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Authors: Ciji Pearl Kurian, V.I.George, Jayadev Bhat & Radhakrishna S Aithal
Address: Manipal Institute of Technology Manipal – 576104, India
E-mail: cpk001@yahoo.com
vig_rcct@yahoo.com
URL: http://www.manipal.edu

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ANFIS MODEL FOR THE TIME SERIES PREDICTION OF INTERIOR DAYLIGHT ILLUMINANCE
Ciji Pearl Kurian, V.I. George, Jayadev Bhat & Radhakrishna S Aithal
Manipal Institute of Technology
Manipal - 576104, India
cpk001@yahoo.com, vig_rect@yahoo.com
http://www.manipal.edu

Abstract
The increasing need for more energy sensitive and adaptive systems for building lighting control has encouraged the use of more precise and delicate computational models. This paper presents a time series prediction model for daylight interior illuminance obtained using Adaptive neuro fuzzy inference system (ANFIS). Here the training data is collected by simulation, using the globally accepted lighting software Desktop Radiance. The model developed is suitable for adaptive predictive control of daylight - artificial light integrated schemes incorporating dimming and window shading control. Matlab's Fuzzy logic Tool box is used for the simulations.

Keywords: ANFIS, Time series prediction, Daylight interior illuminance, Auto regression model, daylight factor, Automatic control, daylight artificial light integrated scheme, desktop radiance.

1. Introduction
To develop, automatic control strategies in addition to evaluate the visual and energy performance provided by daylight requires an accurate prediction of daylight entering a building. Daylight Factor (DF), Daylight Coefficient (DC), Useful Daylight Illuminance (UDI), computer simulations, Average daylight factor...etc. are the various methods adopted for the estimation of interior daylight illuminance. The DF approach has been in practice for the last 50 years. The DF approach has gained favour owing to its simplicity, but it is not flexible enough to predict the dynamic variations in daylight illuminance as the sun's position and sky condition change. DF is defined as the ratio horizontal internal daylight illuminance to the exterior horizontal illuminance under CIE overcast sky. Overcast skies are considered to provide the worst daylighting conditions and the sunlight is completely impeded without any direct component. So DF approach cannot provide sufficient accuracy for automated building control schemes, it can be considered as designer's tool just in the planning stage. The DC concept developed by Tregenza PR, which considers the changes in the luminance of the sky elements, offers more effective way of computing indoor daylight illuminance. As the sky is treated as an array of point sources, the daylight coefficient approach can be used to calculate the reflected sunlight, and is particularly appropriate for innovative daylighting system with complex optical properties. In most daylighting computations the time consuming part is the calculation of inter reflected light. In conventional calculation, a single inter reflected simulation is carried out, but this process needs to be repeated for each change in sky luminance distribution. In a DC based approach, one interreflection calculation is carried out once for each element of sky, the process need not be repeated for change in sky luminance distribution. This approach is even suitable for interiors with static shading devices with reflecting or refracting components. However, daylight coefficients are less suitable to use with movable devices such as Venetian blinds or sun tracking mirrors. This is because a separate set of coefficients need to be found for each position of the shading system.

The UDI approach, a new concept the useful daylight illuminance metrics are based on absolute values of time varying daylight illuminance for a period of full year. But it is doubtful about the assessment of the characteristics of daylighting, with averaged hourly irradiance or test reference years (TRY) data sets, when owing to rapid cloud movements and sky luminance patterns. It is certainly a valuable contribution for computer simulations of annual daylight changes and energy consumption predictions. But it will be more complex when taking into consideration automated blind system. Computer simulations, available in many varieties, are
appropriate for the planning stage to building design phase, but none of them are suitable for real time measurement and control. But to build an intelligent modelling concept, these computer simulations, endow with better assistance. Recently, Kittler et al. proposed a new range of 15 standard sky luminance distributions including five clear, five partly cloudy and five overcast sky types. DHIW Li et al. have proposed average daylight factor concept suitable for all the above 15 standard skies. This proposition may be a useful paradigm for planning and design of daylighting systems, but again uncertain about the effectiveness of this method for automated control strategy as we cannot predict the type of sky ahead. Time varying illuminance predictions, as used for meteorological data sets, offer a more realistic account of true daylighting conditions, than the previously mentioned DF, DC and UDI. ANFIS shows very good learning and prediction capabilities, which makes it an efficient tool to deal with uncertainties encountered in this venture. A variety of computer design tools are available for collecting the data required for training the Adaptive Neuro Fuzzy Inference system. Here, the software Desktop Radiance is used for collecting one full year data with different sky conditions. The interior illuminance level is calculated for a given environment at any time of the year. Instead of using measured values of illuminance levels, here we used the simulated data from the model created using the appropriate design tool. The illuminance levels obtained in this way are used as a training data for ANFIS to predict the six step ahead values for the model under consideration. Hence, these predicted values identify how the system is going to behave ahead of a particular time. This paper highlights how ANFIS can be employed to predict future values of the daylight availability.

2. ANFIS an Overview

In 1993 Roger Jang, suggested Adaptive Neuro Fuzzy Inference system (ANFIS). ANFIS can serve as a basis for constructing a set of fuzzy ‘if-then’ rules with appropriate membership functions to generate the stipulated input-output pairs. Here, the membership functions are tuned to the input-output data and excellent results are possible. Fundamentally, ANFIS is about taking an initial fuzzy inference (FIS) system and tuning it with a back propagation algorithm based on the collection of input-output data. The basic structure of a fuzzy inference system consists of three conceptual components: A rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and the given facts to derive a reasonable output or conclusion.

These intelligent systems combine knowledge, techniques and methodologies from various sources. They possess human-like expertise within a specific domain - adapt themselves and learn to do better in changing environments. In ANFIS, neural networks recognize patterns, and help adaptation to environments. Fuzzy inference systems incorporate human knowledge and perform interfacing and decision-making. ANFIS is tuned with a back propagation algorithm based on the collection of input-output data.

3. Chaotic Time Series Prediction

Here the training data is obtained by simulating the interior illuminance in complex building spaces due to daylight and electric lighting schemes. This enables the user to model interior daylight levels for any sun and sky condition in spaces having windows, skylights or other standard fenestration systems. The program calculates lighting levels on all interior surfaces, as well as planes that can be artificially positioned to represent work surfaces or other locations of interest to user. Model depend on room dimensions, room position, building data windows, outdoor obstructions, sky definition and site definition. Since it takes care of all the relevant information for the prediction of interior illuminance, the data collected for the training will be very effective. Data is collected for one full year for four different sky conditions. Out of the collected data we have used 500 for training and another 500 for the validation of the model. With a proper training scheme and fine filtered data-sets, ANFIS is capable of predicting indoor illuminance values quite accurately since it learns from the training data. This measurement- free architecture also makes it immediately available for operation once they are trained.

In time series prediction the past values of daylight illuminance up to time \( t' \) are used to predict the value at some point in the future \( t + p \). The standard method for this type of prediction is to create a mapping from \( D \) points of the time series spaced \( \Delta \) apart: that is \( [x(t-(D-1)\Delta),...,x(t-\Delta),x(t)] \) to predict a future value \( x(t+p) \), where \( D=4 \) and \( \Delta = p = 6 \) are used. For off-line learning data is updated and predicted only after presentation of entire data set, or only after an epoch. The number of times the entire data set is used to check and validate the prediction is called the epoch number. Matlab's Fuzzy logic toolbox is used for the entire process of training and evaluation of FIS.
4. Model training and validation

In order to build an ANFIS that can predict $x(t+6)$ from the past values of daylight levels, the training data format is $[x(t-18), x(t-12), x(t-6), x(t); x(t+6)]$. Training and checking data are shown in Figure 1 and Input membership functions for training are shown in Figure 2. There are four inputs and three membership functions and therefore the number of rules is $3^4 = 81$ rules. In the generated FIS matrix the number of fitting parameters is 441, including 36 non-linear parameters and 405 linear parameters. Obviously most of the fitting is done by the linear parameters while the non-linear parameters are mostly for fine-tuning for further improvement. The error curves for both checking and training data are shown in Figure 3. Note that the training error is higher than the checking error, which is a common process in non-linear regression; it could indicate that the training process is not close to finished yet. Figure 4 shows the time series prediction of daylight interior illuminance obtained using ANFIS. Here the difference between predicted values and measured values are impossible to differentiate.

Table 1 shows the performance of non-linear ANFIS models with different training data set, number of membership functions and prediction mode. These results are obtained with 20 epochs, and ANFIS with 500 training data and 3 gbell membership functions show better performance with 6 step ahead and 10 step ahead prediction. Membership function 'gbell' is selected because of their smoothness and concise notation and these curves have the advantage of being smooth and non-zero at all points. Table 2 shows the performance of linear auto regression (AR) models for different prediction modes. It is clear that this particular application, non-linear ANFIS outperforms the linear AR models. Selection of number of membership functions, training data and epochs are obtained by trial and error.

Table 1 Comparison of the performance of ANFIS models

<table>
<thead>
<tr>
<th>Prediction</th>
<th>Training data</th>
<th>No. of gbell function</th>
<th>RMSE$_{tr}$</th>
<th>RMSE$_{te}$</th>
<th>Pred error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 step ahead</td>
<td>500</td>
<td>3</td>
<td>0.56</td>
<td>1.12</td>
<td>1.6</td>
</tr>
<tr>
<td>6 step ahead</td>
<td>500</td>
<td>2</td>
<td>0.32</td>
<td>0.24</td>
<td>0.03</td>
</tr>
<tr>
<td>6 step ahead</td>
<td>300</td>
<td>2</td>
<td>66.01</td>
<td>64.44</td>
<td>0.83</td>
</tr>
<tr>
<td>6 step ahead</td>
<td>300</td>
<td>3</td>
<td>0.47</td>
<td>0.33</td>
<td>3.5</td>
</tr>
<tr>
<td>10 step ahead</td>
<td>500</td>
<td>3</td>
<td>0.18</td>
<td>0.13</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Table 2 Comparison of the performance of AR models

<table>
<thead>
<tr>
<th>Prediction</th>
<th>Training data</th>
<th>Pred error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 step ahead</td>
<td>500</td>
<td>0.19</td>
</tr>
<tr>
<td>6 step ahead</td>
<td>500</td>
<td>0.76</td>
</tr>
<tr>
<td>6 step ahead</td>
<td>500</td>
<td>0.91</td>
</tr>
</tbody>
</table>
5. Matlab functions used for time series prediction

GENFIS1 - It generates an initial Sugeno-type FIS for ANFIS training using a grid partition method. FIS = GENFIS1 (DATA) generates a single-output Sugeno-type FIS using a grid partition on the data (no clustering). FIS is used to provide initial conditions for ANFIS training. DATA is a matrix with \(N+1\) columns where the first \(N\) columns contain data for each FIS input, and the last column contains the output data. By default, GENFIS1 uses two 'g-bell' type membership functions for each input membership function. Each rule generated by GENFIS1 has one output membership function, which is of type 'linear' by default.

ANFIS - ANFIS uses a hybrid learning algorithm to identify the membership function parameters of a single-output, Sugeno type FIS. A combination of least-squares and back propagation gradient descent methods are used for training FIS membership function parameters to model a given set of input/output data.

EVALFIS - This performs fuzzy inference calculations. \(Y = EVALFIS(U,FIS)\) simulates the FIS for the input data 'U' and returns the output data 'Y'. For a system with \(N\) input variables and output variables, 'U' is \(M\)-by-\(N\) matrix, each row being a particular input vector and 'U' is \(M\)-by-\(L\) matrix, each row being a particular output vector.

6. Significance of the scheme

In recent decades, technological development has increasingly automated switching/dimming and allowed integration of devices into, larger more flexible systems. Model based predictive control is an inevitable part of automatic intelligent controls. This computational algorithm is developed as a part of the research towards robust control and optimization of daylight artificial light integrated schemes. A PC based photo electrically controlled lighting scheme is given in Figure 8. The model discussed in this paper
helps to predict the future values of interior illuminance and hence generate the control signals for the dimming of lighting circuit in advance. This is actually a simplified form of ANFIS model for the prediction and control of light in integrated lighting schemes incorporating inverse control theory and soft computing. In photo sensor based control strategy, sensors are located in different zones of the room. Compared to individual photo sensor based controls, PC based intelligent scheme requires less number of sensors and connections.

Figure 8 photo electrically controlled lighting system

7. Conclusion

The most important advantage of such a model is the ability to predict natural system’s behavior at a future time, which can be used for lighting control. The implementation of ANFIS model is less complicated than that of sophisticated identification and optimization procedures. Compared to fuzzy logic systems, ANFIS has automated identification algorithm and easier design and compared to neural networks it has less number of parameters and faster adaptation. The non-linear characteristics of the daylighting systems can be tolerably handled in the proposed system. This prediction could be utilized as input for the artificial light and shading controls. Possibility to reduce the number of sensors and connections improve the performance of control strategy. In the projects EDIFICIO, NEUROBAT, DELTA etc. deal about intelligent controllers based on fuzzy logic systems. In HISSTO neural network prediction model is discussed. But ANFIS based time series prediction model for daylight interior illuminance is unique and novel as it is simple, reliable and easily accessible for different room conditions.

8. References


Author Biography
Mrs. CIJI PEARL KURIAN is currently READER in the Department of Electrical & Electronics Engineering, Manipal institute
Dr. V. I. George, was born in Kerala, India 1961. He received graduate degree in Electrical Engineering from university of Mysore, M.Tech degree in Instrumentation and Control engineering from NIT Calicut and received Ph D from Bharathidasan University, in Coqrol systems. He is currently Prof: and Head, in the Department of Instrumentation and Control engineering at MIT Manipal. His research interest are Instrumentation, Control systems, H infinity control, Robust control, MATLAB programming, Multivariable robust control, Optimization, Guidance and control of Aerospace vehicles.

Dr. Jayadev Bhat, is a senior professor in the department of Chemical Engineering, Manipal Institute of Technology, Manipal. He received PhD from IIT Mumbai. His research specialization includes Process control, Chemical Reaction Engg, and Modelling & simulation.

Dr. Radhakrishna S. Aithal, Professor in Illumination Engineering, Department of Electrical & Electronics Engg. at Manipal Institute of Technology, Manipal, is serving in this institution since 1988. Having a total teaching experience of 20 years at U.G.& P.G. level, he has published more than 27 research / review papers in National / International Journals / Conferences.