same basin. [11]Fuzzy based forecasted annual demand is further computed by time series analysis forecasting. Error and absolute deviations are predicted and tracking signal is evaluated for the same.

Keywords : Forecasting, Neurofuzzy, Annual Demand, Back Propagation, Time Series Analysis

I. INTRODUCTION

Air carriers spend vast sums of money on fuel to operate their fleets of aircraft. This major cost area must be managed as wisely as possible. Extensive research is being conducted by a host of organizations, including government, industry, and academia, but the research is essentially confined to engineering related areas. Little exists in the literature on efforts to examine, on a routine basis, the fuel efficiency of operational air carrier aircraft to determine if improvements are possible. Estimation of aircraft fuel plays an important role in determining the impact of air traffic operations as well as in estimating the benefits of efficiency-enhancing procedures, and has been a topic of interest to the research community for several years. (1) Taxi-out fuel consumption is most often determined using the fuel burn indices presented in the International Civil Aviation Organization (ICAO) engine emissions databank. The ICAO fuel burn indices provide fuel burn rates for only four engine power settings (corresponding to 7% or taxi/idle, 30% or approach, 85% or climb-out, and 100% or take-off), and are based on estimates provided by engine manufacturers. (3) Recently published studies(4), (5) have shown that the ICAO estimates can be quite different from the actual fuel burn, when considering the departure flight phase in the terminal area. The terminal area fuel burn considered in these studies includes the fuel consumed during taxi-out as well as the initial part of the climb. In contrast, in order to estimate the benefits of surface traffic management strategies, (6) it is necessary to have accurate estimates of annual demand for fuel. Since fuel is the important factor to be considered in the present era, the forecasting for fuel demand is necessary. On the other hand, an error for the demand has to be calculated, because many of the forecasting leads to failure. . To the best of our knowledge, this paper is the first attempt to develop models of forecasting the future annual demand.

II. METHODS AND MATERIAL

Fuzzy Logic

Economic growth is the most important index among the macroeconomic variables. This variable has been considered as an economical index of government, and its increasing rate shows the welfare condition of the society. Fuzzy logic provides a practicable way to understand and manually influence the mapping behave ours. In general, Fuzzy logic uses simple rules to describe the system of interest, rather than analytical equations, making it easy to implement. It is obvious that forecasting activities play an important role in our daily life. We usually forecast many things concerned with our daily life, such as the economy, stock market, population growth, weather, etc. forecasting with 100% accuracy may be impossible, but we can do our best to reduce forecasting errors. To solve forecasting problems, many researchers have proposed many different methods or models (Cheng, 2004). Fuzzy systems have supplanted conventional technologies in some scientific applications and engineering systems in the past decade (Cheng, 2004).Fuzzy logic has the ability to express the ambiguity of human thinking and translate expert knowledge into computable numerical data. A Fuzzy system consists of a set of Fuzzy if–then rules. Conventionally, the selection of Fuzzy if–then rules often relies on a substantial amount of heuristic observation to express the knowledge of proper strategies. Obviously, it is difficult for human experts to examine all the input–output data from a complex system to find proper rules for the Fuzzy system. To cope with this difficulty, several approaches to generating Fuzzy if–then rules from numerical data have been proposed (Cheng, 2004). An FIS (Fuzzy inference Systems) contains three main components, the; Fuzzification stage, the rule base and the defuzzification stage. The fuzzification stage issued to transform the so-called crisp values of the input variables into Fuzzy membership values. Then, these membership values are processed within the rule-base, using conditional „if-then" statements. The outputs of the rules are summed and defuzzified into a crisp analogue output value. The effects of variations in the parameters of a FIS can be readily understood and this facilitates calibration of the model. In Fuzzy-logic implemented system, six inputs and one output are used on the base on Principles or rules, of triangular with mathematical formulas. That real numbers of variables is converted to Fuzzy values. And then these Fuzzy values have been inserted to the basic process ("if-then" rules), and then are based on linguistic values levels: low, middle, high, very high and are graded by membership functions.

Neuro-Fuzzy-Fuzzy neural network

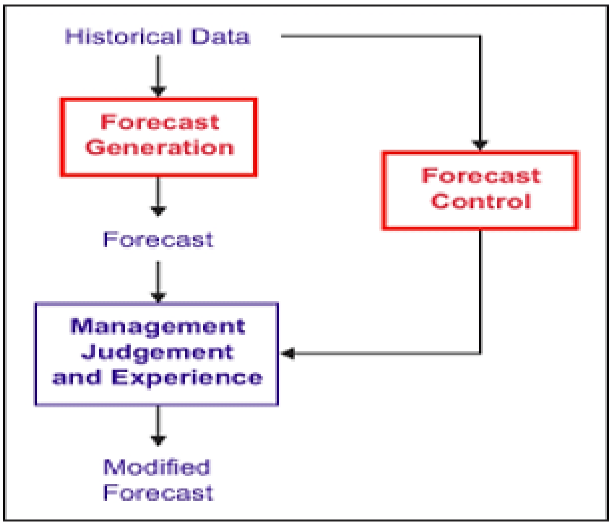
Artificial neural networks (ANN) appear to be particularly suitable to forecast the growth of time series, as they can learn highly nonlinear models, hold effective learning algorithms, handle noisy data, and use inputs of different kinds (Armano et al., 2005). ANNs have been designed to mimic the characteristics of the biological neurons in the human brain and nervous system (Zurada, 1992). An ANN creates a model of neurons and the connections between them, and trains it to associate output neurons with input neurons. The network learns by adjusting the interconnections (called weights) between layers. When the network is adequately trained, it is able to generate relevant output for a set of input data. One of the valuable properties of neural networks is that of generalization where by a trained neural network become able to provide a correct matching in the form of output data for a set of previously unseen input data.

Back Propagation (BP) is one of the most famous training algorithms for multilayer perceptions (Abraham and Baikunth, 2001; Kasabov, 1998). FNNs are a class of hybrid intelligent algorithms that integrate Fuzzy logic with ANNs.A Fuzzy neural network System is defined as a combination of ANN and Fuzzy inference system (FIS) in such a way that neural network learning algorithms are used to determine the parameters of FIS. [13]An even more important aspect is that the system should always be interpretable in terms of Fuzzy if-then rules, because it is based on the Fuzzy system reflecting vague knowledge (Sadeghi, 2008). A neural network - Fuzzy consists which of five levels, are as follow (Abrahim and Baikunth, 2001): 1) Input Layer, 2) Fuzzification Layer, 3) Rule Base Layer, 4) Fuzzy Outputs, 5) utput Layer. In designing neural networks – Fuzzy model, multi-layer feed forward neural network (MFNN) with learning algorithm, the propagation error and Fuzzy inference system "Sugeno" input function "difference between of Sigmoid functions" and the output function linear has been used in this system , on the other hand for to non-Fuzzy also moving average function has been used too. Through continuing changes number of layers and number of hidden neurons layer, and appropriate neural network topology, were evaluated.[13] Through continuous changes of membership functions, and number of membership functions, the suitable Fuzzy inference system was designed

Forecasting Technique

Forecasting product demand is crucial to any supplier, manufacturer, or retailer. Forecasts of future demand will determine the quantities that should be purchased, produced, and shipped [12].] Demand forecasts are necessary since the basic operations process, moving from the suppliers' raw materials to finished goods in the customers' hands, takes time. Most aircraft cannot simply wait for demand to emerge and then react to it. Instead, they must anticipate and plan for future demand so that they can react immediately to customer orders as they occur [21. In other words, most manufacturers "make to stock" rather than "make to order" – they plan ahead and then deploy inventories of finished goods into field locations. Thus, once a customer order materializes, it can be fulfilled immediately – since most customers are not willing to wait the time it would take to actually process their order throughout the supply chain and make the product based on their order. An order cycle could take weeks or months to go back through part suppliers and sub-assemblers, through manufacture of the product, and through to the eventual shipment of the order to the customer.

Aircraft that offer rapid delivery to their customers will tend to force all competitors in the market to keep finished goods inventories in order to provide fast order cycle times. As a result, virtually every organization involved needs to manufacture or at least order parts based on a forecast of future demand. The ability to accurately forecast demand also affords the firm opportunities to control costs through levelling its production quantities, rationalizing its transportation, and generally planning for efficient logistics operations. [21]In general practice, accurate demand forecasts lead to efficient operations and high levels of customer service, while inaccurate forecasts will inevitably lead to inefficient, high cost operations and/or poor levels of customer service. In many supply chains, the most important action we can take to improve the efficiency and effectiveness of the logistics process is to improve the quality of the demand forecasts. The schematic pictorial view is shown in fig.1.



Data Collection:

Data were been collected from International Civil Aviation Organization (ICAO). For one year with the period of 1 to 12 month of 2019 the demand for aircraft is shown in table.1.

Table. 1. Annual Fuel Demand

Period	Month	Demand (Gallons)
1	Jan	121772
2	Feb	996534
3	Mar	452202
4	Apr	250898
5	May	79323
6	Jun	85768
7	Jul	27850
8	Aug	490847
9	Sep	270853
10	Oct	450712
11	Nov	250700
12	Dec	210855

Fuzzy Based Forecasting

The basic concepts that comprise the neural network approach or fuzzy theory, such as weights, learning algorithm, fuzzy set, membership functions, the domain partitions, and fuzzy if-then inference rules are not reproduced in the body of this paper as that have been introduced in numerous hydrological papers and text books [Haykin, 1994; Hundecha et al., 2001; Xiong et al., 2001]. However, as the integration of both techniques is a relatively new concept, brief details of the method are presented in the following sections. [10] Neurofuzzy modelling refers to the way of applying various learning techniques developed in the neural network literature to fuzzy modelling or a fuzzy inference system (FIS). The basic structure of a FIS (Figure 1) consists of three conceptual components:[16] A rule base, which contains a selection of fuzzy rules; a database which defines the membership function (MF) used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and a given condition to derive a reasonable output conclusion. [18]A FIS implements a nonlinear mapping from its input space to an output space. A FIS can utilize human expertise by storing its essential components in a rule base and database, and perform fuzzy reasoning to infer the overall output value. The derivation of if-then rules and corresponding membership functions depends heavily on the a priori knowledge about the system under consideration. [28]However there is no systematic way to transform experience of knowledge of human experts to the knowledge base of a FIS.[29] On the other hand, ANN learning mechanisms do not rely on human expertise. Because of the highly parallel structure of an ANN it is hard to extract structured knowledge from either the weights or the configuration of the ANN. The weights of the ANN represent the coefficients of the hyper plane that partition the input space into two regions with different output values. If one can visualize the hyper plane structure from the training data then the subsequent learning procedures in an ANN can be reduced. On the contrary, a priori knowledge is usually obtained from the human experts and it is most appropriate to express the knowledge as a set of fuzzy if then rules. The general schematic view of fuzzy logic is shown in fig.2.

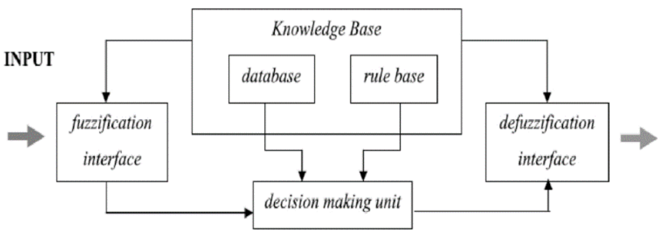
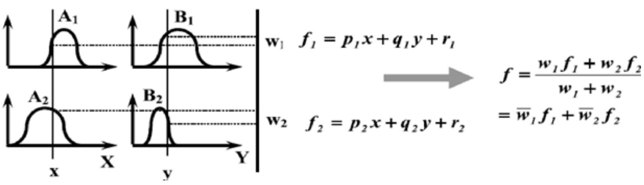
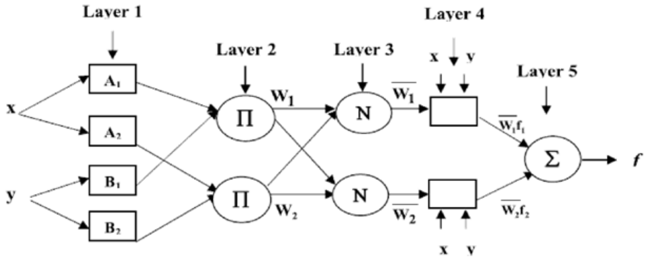


Fig. 2. *Schematic view of fuzzy logic*



(a)



(b)

Fig. 3. Schematic of fuzzy and neurofuzzy paradigm: (a) Fuzzy inference system and (b) Equivalent neurofuzzy architecture

III. RESULTS

The annual demand is forecasted using fuzzy logic. Back propagation algorithm is used to find the future demand and the calculated future demand is further analysed using time series analysis. Mean square error and Absolute deviation are also found. Eventually tracking signal is found and it shown in table.2.

Estimation of tracking signal (Demand for the period of 2019)

Period	Month	Demand (Gallons)	Future Demand by Fuzzy(Gallons)	Tracking Signal
1	Jan	121772	150443	-1
2	Feb	996534	476678	1.8
3	Mar	452202	137202	5.5
4	Apr	250898	188279	5.3
5	May	79323	40827	-5
6	Jun	85768	283282	-4
7	Jul	27850	246790	-12
8	Aug	490847	329631	10
9	Sep	270853	321014	-8
10	Oct	450712	309126	-6.4
11	Nov	250700	351854	1.05

IV. CONCLUSION

The paper addresses the problem of forecasting the fuel demand for aircraft. The objective of the paper was twofold: one was to demonstrate the potential of the neurofuzzy computing forecasting in modelling the aircraft fuel process; and second was to evaluate the relative merits and demerits of this forecasting with reference to already popular time series analysis modelling approaches. The study suggests that the Neurofuzzy model is able to capture the linearity in the forecasting process better than the other forecasting technique, and is able to compare the forecasted method with time series analysis in advance. Avery close fit was obtained between computed and observed in time series analysis forecasting models, but only the Neurofuzzy model tends to preserve this performance at good forecasting with less error. A comparative analysis of prediction accuracy of these models in different ranges of annual demand indicates that the Neurofuzzy is better than the Time series Analysis. The very short computer time required for a single forecast (a fraction of a second when using a normal Pentium processor) does not lead to any constraints in the use of the method for real time annual demand forecasting. The results of the study are highly encouraging and suggest that an adaptive neurofuzzy approach is viable for developing short-term forecasts of annual fuel demands in aircrafts.

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