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The Comparison of Neural Network and Hybrid Neuro-Fuzzy based Inferential Sensor Models for Space Heating Systems

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***Abstract*—Inferential sensors are used to infer the critical control variables that are otherwise difficult, if not impossible, to measure in broad range of engineering fields. All inferential sensors are based on an inferential modelling module that represents the dynamics between the inputs and the outputs. Two commonly used artificial intelligence based approaches for the development of the inferential modelling modules are: (1) Neural Networks and (2) Adaptive Neuro-Fuzzy Inference Systems. This paper is presenting the estimation of average air temperature in the built environment by using Integer Neural Network and Adaptive Neuro-Fuzzy Inference System based inferential sensor models. By comparing the results of these models with one another, advantages and disadvantages of each are discussed.**

***Index Terms*—Integer Neural Network, ANFIS, Inferential Sensing.**

I. Introduction

Inferential sensing allows difficult to measure process parameters to be inferred from other easily made measurements [1], [2]. This technology was originally developed to improve the control of chemical and biological processes [3], [4]. Recent research demonstrates that inferential sensing is used for estimating the average air-temperature in multi-zone heating systems [5]. The estimated temperature provides a closed-loop boiler control scheme (see the feedback loop through dashed line in Fig.1), as in the absence of an economic and technically reliable method for measuring the overall comfort level in the built environment, the boilers are normally controlled to maintain the supply water temperature (see the solid feedback loop in Fig. 1).

All inferential sensors are based on an inferential modelling module that represents the dynamics between the inputs, or easily measurable variables, and the outputs, or undetectable variables. Listed below are some commonly used approaches for the development of the inferential modelling module:

- Physical Model
- Neural Network
- Fuzzy Logic
- Adaptive Neuro-Fuzzy Inference System (ANFIS)

In this paper, Neural Network and hybrid Neuro-Fuzzy modelling approaches are applied for the development of an inferential sensor model. The rest of the paper is organized as follows. Section II and Section III present the inferential sensor model based on Integer Neural Network and ANFIS modelling approaches respectively. Results of the two modelling modules are compared with each other and with experimental results in section IV. Finally, conclusion is given in Section V.

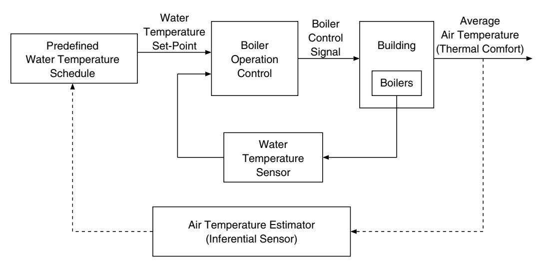

Fig. 1. Block Diagram Representation of Closed-loop Boiler Control Scheme

II. Integer Neural Network Based Inferential Sensor Model

Integer Neural Networks (INN)s are a specialized type of neural network that are designed to use only integer values in their calculations [6],[7]. INNs use only integer operations, allowing for a network capable of operating on low cost microcontrollers that lack floating point hardware. While these microcontrollers through software can implement floating point operations, they do so at a significant cost in performance [8]. INNs however suffer from significant draw backs in their expressivity due to the granular nature of integers [9]. This can greatly limit the accuracy of the network. The granular nature is in part determined by the number of bits used to represent the data. It will be demonstrated that as the number of bits decreases the effects of quantizing the data become more pronounced and eventually prevent the network from being able to accurately estimate the average temperature.

To test the effectiveness of an INN at various levels of quantization, a normal neural network must first be trained. A simple four layer base network, shown in Fig. 2, is trained to infer the average air temperature, T_{avg}, from the external temperature T_0, the solar radiation Q_{sol}, and the energy

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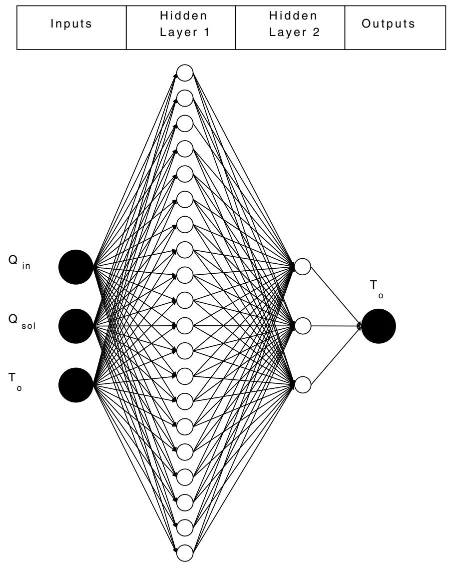

Fig. 2. Normal Neural Network Model

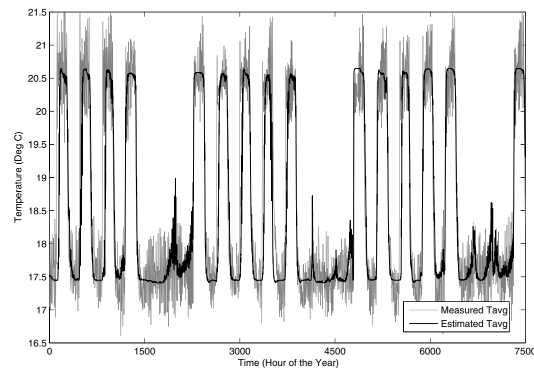

Fig. 3. Measured and Estimated Average Temperature

consumed by the boilers Q_{in}. For training all values are normalized between -1 and +1 to ensure that the network can be converted into an INN at various levels of quantization. Once the base network is trained it is used as a performance reference for the INN.

To create an INN from this network all of the inputs, weights, and biases are multiplied by a scaling factor S_f, the results are then quantized into whole values. By scaling and quantizing each part of the network, a model of a INN is created, while maintaining the underlying base network. For the activation function (the hyperbolic tan function is used for this network) the data is de-scaled down to the range of -1 to +1 for the calculation and re-scaled by scaling factor at then next input. This removes the need to create individual lookup tables for each scaling factor, allowing multiple S_f to be tested with one model. The accuracy of the model as an INN is preserved because all of the inputs to the activation function are already scaled and quantized, meaning that at no time is a non-integer number used. Mathematically the scaling and quantizing are substituted into the normal function of neuron, where O is the output, I is the input vector to that neuron, W is the weight vector, and B is the bias (1).

$$O = \tanh(I \times W + B) \tag{1}$$

For the substitution the scaling factor S_f is applied to each of the values used by the network (2).

$$O = \tanh(I \times S_f \times W \times S_f + B \times S_f^2) \tag{2}$$

A simplification shows that the bias must be multiplied by the S_f^2 to maintain the retaliative magnitude of the inputs and the weights.

$$\begin{aligned} O &= \tanh(I \times S_f \times W \times S_f + B \times S_f^2) && (3) \\ O &= \tanh(I \times W \times S_f^2 + B \times S_f^2) && (4) \end{aligned}$$

All of these values are then quantized $q()$ to whole numbers to ensure that only integers are used in the calculations.

$$O = \tanh(q(I \times S_f) \times q(W \times S_f) + q(B \times S_f^2)) \tag{5}$$

From these equations a simple feed forward neural network can be converted into an INN with varying levels of quantization (5). From this the trade off between accuracy and hardware utilization can be assessed. The goal being to use a level of quantization that minimizes the performance cost, while maintaining an acceptable level of accuracy.

The trained base network produces the results shown in Fig. 3, based on the inputs and measured values shown in Fig. 7. The base network is able to provide a general estimate of the temperature. However the network is not able to estimate in fine detail. This results in a correlation coefficient that is less than what would normally be expected. Additionally, the network estimates temperature peaks during daylight hours of the weekends, this further reduces the correlation coefficient. However despite these drawbacks the base network does provide a reasonable estimate of the average temperature, and provides a good base network on which to build an INN model.

III. ANFIS BASED INFERENTIAL SENSOR MODEL

New AI techniques, which is known as “Soft Computing”, integrates powerful artificial intelligence methodologies such as neural networks and fuzzy inference systems. While fuzzy logic performs an inference mechanism under cognitive uncertainty, neural networks posses exciting capabilities such as learning, adaption, fault-tolerance, parallelism and generalization. Since Jang [10] proposed the ANFIS, its applications are numerous in various fields including engineering, management, health, biology and even social sciences.

ANFIS is a multi-layer adaptive network-based fuzzy inference system. An ANFIS consists of a total of five layers to

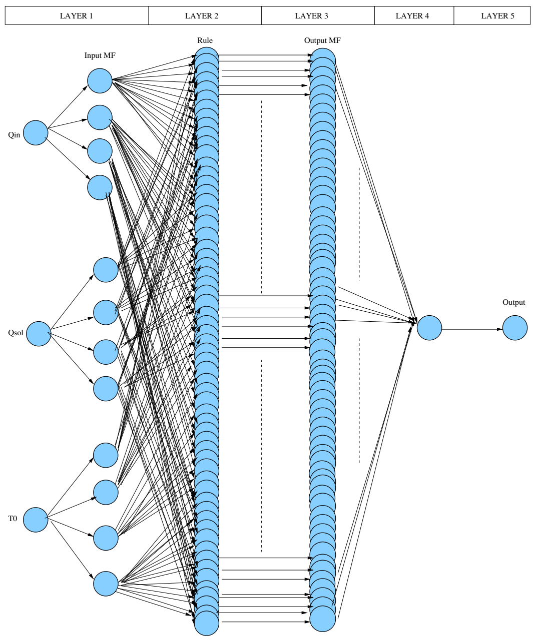

Fig. 4. ANFIS-GRID Model Structure

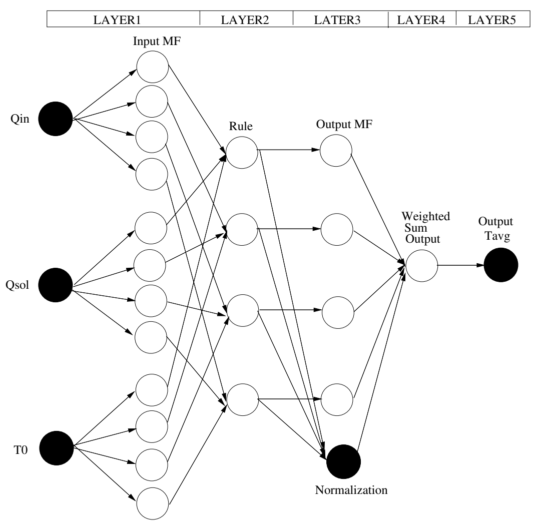

Fig. 5. ANFIS-SUB Model Structure

implement different node functions to learn and tune parameters in a fuzzy inference system (FIS) structure using a hybrid learning mode. In the forward pass of learning, with fixed premise parameters, the least squared error estimate approach is employed to update the consequent parameters and to pass the errors to the backward pass. In the backward pass of learning, the consequent parameters are fixed and the gradient descent method is applied to update the premise parameters. Premise and consequent parameters will be identified for membership function (MF) and FIS by repeating the forward and backward passes. ANFIS has been widely used in prediction problems and other areas. Specially, the literature has several articles on the application of ANFIS to automatic control, robotics, quality control, medicine, pattern recognition and inventory control [11],[12],[13].

The ANFIS based inferential sensor model infers the average air temperature, T_{avg}, from three easily measurable variables. The three variables are external temperature, T_0, solar radiation, Q_{sol} and energy consumed by the boilers, Q_{in}, which are same as the inputs for INN. Two methods have been used to generate the FIS structure, (1) Grid partitioning for ANFIS-GRID, and (2) Subtractive Clustering for ANFIS-SUB. Fig. 4 shows the model structure for ANFIS-GRID. Grid partition divides the data space into rectangular sub-spaces using axis-paralleled partition based on pre-defined number of MFs and their types in each dimension. Premise fuzzy sets and parameters are calculated using the least square estimate based on the partition and MF types. When constructing the fuzzy rules, consequent parameters in the linear output MF are set as zeros. Hence it is required to identify and refine parameters using ANFIS. The wider application of grid partition in FIS is blocked by the curse of dimensions, which means that the number of fuzzy rules increases exponentially when the number of input variables increases. For example, if there are averagely *m* MF for every input variable and a total of *n* input variables for the problem, the total number of fuzzy rules is *mn*. It is obvious that the wide application of grid partition is threatened by the large number of rules. According to [14], grid partition is only suitable for cases with small number of input variables (e.g. less than 6). In this paper, the average air temperature estimation problem has three input variables. It is reasonable to apply the grid partition to generate FIS structure, ANFIS-GRID.

Structure for ANFIS-SUB is shown in Fig. 5. The subtractive clustering method, proposed by Chiu [15], clusters the data points in an unsupervised way by measuring the potential of data points in the feature space. When there is not a clear idea of how many clusters should be used for a given data set, it can be used for estimating the number of clusters and cluster centers. Subtractive clustering assumes that each data point is a potential cluster center and calculates the potential for each data point based on the density of surrounding data points. The data point with highest potential is selected as the first cluster center, and the potential of data points near the first cluster center is destroyed. Then data points with the highest remaining potential as the next cluster center and the potential of data points near the new cluster center is destroyed. The influential radius is critical for determining the number of clusters. A smaller radius leads to many smaller clusters in the data space, which results in more rules, and vice versa. Hence it is important to select the proper influential radius for clustering the data space. After clustering the data space, the number of fuzzy rules and premise fuzzy MFs are determined. Then the linear squares estimate is used to determine the consequent parameters in the output MFs, resulting in a valid FIS.

Gaussian type MFs are used for characterizing the premise

TABLE I
ANFIS ARCHITECTURE AND TRAINING PARAMETERS

Parameters	ANFIS-GRID	ANFIS-SUB
Number of layers	5	5
Number of inputs	3	3
Size of training data set	1081 x 4	1081 x 4
FIS structure	Grid partition	Subtractive clustering
Number of outputs	1	1
Type of MF	Gaussian	Gaussian
Number of MFs	4	4
Number of fuzzy rules	64	4
Training rule	Hybrid Learning algorithm	Hybrid Learning algorithm
Number of epochs	74	60
Size of testing data set	7132 x 4	7132 x 4

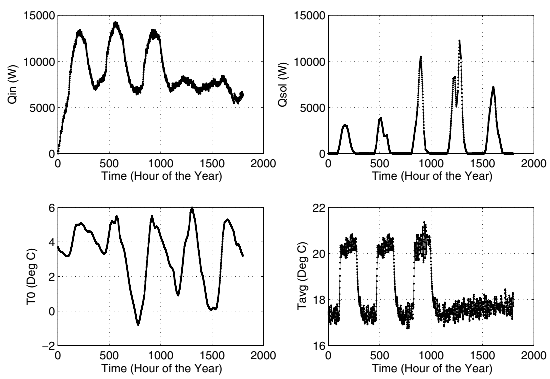

Fig. 6. Training Data Set (February 2000: day 22 to day 27)[16]

variables. The developed structure is trained using hybrid learning algorithm. Subtractive clustering based ANFIS model has been validated by Jassar et al.[16]. The statistical index used for validation is root mean square error (RMSE) method. The ANFIS architectures and training parameters are given in Table I.

IV. COMPARISON OF RESULTS

The same data is applied for training and validation of the two types of models discussed in previous sections. Experimental data obtained from a laboratory heating system is used for training and testing of the developed models. The laboratory heating system was monitored in an EU CRAFT project [17]. The laboratory is located in Milan, Italy. The details of the experimental data for the four variables, Q_{in}, Q_{sol}, T_0 and T_{avg}, is given by Jassar et al. [16]. The data set used for the training process of three models has 1800 data pairs and is shown in Fig. 6. The experimental data used for checking the performance of the developed models is shown

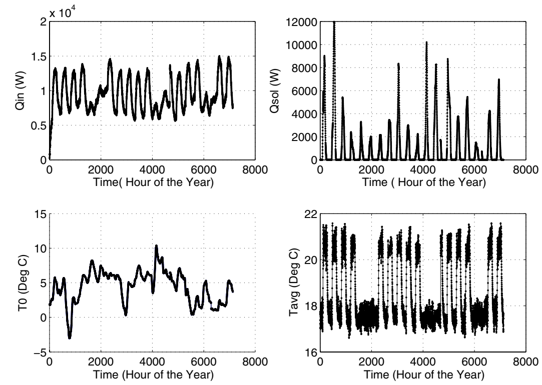

Fig. 7. Testing Data Set (February 2000: day 1 to day 21)[16]

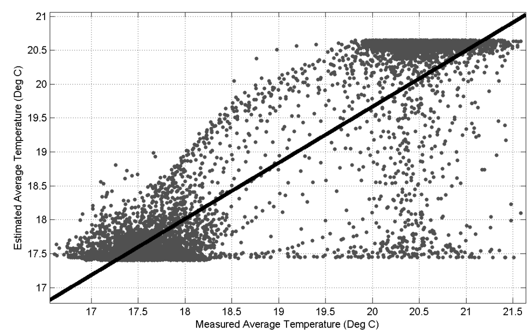

Fig. 8. Estimated and Measured Average Air Temperature Values for INN

in Fig. 7. The testing data has 7132 data pairs for ANFIS, and 7500 data pairs for INN. The results obtained are compared with one another and with the experimental results.

Fig. 8, Fig. 9 and Fig. 10 show the comparison between estimated model output and measured experimental results for average air temperature estimation for INN, ANFIS-GRID and ANFIS-SUB respectively. The estimated and measured

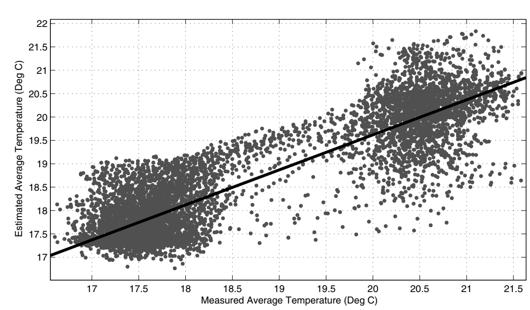

Fig. 9. Estimated and Measured Average Air Temperature Values for ANFIS-GRID

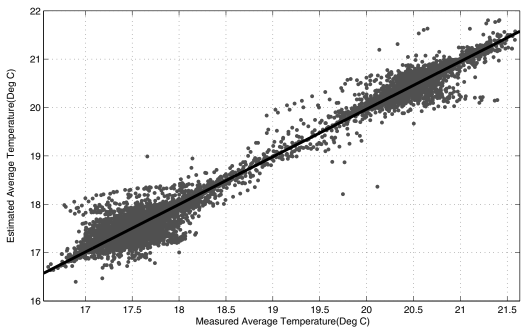

Fig. 10. Estimated and Measured Average Air Temperature Values for ANFIS-SUB

TABLE II
COMPARISON OF RESULTS

Modelling approach	Network	RMSE	R^2	SSE
Neural Network	Base Network	0.60	0.7944	2724
	$S_f = 128$	0.60	0.7942	2423
	$S_f = 64$	0.60	0.7947	2729
	$S_f = 8$	0.63	0.7779	2955
	$S_f = 4$	0.66	0.7331	3281
	$S_f = 2$	0.95	0.6058	6770
ANFIS	$ANFIS{-}GRID$	0.56	0.7831	2304
	$ANFIS - SUB$	0.22	0.9767	932

temperature values are fitted using linear polynomial. The inability of the INN to follow the finer temperature changes is clearly evident in the clustering shown in Fig. 8, the clusters are flattened where the measured temperature changes and the estimated temperature does not. The statistical parameters used for checking the quality of fit are (1) RMSE, (2) R^2 and (3) The sum of squares due to error (SSE). Table II shows the results of fit for the three models. It is interesting to note that the Neural Network fails gracefully as the levels of quantization (S_f) decreases, rather than hitting a hard limit.

V. CONCLUSION

In this paper we have contrasted three different inferential sensor models for space heating systems. Of these three models ANFIS-SUB was best able to accurately estimate the average air temperature in the built environment, it produces the best results in all three statistical comparison methods as shown in Table II. ANFIS-GRID while less accurate than ANFIS-SUB, can be fine tuned by adjusting the parameters responsible for the FIS structure and learning process, however the details of this are outside the scope of the paper. ANFIS-GRID also increases in complexity relative to the number of inputs to the model. The INN, due to its base network, had the lowest level of accuracy of all the models tested. The INN model demonstrated the effects of varying levels of quantization on the performance of the neural networks. The accuracy of the INN is directly proportional to the accuracy of the base network, and the level of quantization. The advantage of INN is that by using integer only calculations and the smallest amount of quantization still accurate, a neural network can be implemented with reduced hardware requirements, reducing the overall cost of an implementation. All of these models can be used as the air temperature estimator for the development of inferential sensor based control schemes, as shown in Fig. 1. These control schemes have a great potential of reducing the energy consumption in space heating systems.

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