Application of Emotional Learning Fuzzy Inference Systems and Locally Linear Neuro-Fuzzy Models for Prediction and Simulation in Dynamic Systems

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Abstract—Mathematical description and modeling of dynamic systems is challenging due to their high level of complexity, their nonlinear and chaotic behaviors, the presence of uncertainties and interference of human behavior in their outputs, and their time-variant nature. Because of such characteristics and the importance of dynamic systems modeling, high-performance modeling tools are required to analyze, identify, model and finally control such systems. Emotional learning fuzzy inference system (ELFIS) and locally linear neuro-fuzzy (LLNF) model can be considered as two potential tools for modeling and prediction of dynamic systems. In this paper ELFIS and LLNF are applied to three various dynamic systems, namely electricity price forecasting in competitive power markets, stock market prediction and prediction of surface ozone concentration. The comparisons between the applied methods (LLNF and ELFIS) and some other methods such as multi-layer perceptron (MLP) neural networks, demonstrated the superiority and computational efficiency of the proposed approaches over the other methods, besides their greater comprehensibility and transparency for dynamic systems modeling and prediction.

Keywords—dynamic systems; ELFIS, LLNF, prediction

I. INTRODUCTION

Over the past decade, considerable efforts have been dedicated to prediction, modeling and control of dynamic systems. In this area of research, various tools and methods have been applied to study commodity markets, foreign exchange, securities and other economic activities, human behaviors in different environments such as traffic, human decision-making process and inference and etc. Various solutions have been proposed for these problems depending on the problem conditions, structural characteristics and other influential factors [1-3].

Different methods have been proposed for controlling, modeling and simulating dynamic systems. Recent studies in price forecasting in various markets, behavioral analysis of human in different conditions, decision-support and control systems development represent some of the undertaken efforts in the field of dynamic systems modeling [4-5].

Neuro-fuzzy models are a combination of artificial neural networks (ANN) and fuzzy inference systems and benefit from excellent features of both of them. Incorporating data-based learning capability and use of linguistic rules, Neuro-fuzzy models are appropriate tools to deal with uncertainty and inaccuracy. Fast convergence rate and robustness against noise, has made locally linear model tree (LOLIMOT) learning algorithm, a popular learning method, used for optimal tuning of parameters of locally linear neuro-fuzzy (LLNF) models [6-8].

Emotional factors such as stress, excitement and emotion are influential in human decision-making. Human always tries to reduce stress and anxiety. This fact forms the main basis in the emotional learning. In emotional learning systems, the critic is responsible for generating the reinforcement signal and producing proper emotion signal, navigating system to the desired condition. Indeed the concept of the optimal performance has been replaced by desirable performance in emotional learning systems [9-10].

In this paper, first a brief description of locally linear neuro-fuzzy systems and emotional learning fuzzy inference systems (ELFIS) is presented. Then these algorithms are applied for modeling, simulation and prediction in three dynamic systems, including electricity price forecasting in competitive power markets, stock price prediction in a stock market, and prediction of surface ozone concentration. Obtained results show LLNF and ELFIS systems outperform other methods proposed in previous studies, such as MLP networks, and yield to results which better match the reality.

II. LOCAL LINEAR NEURO-FUZZY MODEL

Neuro-fuzzy models combine the learning and generalization capabilities of neural networks and logicality, transparency and use of a priori knowledge in fuzzy systems. In
fact, in neuro-fuzzy models by combining the observation-based learning and use of human knowledge, expressed by linguistics variables, a powerful tool is developed to cope with inaccuracy and uncertainties. Among various neuro-fuzzy models, locally linear neuro fuzzy models efficiently divide a complex modeling problem into several smaller and hence less complicated sub-problems [5]. Therefore LLNF models can be recommended as an effective solution for modeling problems.

LLNF models successfully divide the original model into smaller independent and linear models. Fig. 1 depicts the network structure of an LLNF network. Each neuron is realized as a locally linear model (LLM) and a validity function which determines contribution of its corresponding locally linear model to the final output.

A mathematical description of the locally linear neuro fuzzy model is presented in the following.

Considering a Takagi-Sugeno fuzzy rule as follows:

\[ \text{If } u \text{ is } A_j \text{ then } y_j = \phi_j T \theta_j u, \quad j = 1, 2, \ldots, M \]  
(1)

where, \( u = [u_1, u_2, \ldots, u_p]^T \) is the \( p \)-dimensional input vector, \( A_j \) is the fuzzy set for rule \( j \) and \( \theta_j = [\theta_{j0}, \theta_{j1}, \ldots, \theta_{jp}]^T \) is the parameters if the LLM. Considering Fig. 1, the output \( y \) can be expressed as

\[ y = \sum_{j=1}^{M} y_j \mu_j(u) \]

(2)

where \( \mu_j \) is the Gaussian membership function for the fuzzy set \( A_j \).

Defining:

\[ \phi_j(u) = \frac{\mu_{A_j}(u)}{\sum_{j=1}^{M} \mu_{A_j}(u)} \]

(3)

As the normalized validity function, leads us to the locally linear neuro-fuzzy model (or weighted summation of a series of the nonlinear functions):

\[ y = \sum_{j=1}^{M} y_j \phi_j(u) = \sum_{j=1}^{M} \sum_{i=1}^{p} \theta_{ji} u_j \phi_j(u) \]

(4)

Equation (4) is the neural network representation of the locally linear model. Thus, learning methods can be used to optimize two sets of parameters in LLNF network: rule consequent parameters (parameter vector \( \theta \)) and rule premise parameters (the center and variance of membership functions). Rule consequent parameters can be simultaneously estimates using a single least square optimization process. Here, a locally linear model tree (LOLIMOT) learning algorithm has been used for determining rule premise parameters. LOLIMOT algorithm is described in the following.

LOLIMAT algorithm partitions the input space into hyper-rectangles by axis-orthogonal splits. It implements a heuristic search for the rule premise structure and avoids time-consuming nonlinear optimization. In every iteration, the worst LLM is determined to be divided. All possible divisions in the \( p \)-dimensional input space are tried and the best is performed. Division ratio is simply set at 1/2, which means that the locally linear neuron is divided into two equal halves on the selected input dimension. On each division, a new Gaussian validity function is fitted to each newly generated hyperrectangle. Centers of validity functions are the centers of the hyperrectangles and the standard deviations are usually set at 1/3 of the hyperrectangles’ extensions.

LOLIMOT algorithm has been summarized here in 4 steps, according to [5]:

1- Start with the initial model: set \( M=1 \) and start with a single LLM whose validity function covers the whole input space with \( \phi_1(u) = 1 \).
2- Find the worst LLM: calculate a loss function for each of LLMs, $i = 1, 2, \ldots, M$ and find the LLM with worst performance.

3- Check all divisions: the worst LLM is considered for further dividing. The hyperrectangle of this LLM is then split into two equal halves with an axis-orthogonal split. Divisions in all dimensions are checked. Construct validity functions for both hyperrectangles and estimate rule consequent parameters for both newly generated LLMs. Finally compute the loss function for overall model.

4- Find best division: the best division in step 3 (yielding least value of error) is selected. The validity function constructed and the LLMs optimized in step 3 are adopted for the model. The number of LMMs is incremented: $M \rightarrow M + 1$. If the termination criterion is met stop, otherwise go to step 2.

III. EMOTIONAL LEARNING FUZZY INFERENC SYSTEM

Excitement, stress and emotion are factors which influence human learning, and human constantly tries to reduce anxiety and stress. This is the main idea leading to the emotional learning. In other words, in emotional-based decision making processes, system attempts to change its behavior to bring about reduction in critic stress [9].

This method is established based on an emotional signal, showing critic’s emotions with respect to system’s total performance. Emotion signal can be generated by any combination of goals and limitations, resulting in prediction and decision making improvement. Emotional learning would present solutions to the different problems such as modeling, control, decision making, estimation and prediction without increasing computational complexity [10].

In the emotional learning a loss function is constructed based on the emotional signal. This function can be defined depending on the problem requirements. In this paper, the loss function is defined as follows:

$$J = \frac{1}{2} \sum_{i=1}^{N} (es(i))^2$$

(5)

Where, $es(i)$ is emotional signal associated with $i^{th}$ observation and $N$ is the number of observations. Generally, emotional signal can be defined as a mathematical function of error or problem’s limitations. But this procedure requires investigation of intricate designs and use of different architectures. Fuzzy inference systems are employed in this paper in order to overcome problem complexities and present a transparent definition of the emotional signal. Learning process includes optimization of model’s weights. Here, steepest descent algorithm is applied for optimization of model’s weights.

$$\Delta w = -\eta \frac{\partial J}{\partial w}$$

(6)

where, $\eta$ is the Learning rate and $w$ are the weights of the neuro-fuzzy model. Recalling derivation chain-rule, $\frac{\partial J}{\partial w}$ can be rewritten as follows:

$$\frac{\partial J}{\partial w} = \frac{\partial J}{\partial es} \frac{\partial es}{\partial y} \frac{\partial y}{\partial w}$$

(7)

Remembering loss function defined in (5), we arrive at the following equality:

$$\frac{\partial J}{\partial es} = es$$

(8)

$\frac{\partial J}{\partial es}$ is calculated from the following equation:

$$\dot{e} = \sum_{i=1}^{M} f_i(u) \mu_i(u)$$

(9)

$$\mu_i(u) = \prod_{j=1}^{p} \mu_{ij}(u_j)$$

where $f$ is linear combination of weights. Calculation of the term $\frac{\partial es}{\partial y}$ is not easily done in most problems. But some simplifying assumption could be employed [9]. In this paper, simply defining error signal as $e = y - \dot{y}$ leads us to the following:

$$\frac{\partial es}{\partial y} = -\frac{\partial es}{\partial e}$$

(10)

Ultimately, weights updating rule is obtained as presented in (11).

$$\Delta w_{ij} = -\eta es \sum_{i=1}^{p} u_i u_j \mu_i(u)$$

(11)

In next sections, several real world case studies are considered for evaluation of the LLNF and ELFIS performances in dynamic systems description and modeling.

IV. PREDICTION ACCURACY ASSESSMENT

Several error criteria are used in this paper in order to investigate accuracy and efficiency of the LLNF and ELFIS in performing prediction in various case studies. Mean absolute percentage error (MAPE), mean square error (MSE) and standard deviation of error (SDE), are computed here to investigate prediction performance:
\[ MAPE = \frac{100}{N} \sum_{h=1}^{N} \left( \frac{\hat{P}_h - P_h}{\bar{P}} \right) \]  

(12)

Where,
\[ \bar{P} = \frac{1}{N} \sum_{h=1}^{N} P_h \]

\[ MSE = \frac{1}{N} \sum_{h=1}^{N} \left( \frac{\hat{P}_h - P_h}{P} \right)^2 \]  

(13)

and,
\[ SDE = \frac{1}{N} \sum_{h=1}^{N} (e_h - \bar{e}_h) \]  

(14)

where,
\[ e_h = \hat{P}_h - P_h \]

(15)

\[ \bar{e} = \frac{1}{N} \sum_{h=1}^{N} e_h \]  

(16)

In (12), (13) and (15), \( \hat{P}_h \) and \( P_h \) indicate predicted and actual values, respectively and \( N \) is number of predictions.

Root Mean Squared Error (RMSE) and R-Squared (R\(^2\)) criteria are used in presented comparison. These criteria are formulated in (17) and (18), respectively.

\[ RMSE = \sqrt{\frac{1}{N} \sum_{h=1}^{N} (\hat{P}_h - P_h)^2} \]  

(17)

\[ R^2 = 1 - \frac{\sum_{h=1}^{N} (P_h - \hat{P}_h)^2}{\sum_{h=1}^{N} (P_h - \bar{P})^2} \]  

(18)

V. APPLICATION TO ELECTRICITY MARKET

Power systems, all over the world, are moving toward a competitive framework and a market environment is replacing traditional monopolistic perspective in power industry. Starting from Chile in 1982, this disguise gradually swept Britain, Norway, Argentina, Australia, Spain and different regions of United States. Various studies have concluded following features in electricity price variations: Pricing mechanism, Amount of reserve, Import MW, Temperature, and Loss of generation [11].

According to the previous studies, effect of temperature and other climate parameters are incorporated into system demand. Other studies revealed that use of demand series in neural networks (NNs) and auto-regressive integrated moving average (ARIMA) models, does not improve prediction accuracy [11]. Other features such as loss of generation are not available and bidding strategies are confidential data and therefore cannot be included as predictor’s input. Thus, historical price are most effective parameter used in electricity price forecasting.

The price behavior in Spain electricity market in 2002 has been considered in this paper for price forecasting. Hourly electricity prices from Apr. 8 to May 19 have been used to predict electricity price from may 20-26 [12]. In [11], hourly prices of 42 day ago have been used for prediction of next week prices. Therefore there are 1008 training data and 128 test data.
A sample auto-correlation analysis, as a common input selection technique, has been carried out on Spanish market data, to find appropriate input prices. Considering auto-correlation coefficients, as shown in fig. 3, the following price lags are selected as network inputs for prediction of electricity price at hour \( h \) (\( P_h \)):

\[
\{ P_{h-1}, P_{h-2}, P_{h-3}, P_{h-24}, P_{h-25}, P_{h-48}, P_{h-49}, P_{h-72}, P_{h-73}, P_{h-96}, P_{h-97}, P_{h-120}, P_{h-121}, P_{h-144}, P_{h-145}, P_{h-168} \}
\]

Applying orthogonal least square (OLS) method, three final inputs, were selected as predictor’s inputs to forecast electricity price at hour \( h \) (\( P_h \)):

\[
\{ P_{h-1}, P_{h-2}, P_{h-168} \}
\]

Employing aforementioned inputs in LLNF model with LOLIMOT learning algorithm, the network with 8 neurons produced best performance. Fig. 4 shows predicted prices by LLNF along with actual prices for Spanish market.

Next, emotional learning is used to predicted day-ahead electricity prices. A fuzzy inference system is employed to generate emotional signal. Emotional signal is defined in terms of error and its derivative and then the loss function is created. 13 fuzzy rules with 5 membership functions associated with error, 3 membership functions associated with error derivative and 7 membership functions associated with emotional signal, are used to generate emotional signal. Fig. 5 shows the surface generated by the fuzzy inference system. The main system is comprised of a Sugeno-type fuzzy system with three fuzzy rules, whose output weights are updated by emotional learning. The neuro-fuzzy system in this model consists of 27 Sugeno-type fuzzy rules in which three Sigmoid membership functions are used for three inputs. The actual and forecasted prices by ELFIS are illustrated in Fig. 6.

Prediction results of electricity price using ELFIS and LLNF in Spanish market is presented in table I. in order to show desirable performance of applied methods, their results are compared to those of MLP network [13] and ARIMA [11] in table (I). This comparison clearly demonstrates superiority of LLNF and ELFIS over MLP network and ARIMA.

### VI. APPLICATION TO STOCK MARKET

Development of economic sciences and emergence of modern managerial methods in economics and financial markets, have offered hope to thousands of small investors to make more profit by proper decision-making at the right time.

Prediction in financial markets, if it’s to be based on effective parameters on price, requires sufficient know-how and experience about these parameters and the way they affect prices. But few people are capable of doing this. Hence, decision-support systems are considered important in this area. Today, various tools can be employed for prediction purposes. Transition from traditional time series analysis to more powerful tools, introducing causal variables into forecasting process, use of learning algorithms based on observations and incorporation of human knowledge seems to be necessary.

In this paper, ELFIS and LLNF methods have been applied to predict stock price of “HENAN JOYLINE & JOYSUN PHARMACEUTICAL STOCK CO.LT” in 2000. Observations from May 15 to Aug. 21 have been selected to train network to forecast stock prices from Aug. 22 to Oct. 9 [14]. Eight times series have been considered as proper inputs to predict tomorrow’s closing price of the company’s stock, as follows:

Today’s max price, today’s min price, today’s opening price, today’s closing price, today’s transaction volume, yesterday’s transaction volume, transaction volume of two days ago and transaction volume average of 30 days ago.

LLNF network with LOLIMOT learning has been modeled for different number of neurons and various parameters. The
network with 7 neurons exhibited the best performance and selected for prediction of stock price.

Emotional signal has been generated by a fuzzy inference system. First, the emotional signal defined based on error and its derivative, formed the loss function. 15 fuzzy rules with 7 membership functions associated with error, 3 membership functions defined for error derivative and 9 membership functions related to emotional signal, were used to generate emotional signal. The main system is comprised of a Sugeno-type fuzzy system with nine fuzzy rules, whose output weights are updated by emotional learning. The Surface created by the fuzzy inference system and membership functions used to generate emotional signal are shown in figs. 7 and 8, respectively.

Figs. 9 and 10 illustrate real and predicted prices associated with LLNF and ELFIS, respectively. In order to perform a comprehensive comparison, the authors optimized an MLP network for selected inputs. The optimized MLP network had 15 neurons in its middle layer. RMSE, MAPE and SDE values associated with the LLNF, ELFIS and the optimized MLP network are presented in table II. The MLP network was optimized by authors for selected inputs. Obviously, ELFIS has yielded best accuracy. The second best accuracy belongs to LLNF and MLP network has performed the worst.

VII. FORECASTING OF SURFACE OZONE CONCENTRATION

Ozone concentration in Edmonton, Canada is forecasted as our last case study. The data of sep. 16 to sep. 30, 2000 is used to train the model in order to forecast the ozone concentration...
in sep. 2001. The data is collected in one-hour intervals [15]. To forecast the ozone concentration, 4 variables are selected as model’s inputs. These variables are introduced in Table III.

The Latter three variables are selected to complement the historical ozone concentration time series data as casual variables and to empower the forecasting. Figures 11 to 14 illustrate the aforementioned variables in the training period.

ANFIS and LLNF models are trained with the introduced data. The LLNF model with 7 neurons and ANFIS model with 4 Sugeno-type fuzzy rules are selected as the best models using validation data. Three Gaussian membership functions are assigned to each input in the ANFIS model. Figures 15 and 16 show the forecasting results of LLNF and ANFIS models, respectively. The results are tabularized in table IV.

Furthermore, a comparison with a pure fuzzy logic-based approach developed in [16] was performed. Root Mean Squared Error (RMSE) and R-Squared (R2) criteria are used in the presented comparison.

Both criteria prove the better performance of neuro-fuzzy approaches. The LLNF model demonstrates the best performance having the highest $R^2$ and the lowest RMSE.

The desirable performance of the LLNF model can be described as follows:

1- The performance of ANFIS and Fuzzy approaches is strongly dependent on the initial adjustment of their structures and parameters. The ANFIS model is
vulnerable of getting stuck in local minima and the process of optimal tuning of this model is highly computational-intensive.

2- The high convergence rate of the LLNF model is an outstanding characteristic in this model, resulted from the simple but efficient training algorithms used in this model.

3- The noise effects locally in the LLNF model and in the case that some regions of the training dataset are noisy or imprecise, the overall performance of the model will not degrade.

Moreover, the transparency and simple structure of the LLNF models allow a range of possible modifications that can possibly enhance the performance of these models. Some recent researches have been conducted in this regard and reported valuable improvements [20].

VIII. CONCLUSION

This paper proposed two models for simulation and prediction of complex dynamic systems. The locally linear neuro-fuzzy (LLNF) and emotional learning fuzzy inference systems (ELFIS) were applied to prediction and simulation of three different kinds of dynamic systems and their performance was evaluated. The presented comparisons with other methods in three different case studies, including electricity price forecasting, stock price prediction and prediction of surface ozone concentration, clearly demonstrated the effectiveness and computational efficiency of the LLNF and ELFIS algorithms. Considering the obtained results, these two methods exhibited more desirable performances with respect to other models in terms of accuracy and structural transparency for modeling and simulation of the aforementioned dynamic systems.

REFERENCES


