A Performance Comparison of Neural Networks and Fuzzy Systems for Time Series Forecasting

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Abstract – Artificial neural networks and fuzzy structures have gained significant popularity in the last decade for time series forecasting. The objective is to conduct a performance comparison of various strategies to determine which ones are more effective for time series forecasting. The dataset provides instruction and evaluates forecasting models, utilizing artificial neural networks and fuzzy architectures. The observation evaluates the overall effectiveness of the forecasting models and the use of the root mean square error and means absolute error measures. This comparison analysis provides initial insights into the efficacy of artificial neural networks and fuzzy structures for predicting time series data. In predicting time series data, this study examines the precision of two renowned artificial intelligence systems, Neural Networks and Fuzzy structures. To evaluate the two algorithms, two distinct types of time series were utilized: a synthetic dataset consisting of 150 variables and a real-world dataset including 129 data points about monetary forecasts. The models' forecasting accuracy, training duration, and generalization abilities were compared. The findings validated that neural network surpassed fuzzy structures in all performance metrics when handling synthetic data. This research emphasizes the capabilities of artificial neural networks and fuzzy structures in addressing complicated forecasting problems. It demonstrates that both techniques may be utilized for predicting future time series values.

Keywords – Neural Networks, Fuzzy Systems, Forecasting Models, Mean Square Error, Time Series.

I. INTRODUCTION

Time series forecasting is a complex task requiring high expertise, knowledge, and specialized training. Neural networks and fuzzy systems are widely recognized methods for forecasting future values in time series [1]. Neural networks consist of interconnected layers of mathematical models that enable the network to analyze data and accurately represent the current situation. Subsequently, the data regarding historical trends is utilized to predict forthcoming values of the temporal dataset. Neural networks can rapidly analyze large quantities of data and identify intricate patterns and relationships [2]. Some typical neural networks employed for time series prediction are recurrent neural networks, convolutional neural networks, and extended short-term memory networks. The fuzzy structures rely on the principles and criteria of fuzzy logic. This approach employs fuzzy sets and rules, enabling computers to infer and approximate instead of generating precise solutions. Fuzzy systems typically offer behavior-based selection guidelines in cases where conventional rule-based systems are inadequate [3]. Fuzzy systems are highly suitable for time-series forecasting, as they can effectively predict future values of a given time series by utilizing historical data. Both neural networks and fuzzy systems have exceptional potential for time series forecasting. By utilizing cutting-edge methodologies and extensive datasets, these two frameworks have the capability and necessity to predict the future values of a particular time series [4]. Although they possess distinct advantages and challenges, both methods offer significant benefits in time series forecasting. Researchers worldwide are developing diverse artificial intelligence (AI) models to meet the growing need to predict future events accurately [5]. **Fig 1** depicts the hidden-layer feed-forward neural network.

Neural Networks (NNs) and Fuzzy Systems (FS) are two types of artificial intelligence models that are increasingly utilized to make precise and dependable predictions in time series forecasting. Neural networks are computational models inspired by the human brain, aiming to mimic its behavior and function by dynamically incorporating new input into existing knowledge. Neurons are interconnected, forming complex networks of basic processing units or nodes. A standard neural network consists of at least one layer of input nodes for receiving data, multiple layers of connection nodes for various computations, and one layer of output nodes [6].

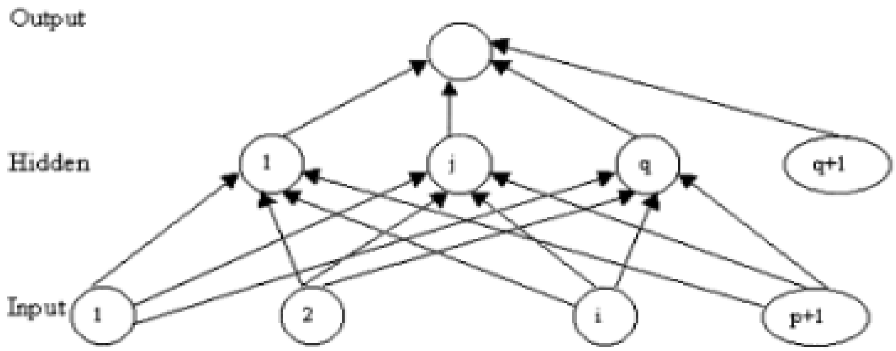

Fig 1. Hidden-Layer Feed Forward Neural Network

Each neuron is responsible for receiving, storing, and processing information. Neural networks are frequently employed for prediction using a technique called back-propagation, which involves adjusting the weights of neurons to improve the accuracy of forecasts. A fuzzy machine (FS) is an AI system that combines computational techniques with decision-making methods based on sound judgment to detect subtle changes in datasets [7]. It involves a collection of indistinct components with limited degrees of potential, which make up imprecise data. The FS enables the user to recognize and establish datasets' many elements, trends, and patterns. Fuzzy logic approaches can identify the optimal approach to problem-solving by analyzing a dataset using a series of guidelines [8]. NN and FS have become progressively indispensable for time collection prediction. By integrating neural networks (NNs) and fuzzy systems (FS) into existing forecasting models, we can enhance the precision of predicting future events. Furthermore, these fashion trends help us comprehend nuanced variations in datasets and enhance our ability to use resources efficiently. As the development of artificial intelligence applications for time series forecasting progresses, these models will improve accuracy and provide valuable insights to aid decision-making [9]. The research's primary contribution encompasses the following:

Artificial neural networks: Neural networks have been employed to predict time series data by utilizing a wide range of designs, including recurrent neural networks (RNNs), long short-term memory (LSTM) models, and convolutional neural networks (CNNs). These fashion models can analyze intricate non-linear relationships between past and future data points in a time series. They possess the ability to predict future outcomes with more accuracy compared to traditional approaches, including multiple linear regression or ARIMA models.

Fuzzy systems consist of inference rules that rely on fuzzy common sense and make conclusions based on inputs and outputs. It enables them to capture non-linear correlations between input and output variables and to create precise forecasts more effectively than linear and statistical methods. They are excellent for predicting chaotic time series, as their machine settings can be quickly modified to resynthesize the fuzzy guidelines in response to changing dynamics.

Models that combine different elements or components: Hybrid designs, such as fuzzy neural networks (FNNs) and fuzzy adaptive resonance principle (FART) models, combine neural networks with fuzzy systems by including a fuzzy inference mechanism into a neural network structure. These models enable the detection of non-linear connections between input and output variables while maintaining the stability of conventional neural networks. Hybrid styles are frequently utilized for forecasting chaotic time series due to their ability to adjust to changes in the underlying dynamics.

II. MATERIALS AND METHODS

Neural networks have fundamentally transformed how computers handle and analyze information. Neural networks can achieve greater efficiency and sophistication in solving complicated problems than typical computer methods by emulating the brain's structure [10]. This development has promising prospects in time series forecasting, wherein precise anticipation of future events can empower well-informed decision-making for enterprises, governments, and individuals. Although neural networks have the potential to bring advantages, there are also various potential concerns linked to their usage in time series forecasting. A significant concern is the possibility of overfitting the model. Neural networks tend to become excessively specialized in specific activities, resulting in forecasts that require greater concentration and adaptability to accommodate changing situations. The outcomes of a neural network prediction typically require further effort to comprehend. Unlike conventional forecasting methods, neural networks do not always offer a clear understanding of the underlying reasons behind a specific outcome [11]. Understanding the neural network's inner workings is essential to elucidate the reasons behind a specific outcome. Ultimately, the intricate nature of neural networks can result in challenges regarding scalability. As the level of complexity rises, the duration required for training the neural networks and executing the forecasts might become overwhelming [12]. It can pose challenges in reliably predicting outcomes over extended timeframes or scaling the models to larger datasets. In general, the problems related to utilizing neural networks for time series prediction provide possible difficulties that must be resolved. Comprehending and effectively dealing with these concerns is essential for optimizing the advantages of neural networks, notwithstanding their significant potential. When neural networks are given appropriate care and attention, they can become a powerful tool for forecasting as long as they are correctly utilized [13]. Fuzzy systems are mathematical models employed in computer algorithms to discern patterns or resemblances within data sets. These models can generate predictions of forthcoming occurrences within time series forecasting and discern connections among data points. The utilization of fuzzy systems in time series forecasting presents some possible difficulties. Fuzzy systems mainly depend on subjective evaluation. Their achievement relies on the precision of the dataset utilized to train the algorithm, together with the proficiency of the modeler in formulating the system's logic. For a fuzzy system to generate dependable predictions, it must undergo training using a data set that is both comprehensive and precise [14]. Interpreting fuzzy systems can pose difficulties.

To generate precise forecasts and insights, analysts must comprehensively understand the system's cognitive processes and operational mechanisms. Understanding the functioning of fuzzy logic and identifying the inputs that influence the model's output most may necessitate a substantial amount of effort. Fuzzy systems can incur high computational costs. Consequently, incorporating them into extensive real-time applications might be excessively intricate and costly. Furthermore, if the model lacks perfection or is not regularly updated, extensive applications may become obsolete, inefficient, and susceptible to errors[15]. Although there are difficulties to overcome, fuzzy systems have the potential to be a robust and vital tool for analyzing and predicting time series data. Fuzzy systems can generate dependable forecasts of future events with meticulous data collection, deliberate logic development, and effective execution. To effectively utilize fuzzy systems for time series forecasting, it is essential to comprehend their constraints and resolve the above concerns to achieve precise and dependable outcomes [16]. Neural networks and fuzzy systems are highly effective methods for predicting future values in a time series. Although these techniques offer an efficient method for forecasting future values, they also pose certain obstacles. Time series forecasting necessitates a substantial quantity of data.

Due to their intricate nature, neural networks and fuzzy systems necessitate a substantial volume of data to produce precise predictions [17]. Fulfilling these criteria can be difficult if the user has sufficient access to historical data. In such instances, it may be unfeasible to only depend on these technologies for accurate prediction. Time series forecasting poses numerous segmentation challenges. Both neural networks and fuzzy systems utilize segmentation methods to partition the data into discrete units, impacting the predictions' precision [18]. Therefore, it is crucial to guarantee that the segmentation process is conducted systematically and with sufficient knowledge to minimize the errors that arise from this procedure. The effectiveness of neural networks and fuzzy systems depends on the data quality they are trained on. In the event of inconsistencies in the data or inaccuracies in single data points, the model may be unable to generate precise predictions. Before constructing any model, the user must meticulously verify the data's precision. Time series forecasting is an intricate procedure due to the inherent unpredictability of the future. The accuracy of predictions generated by a forecasting model is heavily reliant on the quality of the input data, regardless of the model's level of sophistication [19]. Therefore, it is crucial always to keep skepticism when utilizing these technologies. Neural networks and fuzzy systems are effective instruments for predicting time series data. However, they do present particular difficulties. To achieve success in their forecasting endeavors, users must possess an awareness of these challenges. From the above analysis, the following issues were identified. They are,

- Difficulties in training neural networks: The process of training neural networks for time series forecasting can be challenging when the dataset is either too small or too large, leading to the problems of overfitting or underfitting.
- Ambiguity in Fuzzy System Outputs: Fuzzy logic-based problems lack a definitive solution, posing challenges in interpreting the outcomes. The repeated processing of identical data can result in output discrepancy.
- Neural networks and fuzzy systems are sensitive to outliers in the data, making them prone to poor performance or complete system failure.
- Extended Training Duration: Neural networks necessitate lengthier training periods than alternative algorithms like ARIMA.
- The process of estimating suitable parameters for neural networks is arduous and time-consuming. Similarly, achieving an acceptable level of accuracy in fuzzy systems necessitates the meticulous adjustment of parameters.
- Dealing with Enormous Amounts of Data: Large datasets further complicate the challenges in the time series forecasting process, increasing the difficulty for neural networks and fuzzy systems to acquire knowledge consistently.

Neural Networks and Fuzzy Systems for Time Series Forecasting provide various innovative methods for forecasting future outcomes. Neural Networks enable the utilization of sophisticated algorithms like multilayered perceptions and deep belief networks to handle large volumes of data and detect intricate patterns. Simultaneously, fuzzy systems can integrate fuzzy logic and fuzzy rule sets to produce more precise predictions. These methodologies provide an unparalleled blend of adaptability, expandability, and application accuracy beyond conventional forecasting systems' capabilities. Furthermore, Neural Networks and Fuzzy Systems alleviate the choice and validation of models, offering enhanced interpretability and transparency.

III. PROPOSED MODEL

Fractal dimension is a quantitative assessment of the intricacy of an object based on the quantity of self-repeating patterns or qualities it displays when observed at various scales. The concept is founded on the notion that smaller components of an entity exhibit the same patterns as the entire entity. For instance, when a fractal shape possesses a fractal dimension of 2, it comprises smaller components that are two-dimensional entities. **Fig 2** illustrates the structure of the proposed ensemble, which incorporates kind-three fuzzy response aggregation.

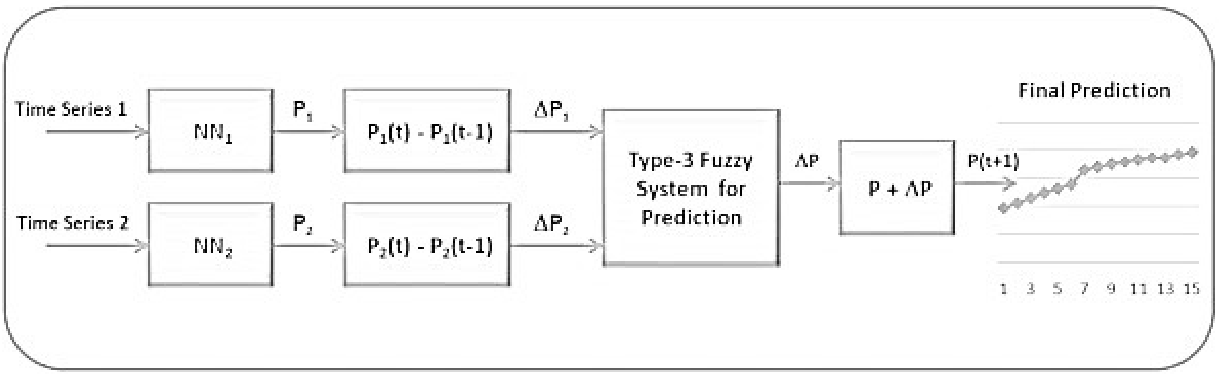

Fig 2. Structure of the Proposed Ensemble with Kind-Three Fuzzy Response Aggregation

The suggested ensemble is a structure for aggregating responses that blends fuzzy logic and machine learning algorithms. The system comprises three elements: the fuzzy clustering module, the weighted voting module, and the aggregation module. The fuzzy clustering module utilizes fuzzy logic methods to classify the input data and generate a split of fuzzy responses. The weighted voting module utilizes these clusters to compute each machine learning model's weighted votes. Ultimately, the aggregation module computes the fuzzy response aggregation by considering the weighted votes. This architecture demonstrates efficacy in delivering resilient and uniform performance by amalgamating numerous models and employing fuzzy logic to generate judgments of higher precision.

Fractal Dimension Object Detection

Fractal dimension object detection is a technique for identifying and segmenting items in a picture using fractal dimension. The approach is based on the concept that the characteristics of objects in an image can be determined by their topological properties or fractal dimensions. The method employs fractal dimension analysis to discern items based on their shape and size.

$$\overline{a}(b) = exp\left[-\frac{1}{2}\left(\frac{b-c}{\alpha}\right)^2\right] \tag{1}$$

$$\underline{a}(b) = \theta * exp\left[-\frac{1}{2}\left(\frac{b-c}{\alpha^*}\right)^2\right] \tag{2}$$

It involves assessing the level of intricacy present in the boundaries of an object, as well as its spatial structure. Through the analysis of the criteria utilized to characterize these intricate forms, it is possible to identify and segment items.

$$\chi(a) = \overline{a}(b) - \underline{a}(b) \tag{3}$$

$$\chi(a) = \overline{a}(b) - \underline{a}(b) \tag{4}$$

The obtained segmentation can subsequently be employed in any application necessitating object detection. Fractal measurement item detection is a method that involves identifying and separating objects in an image by analyzing their fractal measurement.

$$\alpha_a = \frac{\lambda(a)}{2\sqrt{3}} + \pi \tag{5}$$

$$c(b) = exp\left[-\frac{1}{2}\left(\frac{b-c}{\varepsilon}\right)^2\right] \tag{6}$$

The process involves comparing pixels with a high fractal measurement representing items within the image to pixels with a low fractal value representing the background or heritage within the photograph. This method is advantageous for segmenting objects with varying lengths, shapes, and occlusion.

Neural-Network Models for Time Series Forecasting

Neural network models for time series data forecasting are a type of Artificial Intelligence (AI) model that combines artificial neural networks with time-series techniques such as Auto Regression (AR) and Moving Average (MA) to predict future outcomes. **Fig 3** depicts type-3 equipment used for calculating weights.

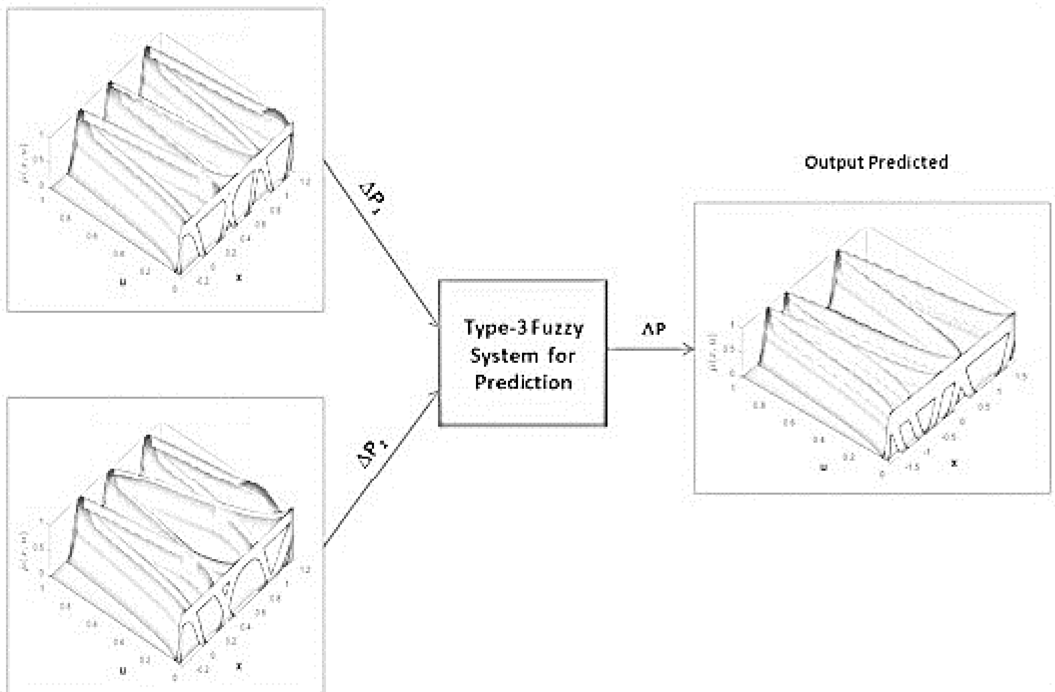

Fig 3. Fuzzy type-3 Machine to Compute the Weights

$$\overline{\beta}_{A(b)}(a) = \exp\left[-\frac{1}{2}\left(\frac{a-a(b)}{\alpha_a}\right)^2\right] \tag{7}$$

$$\beta_{A(b)}(a) = \theta.\exp\left[-\frac{1}{2}\left(\frac{a-a(b)}{\alpha^*{}_a}\right)^2\right] \tag{8}$$

This version is appropriate when the content has intricate patterns or advancements to capture classical styles. The neural network model effectively learns and adjusts to different approaches, facilitating quicker and more precise predictions. The version may also analyze many inputs, including external factors or data from separate instances, to generate more accurate predictions.

Fuzzy Logic For Object Classification

Fuzzy common sense for item categories refers to a form of artificial intelligence (AI) algorithm that utilizes fuzzy logic to classify objects. Fuzzy logic employs a fuzzy set to represent the inherent uncertainty associated with items. This method can assign labels to things by considering their similarities and variances. The comprehensive set of norms, rooted in practical wisdom, seeks guidelines: If A exhibits similarity to B in feature C, then A is categorized inside the identical object class as B. It facilitates the cultivation of diverse categories for identical objects.

$$n = \lim_{\phi \to 0} \left[InN(\phi) \right] \Big/ \left[In\left(\frac{1}{\phi} \right) \right] \tag{9}$$

$$InN(\phi) = In\mu - nIn\phi \tag{10}$$

Artificial intelligence systems can arrange items based on their closest similarity and assign them a category name. It enables computers to effectively recognize and categorize items, regardless of their varying levels of quality.

$$F_{(b)} = \sin K(b) \tag{11}$$

$$E_1 = \frac{1}{2} \sum_{l=1}^{d} \left(n_l - y_l \right)^2 \tag{12}$$

Fuzzy estimation of the fractal dimension is a mathematical technique employed to determine the fractal measurement of an object's geometry; however, it has an uncertain or ambiguous outcome. This process involves converting the image of the object into a shape based on fuzzy logic and subsequently calculating the anticipated fractal dimension.

Neural-Network Approach for Time Series Prediction

The neural network approach for time series prediction is a widely used method in machine learning algorithms that aims to forecast the future values of a sequence. The system relies on nonlinear recurrent neural networks capable of capturing intricate nonlinear correlations in data. The neural network assimilates past data and forecasts future values. The model acquires knowledge by establishing weights for each connection between neurons, adjusted over time according to the prediction error.

$$\Delta w_{ij} = -\eta \frac{\partial E_1}{\partial w_{ij}} + \lambda \Delta w_{ij} \tag{13}$$

$$B_t = \mu A_{t-1} + \pi_t \tag{14}$$

$$\beta_o = 1 \Big/ \left[1 + \left| \frac{(b-m)}{u} \right|^{2b} \right] * a \tag{15}$$

The weights are optimized using a set of optimization rules, which may involve back propagation or gradient descent. The version can capture dependencies that span over extended periods as well as short-term patterns. It can analyze the connections between distinct temporal points in a series of values and generate predictions based only on these associations.

Proposed Algorithm

Time series forecasting is a predictive modeling technique that uses historical data to anticipate future events. Time series models utilize previous data to forecast the future value of a specific variable. The proposed works' functions are demonstrated in Algorithm 1.

Algorithm 1. Time Series Forecasting algorithm

```
Step.1:    FPDG ( );
Step.2:    IP: GATE_LVL_Circuit_List ( );
           OP: TST_Pattern ( );
Step.3:    Repeat {
Step.4:    SELECT_f_from_list; //f is a fault list
Step.5:    If (f=BF) //BF is a bridging fault
Step.6:    REPLACE_with_XOR;
Step.7:    REDIFINE_f;
Step.8:    }
Step.9:    FIND_TV_for_f; //TV is a test vector
```

```
Step.10:    If (YES) {
Step.11:    RUN_fuzzy_Simulaator;
Step.12:    RETURN_(TV);
Stpe.13:    }
```

Time series forecasting primarily aims to anticipate a variable's future values. Time series forecasting can be used in various applications, such as predicting earnings in increasing businesses, forecasting stock market trends, and predicting climatic patterns. Time series forecasting relies on the notion that data may be utilized to produce accurate forecasts about future events. Algorithm 2 outlines the functionalities of the suggested works.

Algorithm 2. Neural Networking algorithm

```
Step.1:     IP:W,OP:W_// W is a*b matrix;
Step.2:     FOR i =1:a;
Step.3:     FOR j=1:b;
Step.4:     IF W(I,j)<0
Step.5:     W_s=1;
Step.6:     Else_W_s=0;
Step.7:     END_W_IF_bit=W_IF->bit;
Step.8:     If_bit=length(W_IF_bit);
Step.9:     LF_bit=Total_bit-IF_bit-1;
Step.10:    W_LF_bit=(W_IF_bit)->bit;
Step.11:    W_new(i,j)=W_IF_bit->dec+W_LF_bit->dec;
Step.12:    If W_s=1
Step.13:    W_new(I,j)=W_new(i,j);
Step.14:    If(W_new(i,j)=W(i,j))>R_max
Step.15:    W_new(i,j)=0;
Step.16:    End
```

Standard techniques employed in time series forecasting comprise linear regression analysis, seasonal autoregressive integrated moving averages (ARIMA) models, and dynamic neural networks. Time Series Forecasting (TSF) is a set of principles to predict future events by analyzing the patterns and trends observed in the time series data. It has been applied in various domains, including income forecasting, financial forecasting, weather forecasting, and inventory control. The set of regulations employs a combination of statistical approaches, specifically linear regression. Time series statistics are used to forecast future outcomes accurately. Using TSF enables one to gain awareness of trends and patterns in the data, predict future values, and make informed decisions on future investments and stock holdings. The TSF can also aid in identifying the seasonal behavior of a time series to improve forecasting accuracy.

IV. RESULTS AND DISCUSSION

Neural networks provide numerous benefits for time-series forecasting, such as handling large amounts of data, comprehending complex patterns, and dynamically adjusting to evolving circumstances. Here the time series forecasting dataset from kaggle has been used and the Python simulator has been used to execute the results. The following **Table 1** shows the simulation parameters,

Table 1. Simulation Parameters

Parameter	Value
Simulator Duration	120 s
No. of Initial Forecasting Epoch	10
No. of forecasting clusters	5
Forecasting Sources	6
Forecasting Destinations	6

Computation of time period Forecasting in Fuzzy Systems

Term forecasting in fuzzy structures is a method that aims to predict uncertain future events by utilizing fuzzy logic. More precisely, fuzzy systems employ fuzzy time intervals to represent uncertain future events. The fuzzy time durations are represented by durations about a given period. Figure 4 depicts the sort-3 fuzzy model used for prediction.

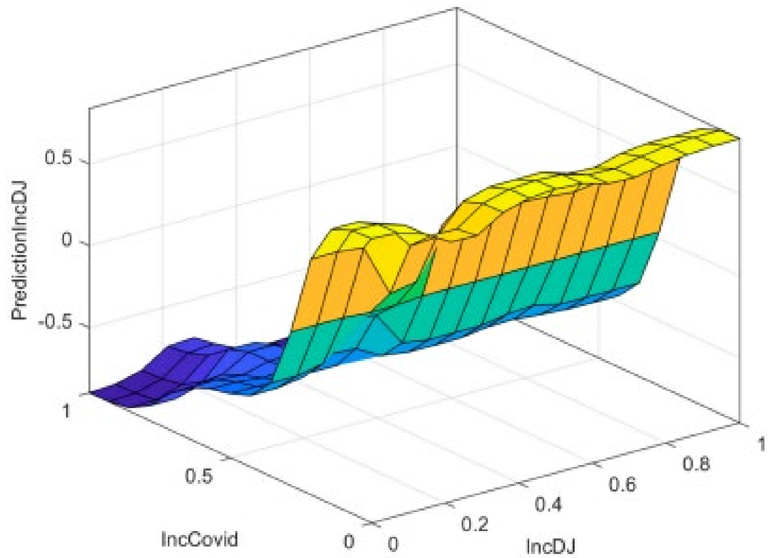

Fig 4. Representing the sort-3 Fuzzy Model for Prediction

They are particularly well-suited for modeling physical systems in non-linear time series processes. Fuzzy sound judgment systems are beautiful for situations characterized by uncertainty in the data, as they can quantitatively describe this ambiguity in a manageable manner. The period forecasting method uses fuzzy logic to find pertinent factors from historical data, which are subsequently employed to predict future events. Fuzzy systems utilize inference rules to integrate prior knowledge and direct the machine in making accurate predictive decisions.

Computation of Time Period Forecasting in Neural Networks

The word "Forecasting" in neural networks refers to utilizing predictive models to anticipate future values of a specific variable, relying on historical data. The method has various components: input data, neural networks, network parameters, training, and testing. These parts are combined to create a model that can reliably forecast future periods. Figure 5 depicts the process of reduction and defuzzification.

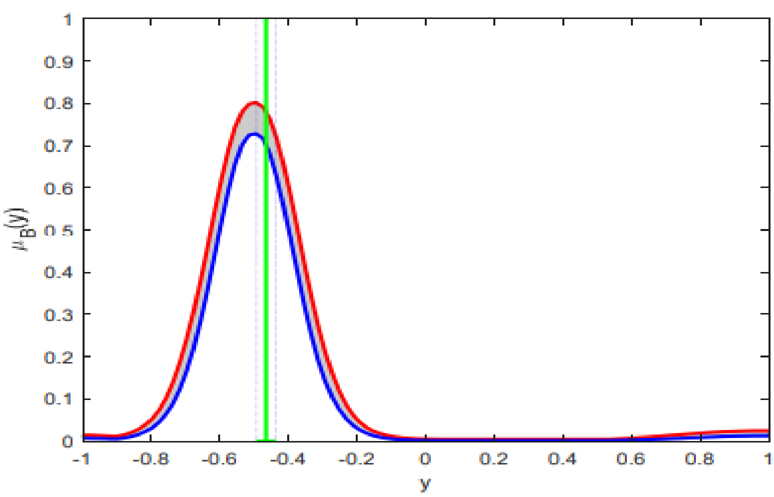

Fig 5. Reduction and Defuzzification

Neural network structures are commonly employed for this objective. They can be trained and evaluated using backpropagation and various hyper parameter tuning techniques. Subsequently, the version forecasts the variable's value for a certain period. For example, the computer may also consider the frequency, kind, and intensity of previous occurrences that enable it to assess the likelihood of the event happening in the future. Fuzzy systems consist of fuzzy uncertainty, which captures the uncertainty in forecasting outcomes to imitate the reality of the predicted events more accurately.

Computation of real Forecasting in Fuzzy Systems

Real-time forecasting in fuzzy systems is a method of predicting future values of a quantity or phenomenon using fuzzy logic and a set of fuzzy rules derived from past data. Incorporating fuzzy common sense allows for a certain degree of flexibility in predicting, allowing us to consider various assumptions about the future. Additionally, it enables us to promptly and seamlessly incorporate any new data that may impact the forecast. As an illustration, we shall employ fuzzy common sense to accurately estimate inventory costs, economic indicators, customers' preferences, or any other challenging approach. The forecasting process involves developing and refining fuzzy guidelines, which are then integrated into the system to achieve the intended outcome. **Fig 6** depicts the Dow Jones index's projected performance during the initial period.

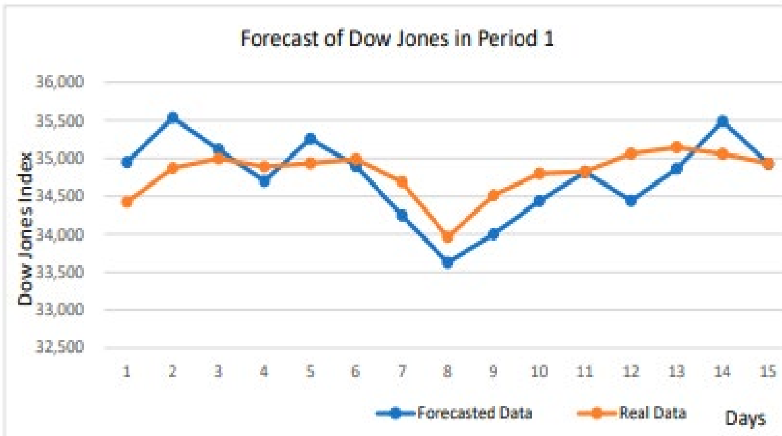

Fig 6. Forecasting in Fuzzy Systems

It involves setting the comprehensive criteria for each rule and adjusting them in real time when new data becomes available. The forecasting algorithm also considers any external factors likely to impact the forecast. It may comprise items that encompass hobby rates or financial indicators. After the completion of the forecast, it is imperative to verify it to ascertain its accuracy and trustworthiness. Ultimately, the forecast must be examined to identify any future events that could impact its accuracy.

Computation of real Forecasting in Neural Networks

Real-time prediction using ANNs has to predict future events based on historical data. Neural networks can discern patterns in past data, which they utilize to forecast future events. Figure 7 depicts the projected performance of the Dow Jones index over the second term.

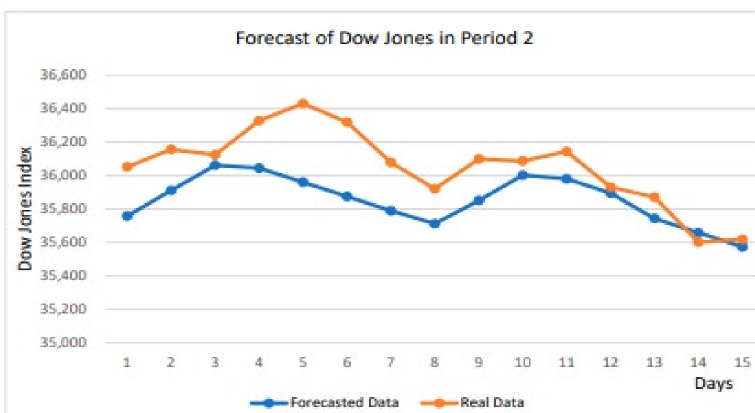

Fig 7. Forecasting in Neural Networks

Neural networks offer several advantages compared to traditional forecasting models, such as capturing intricate non-linear connections, faster training times, and improved generalization. Consequently, neural networks have emerged as the preferred forecasting model for numerous applications, ranging from financial markets to weather prediction. In addition, neural networks demonstrated exceptional performance in time-series forecasting tasks. **Table 2** displays the parameter values for the Gaussian membership functions (MFs) utilized in the linguistic values.

Table 2. Parameter values for the Gaussian MFs used in the linguistic values.

Variable	MF	Mean	Variance
IP-1	S	0.238	0.11
IP-1	M	0.24	0.60
IP-1	H	0.36	1.20
IP-2	S	0.31	0.11
IP-2	M	0.26	0.61
IP-2	H	0.41	1.11
OP-1	S	0.26	-1.11
OP-1	M	0.29	-0.61
OP-1	H	0.36	1.11

Where, MF – Membership function, IP – Input, OP – Output, S – Small, M – Medium, H- High. The parameter values for the Gaussian membership functions used in linguistic values are the Gaussian distribution's mean, standard deviation, and amplitude. The recommendation refers to the midpoint of the Gaussian membership function. The standard deviation represents the extent to which the distribution is spread out, and the height is a parameter that quantifies the significance of a particular function in the rule of thumb set. The parameter values are determined based on the desired output. The implication is generally prepared to reflect the linguistic significance, where the suggestion is equivalent to the linguistic cost. For example, when representing a linguistic term "hot," the mean of the Gaussian is adjusted to the value "warm." The standard deviation and peak of the membership function are then determined based on the intended response output. The membership capabilities generate fuzzy logic regulations when the parameter values are set.

V. CONCLUSION

The comparative performance difference between Neural Networks and Fuzzy systems for Time series predicting lies in the potential of a hybrid approach to yield superior predicting results while mitigating the complexities associated with each technology. Neural networks have been found to provide superior and precise outcomes but at the expense of longer training duration and more complexity. On the other hand, fuzzy systems can provide satisfactory performance using a simpler model and require less time for training. The combination of the two techniques provides exceptional stability, resulting in the high quality of both components. The potential for utilizing neural networks and fuzzy structures in time series forecasting is substantial. ANNs are currently being investigated for time series forecasting because of their ability to analyze data and adjust to changing circumstances. Fuzzy sound judgment systems possess the capability to identify intricate patterns in time-series data and exhibit both deductive and inductive reasoning abilities. The potential of neural networks and fuzzy logic systems for time series forecasting is highly encouraging. Ongoing research is being conducted on ANNs and FL systems, resulting in exciting breakthroughs in their software for predicting future scenarios. Novel fashion trends are being developed to improve the precision and reliability of forecasting, while other metrics are also being investigated. As fashion trends continue to evolve, they will become a regular component of the forecasting toolkit.

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Data Availability
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests
There are no competing interests.

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