Modeling of call center operators performance by ANFIS expert system

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Abstract: A neuro-fuzzy computing provides the system identification and interpretability of fuzzy models and learning capability of neural networks in a single system. In the last decade, various neuro-fuzzy systems have been developed. Among them, adaptive neuro-fuzzy inference system (ANFIS) provides a systematic and directed approach for model building and gives the best possible design parameters in minimum time. They have got wide acceptance for modelling many real world problems. One such problem frequently encountered is the effects of illumination level on human work efficiency. From the literature survey, it is observed that the three most important factors influencing human work efficiency are noise level, type of task, and exposure time. The cause effect relationships of these parameters are complex, uncertain, and non-linear in nature. Therefore, it is quite difficult to properly examine it by conventional methods .Hence, an attempt is made in this paper to develop a neuro-fuzzy model for predicting the effects of illumination problems on human work efficiency as a function of illumination level, type of task, and exposure time. The model is implemented on Fuzzy Logic Toolbox of MATLAB# using ANFIS. The data used in the present study is obtained with the help of the original fuzzy model developed by the authors. Out of the total input/output data sets,80%was used for training the model and 20% for checking to validate the model.

1. Introduction:

The traditional equation based techniques for the solution of the real world problems are not suitable for modelling non-linearity in the complex and ill-defined systems. A neuro-fuzzy computing provides the system identification and interpretability of fuzzy models and learning capability of neural networks in a single system. In the last decade, various neuro-fuzzy systems have been developed. Among them, adaptive neuro-fuzzy inference system (ANFIS) provides a systematic and directed approach for model building and gives the best possible design parameters in minimum time. They have got wide acceptance for modelling many real world problems. One such problem frequently encountered is the effects of illumination on human work efficiency. From the literature survey, it is observed that the three most important factors influencing human work efficiency are illumination level, type of task, and exposure time. The cause effect relationships of these parameters are complex, uncertain, and non-linear in nature. Therefore, it is quite difficult to properly examine it by

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conventional methods. Hence, an attempt is made in this paper to develop a neuro-fuzzy model for predicting the effects of visual problems on human work efficiency as a function of illumination level, type of task, and exposure time. The model is implemented on Fuzzy Logic Toolbox of MATLAB using ANFIS. The data used in the present study is obtained with the help of the original fuzzy model developed by the authors. Out of the total input/output data sets, 80% was used for training the model and 20% for checking to validate the model.

2. Neuro-fuzzy computing

Neuro-fuzzy computing is a judicious integration of the merits of neural and fuzzy ap-proaches. This incorporates the generic advantages of artificial neural networks like massive parallelism, robustness, and learning in data-rich environments into the system. The modelling of imprecise and qualitative knowledge as well as the transmission of uncertainty is possible through the use of fuzzy logic. Besides these generic advantages, the neuro-fuzzy approach also provides the corresponding application specific merits [21–23]. Some of the neuro-fuzzy systems are popular by their short names. For example, ANFIS [24], DENFIS [25], SANFIS [26] and FLEXNFIS [27], etc. Our present model is based on adaptive neuro fuzzy inference system (ANFIS). An ANFIS is a fuzzy inference system implemented in framework of adaptive neural networks. ANFIS either uses input/ output data sets to construct a fuzzy inference system whose membership functions are tuned using a learning algorithm or an expert may specify a fuzzy inference system and then the system is trained with the data pairs by an adaptive network. The conceptual diagram of ANFIS based on latter approach is shown in Fig. 1. It consists of two major components, namely, fuzzy inference system and adaptive neural network. A fuzzy inference system has five functional blocks. A fuzzifier converts real numbers of input into fuzzy sets. This functional unit essentially transforms the crisp inputs into a degree of match with linguistic values. The database (or dictionary) contains the membership functions of fuzzy sets. The membership functions provide flexibility to the fuzzy sets in modelling commonly used linguistic expressions such as ''the noise level is low'' or ''the person is young.'' A rule base consists of a set of linguistic statements of the form, if x is A then y is B, where A and B are labels of fuzzy sets on universes of discourse X and Y respectively. These labels of fuzzy sets are characterized by appropriate membership function of database. An inference engine performs the inference operations on the rules to infer the output by a fuzzy reasoning method. Defuzzifier converts the fuzzy outputs obtained by inference engine into a non-fuzzy output real number domain. In order to incorporate the capability of learning from input/output data sets in fuzzy inference systems, a corresponding adaptive neural network is generated. An adaptive network is a multi-layer feed-forward network consisting of nodes and directional links through which nodes are connected. As shown inFig. 1, layer 1 is the input layer, layer 2 describes the membership functions of each fuzzy input. Layer 3 is the inference layer and normalization is performed in layer 4. Layer 5 gives the output and layer 6 is the defuzzification layer. The layers consist of fixed and adaptive nodes. Each adaptive node has a set of parameters and performs a particular function (node function) on incoming signals. The learning module may consist of either back propagation or hybrid learning algorithm. The learning rule specifies how the parameters of adaptive nodes should be changed to minimize a prescribed error measure

[24]. The change in values of the parameters results in change in shape of membership functions associated with fuzzy inference system.

3. Methodology:

Our present study is to predict the effects of visual problems on human work efficiency as a function of illumination level, type of task, and exposure time. Among these, only parameters like illumination level and exposure time can be measured with the help of some scientific instruments, like luxmeter and stop watch which provide the numerical values to the researchers. But the type of task and effects of illumination level on human beings are studied through social surveys based on questionnaires. These questionnaires are generally words and propositions drawn from a natural language. For example, type of task may be represented by the words like simple, moderate, and complex. These linguistic variables (words) cannot be precisely measured and inherently contain imprecision, uncertainty, and partial truth. They can best be represented by fuzzy logic. Hence, the study of illumination level is the unique combination of linguistic and numerical values. Therefore, neuro-fuzzy computing seems to be the natural choice for developing a model to study the effects of illumination problems pollution on human work efficiency.

An adaptive network is a multi-layer feed-forward network consisting of nodes and directional links through which nodes are connected. As shown in Fig. 1, layer 1 is the input layer; layer 2 describes the membership functions of each fuzzy input. Layer 3 is the inference layer and normalization is performed in layer 4. Layer 5 gives the output and layer 6 is the defuzzification layer. The layers consist of fixed and adaptive nodes. Each adaptive node has a set of parameters and performs a particular function (node function) on incoming signals. We have implemented our model using ANFIS (Fuzzy Logic Tool box) of MATLAB. The system is first designed using Sugeno Fuzzy Inference System. It is a three input–one output system.

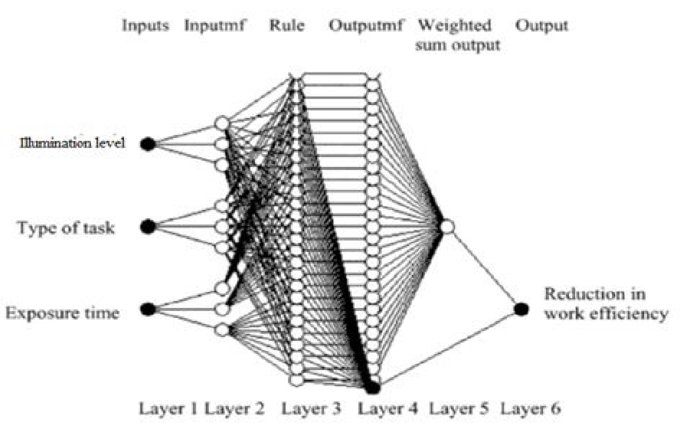

Figure 1. ANFIS structure of model

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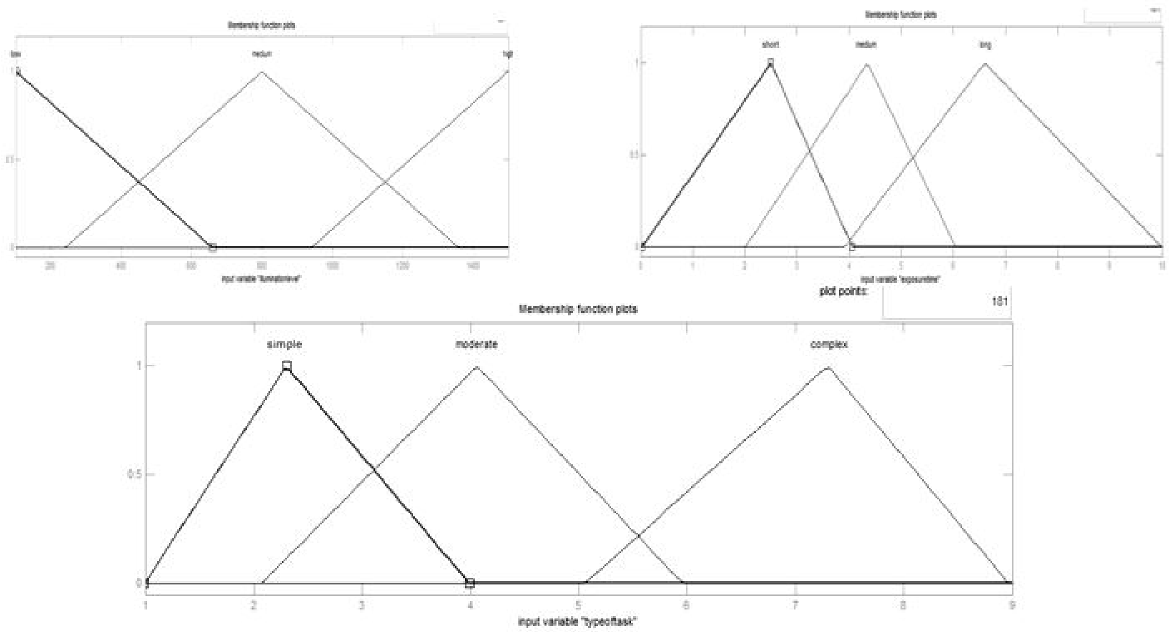

Figure 2(a). Membership functions for illumination level, (b) Membership functions for exposure time (d) Membership functions for type of task

4. Results and Discussion-

The model was trained for 200 epochs and it was observed that the most of the learning was completed in the first 150 epochs as the root mean square error (RMSE) settles down to almost 0% at 150th epoch. Fig.3 shows the training RMSE curve for the model. After training the fuzzy inference system, it is found that the shape of membership functions is slightly modified. This is because of the close agreement between the knowledge provided by the expert and input/output data pairs.In order to validate the model, we have compared some of our model results with the deduction based on the criterion of Safe Exposure Limit recommended for call center operators.

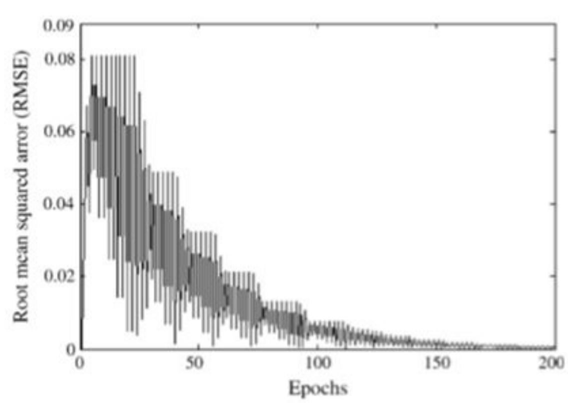

Figure 3. Training root mean squared error curve

5. Conclusion

The main thrust of the present work has been to develop a neuro-fuzzy model for the prediction of work efficiency as a function of illumination level, type of tasks and exposure times. It is evident from the graph that the work efficiency, for the same exposure time, depends to a large extent upon the illumination level and type of task. It is to be appreciated that the training done using ANFIS is computationally very efficient as the desired RMSE value is obtained in very less number of epochs. Moreover, minor changes are observed in the shape of the membership functions after training the model. This is because of close agreement between the knowledge provided by expert and in-put/output data pairs.

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Appendix

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