Laboratory Exercise 3: Adaptable Neuro Fuzzy Inference Systems

Computational Intelligence

Master in Artificial Intelligence

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ANFIS

1 | Abstract

In the current work, we present a comparison of the performance of different architectures of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) used in the field of energy performance of buildings, to achieve the best prediction of Heating Load using a data set of 786 simulated building configurations considered as ground truth. The best architecture performance is compared to the results obtained in the original paper that the current work is based on. Also, a final comparison with the performance of the same architecture with a decreasing number of inputs is performed. Results demonstrated that ANFIS models have a high adaptation to non-linear relationships in the data since outperformed the RF and IRLS in all tested configurations, even the one with just two input variables.

2 | Introduction

Machine learning encompasses a diverse range of problems, from classification and regression to optimization and decision-making. Traditional approaches often struggle with complex, nonlinear relationships and imprecise data. Neural networks, on the other hand, excel at capturing intricate patterns and representations but may lack interpretability and transparency.

Is in these cases where hybrid approaches, such as the ANFIS, address the limitations of individual methodologies and leverage their complementary features. This model enhances adaptability, interpretability, and generalization, making it a relevant and powerful tool, especially in situations where both precision and transparency are critical.

However, there are no perfect tools, and ANFIS is not an exception. Two well-known drawbacks are the need for the identification of the proper structure itself, and the limitation of the number of inputs due to the increasing computational cost given by the so-called curse of dimensionality. Having this in mind, ¿Is this specific problem still suitable for using ANFIS? ¿What architecture could perform better? ¿Can we justify its use in terms of error compared to the traditional approaches described in the paper? The purpose of this work is to solve these questions by comparing the performance of different architectures, to the RF approach, and with an architecture with only the two most relevant inputs of the dataset.

With the previous theoretical knowledge acquired in class, we expect to observe an important trade-off between all the metrics of error of the model and the computational cost, due to the complexity, given by the number of membership functions and epochs. In general, the higher the complexity of the architecture and epochs, the lower the error and the higher the computational time.

Our intuition tells us that given the learning component of the ANFIS, these approaches will outperform the RF. However, we do not think that will be an enormous difference. We also expect that the performance of the model will slightly decrease by reducing the number of inputs and in this case, it may underperform the RF, but with a very important decrement of the time compared with the architectures with all of the inputs.

3 | Dataset Overview

The dataset used in this study aims to assess the heating load (HL) requirements of residential buildings as a function of various building parameters, contributing to the broader domain of energy efficiency evaluation. Characterized by its multivariate nature, the dataset comprises 768 instances with eight input variables: Relative Compactness (RC), Surface Area, Wall Area, Roof Area, Overall Height, Orientation, Glazing Area, and Glazing Area Distribution. These variables are utilized to predict the output variable, HL, of residential buildings. Previous studies have identified Relative Compactness and Glazed Area as the most significant predictors amongst the available features. The dataset spans a subject area in Computer Science, with associated tasks including classification and regression. Features within the dataset are of integer and real types.

4 | Experimental setup

The main goal of this work is to study the performance of a predictive model of building heating load through an Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture, a general example of this architecture is shown in Figure 3.1. Utilizing a comprehensive dataset reflective of various building parameters, this study explores the efficacy of ANFIS models under diverse configurations. The MATLAB Fuzzy Logic Toolbox serves as the primary tool for implementing these models, leveraging its extensive array of fuzzy logic functionalities. The experimental phase is structured into two distinct segments: the first involves a comparison of multiple ANFIS configurations, while the second narrows the focus to the most significant predictors identified during the first phase. This methodical approach aims to not only ascertain the most effective configuration for heating load prediction but also to evaluate the impact of simplifying the model to essential features.

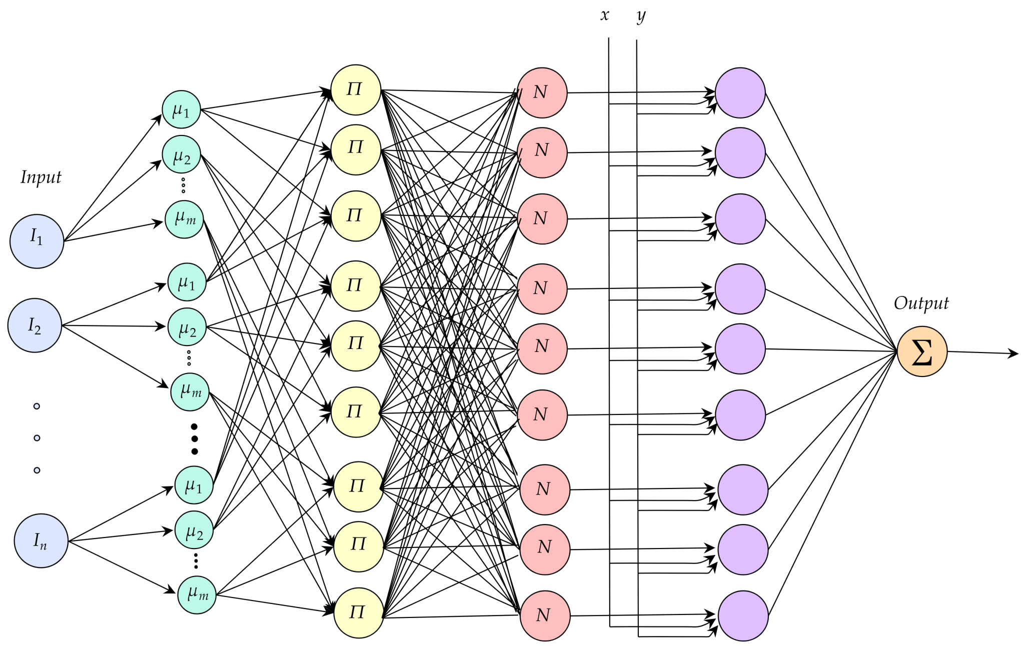

Figure 3.1: ANFIS general architecture.

4.1 | Experiment 1: Multiple ANFIS Configurations

The initial phase of experimentation is designed to explore the performance of various ANFIS configurations across a broad spectrum of parameters. This involves adjustments in data normalization techniques, clustering types for rule generation, and the number and type of membership functions per variable. In this experiments, the number of epochs remained fixed to 200. Each configuration's performance is rigorously evaluated through a 3-fold cross-validation methodology, further reinforced by repetition to ensure consistency and reliability in the findings, to report the average of 3 repetitions of each 3-fold CV experiment.

The reason for the previous decisions was first, to focus our work on varying only a few parameters to isolate the performance and get a better insight into their individual impact; second, to keep the work time manageable and be able to run each of the architectures at least 3 times to obtain a mean of the error metrics.

The configurations tested for the first experiment are as follows:

- 200 Epochs + Z-Score Normalization + Grid Partitioning + 2 Membership Functions (MF) per Variable + Generalized Bell MF (gbellmf)
- 200 Epochs + Min-Max Normalization + Grid Partitioning + 2 MF per Variable + Generalized

Bell MF

- 200 Epochs + Min-Max Normalization + Grid Partitioning + 2 MF per Variable + Gaussian Combination MF (gauss2mf)
- 200 Epochs + Min-Max Normalization + Grid Partitioning + 2 MF per Variable + Trapezoidal MF (trapmf)
- 200 Epochs + Min-Max Normalization + Grid Partitioning + 3 MF per Variable + Best MF Type from Previous Experiments
- 200 Epochs + Min-Max Normalization + Grid Partitioning + Variable MF Numbers Based on Distinct Value Ranges + Best MF Type
- 200 Epochs + Min-Max Normalization + Subtractive Clustering + Automatically Determined MF Numbers + Gaussian MF (gaussmf)
- 200 Epochs + Min-Max Normalization + Fuzzy C Means Clustering + Automatically Determined MF Numbers + Gaussian MF

This comprehensive analysis aims to identify the optimal configuration in terms of predictive accuracy and computational efficiency for the dataset at hand.

4.2 | Experiment 2: Focused ANFIS Model on Significant Predictors

Building on the insights gained from the initial experiment, the second phase concentrates on the predictive capability of an ANFIS model utilizing only the two most significant variables: Relative Compactness and Glazed Area. This experiment adopts the best-performing configuration from Experiment 1 as its foundation, with an additional focus on evaluating the effect of varying training epochs on the model's performance. The objective is to assess how model simplification—focusing on key predictors—affects accuracy and efficiency, particularly in comparison to the more complex models explored in Experiment 1.

5 | Experimental Results

5.1 | First experiment.

The results in table 3.1 show that all the GridPartition clusterizations outperformed the subtractive CL and FCM. However, we can see that the cost in Time also increases even nine times when we

Table 3.1: Experiments and values obtained

Epochs	Norm.	Clust. Type	# M.F	M.F	RMSE	MSE	MRE	MAE	Time (m)
200	Z-Score	Grid Parition	2	gbellmf	1.56	155.99	0.03	5.82	106.11
	Min-Max			gbellmf	2.13e-07	1.38e-12	3.12e-06	4.42e-07	113.29
				gauss2mf	3.83e-09	2.15e-12	6.22e-06	1.47e-08	58.31
				trapmf	8.78e-08	5.20e-8	7.86e-05	1.14e-05	98.88
			3	gauss2mf	NaN	NaN	NaN	NaN	NaN
			Pers.	gauss2mf	7.76e-07	3.25e-12	5.28e-06	1.09e-06	225.69
		Subtractive Cl.		gaussmf	1.73e-06	1.25e-06	2.50e-03	6.00e-04	20.74
		FCM		gaussmf	1.23e-06	7.10e-03	2.05e-03	2.93e-04	11.71

compare the fastest approach, FCM with 11.71 min on average, with the slowest one, gbellmf with 113.29 min on average.

This may be due to the fact that the Gridpartition Clusterization performs a more exhaustive search and possible combinations when creating the initial Fuzzy Inference System.

Now, when analyzing in detail the results from the gridpartition with 2 membership functions we can see the impact that the membership function type has in both the metrics of error and the time. Where is clear that the Gaussian membership function *(gauss2mf)*, obtained the best performance in terms of the minimum error overall in the metrics. What is interesting about this result, is that it did not have the highest time of execution across the three functions tested.

Can we then say in this case, that the best structure for the ANFIS (considering the fixed parameters) from the different configurations tested is the Grid Partition with 2 Gaussian membership functions for each input? We agreed that for this particular problem, where the domain is architecture and construction of the buildings where each project requires a lot of planning and multiple approvals, the execution time of the modal is not a crucial variable to take into consideration, as much as the minimum error in the prediction. So we agree that it is the best structure.

Table 3.2: Best Model vs. IRLS vs. Random Forest

Method	MSE	MRE	MAE
ANFIS	2.15e-12	6.22e-06	1.47e-08
IRLS	7.46	9.08	1.9
RF	0.49	1.54	0.4

Having the best model selected as the first step, then in table 3.2 we can see the comparison of the three error metrics of this model versus both approaches reported in the original paper: The Iteratively Reweighted Least Squares (IRLS) and the Random Forest (RF). Since we did not perform as many tests for each configuration as the authors did for both approaches, we could not report significant values for the mean and standard deviation, therefore we decided to show on the table the minimum values reported for the IRLS and RF (the mean minus the standard deviation), to have just one value to compare with our results.

It is obvious from the order of magnitude of the values that are on the table, that the ANFIS model outperformed the original approaches. What is also important to note, is that in table 3.2 we are only comparing the best structure from all we tested. However, even if we take the "worst" structure from table 3.1 we would also obtain an enormous difference in the error metrics as we have with the best structure. We can attribute this behavior to the high generalization capacity that the ANFIS poses, and the good performance over the non-linear relationships.

5.2 | Second experiment.

Table 3.3: Experiments and values obtained

# M.F	Epochs	RMSE	MSE	MRE	MAE	Time (s)
2	10	9.27e-09	9.68e-17	5.10e-08	7.16e-09	0.48
	50	9.38e-09	9.76e-17	5.10e-08	7.15e-09	0.68
	100	9.46e-09	9.84e-17	5.11e-08	7.17e-09	1.02
3	10	2.40e-08	6.50e-16	1.34e-07	1.87e-08	0.59
	50	4.07e-10	1.12e-17	2.22e-09	3.09e-10	0.88
	100	1.36e-08	4.59e-16	1.04e-07	1.45e-08	1.33

Once we have found what the best model is from the ones that we tested, and that it has a much smaller error. We then can compare its performance with a different approach. Keeping the same structure, maintain only the two most relevant inputs according to the original paper.

In table 3.3 we can see the same metrics reported in the first experiment, but this time we only vary the number of MFs and the number of epochs, fixing all the other parameters found to perform best.

The three main insights we can get form this table are: first, in the three configurations with 2 MFs, there was no improvement with the increase of the epochs. Even if it is a small range, we expected to see some improvement in the performance while increasing the epochs.

Second, in the three configurations with 3 MFs, we can see that there is a *sweet-spot* of the number of epochs, since the selection of 50 epochs outperformed both 10 and 100 epochs. This was also counter-intuitive since we expected to observe the best performance with the highest value of epochs.

Finally, the performance of the model with two MFs was consistently better than with three MFs, even if the best result was with 3 MFs and 50 epochs. Also, we can see that the model obtained better results than in table 3.1 when we are practically keeping 2/8 of the dataset inputs, this was the most unexpected finding of the whole work since we expected to observe even a small decrease of the performance. This may be explained by considering that the other variables are only adding noise to the system, however further investigation would be necessary to prove this point.

6 | Conclusions and future work

In this work, the ANFIS model was explored to predict the heating load of residential buildings, using a dataset characterised by multiple building parameters. Through extensive experimentation with various configurations of ANFIS, significant data on the optimal settings for such predictive models were obtained. Results indicate that the configuration using Min-Max normalisation, Grid Partitioning, 2 Membership Functions per variable, and Gaussian Combination Membership Functions (gauss2mf) produced the most accurate predictions, as evidenced by its superior performance across several error metrics.

A critical limitation identified in this study was the computational infeasibility of models with an excessive number of rules, as occurred in configurations that attempted to use three membership functions per variable. This challenge underscores the need for scalable and efficient modelling approaches, especially as the complexity of the input data increases. In addition, the comparative analysis highlighted the advantages of Min-Max normalisation over Z-score normalisation and revealed the potential limitations of grid partitioning in handling datasets with a larger number of inputs, which can be overcome by Subtractive Clustering, or Fuzzy C Means Clustering, at a slight cost in model performance. Even though, ANFIS showed great performance compared to basic modelling and machine learning techniques.

In addition, it was found that alternative analyses, such as the feature selection process prior to the training of the predictive model, can contribute to the construction of an integral model with good predictive capacity and reduce the time and computational cost required.

In the future, it would be interesting to further investigate alternative clustering techniques to overcome the computational limitations encountered with grid partitioning in complex datasets. Research on different strategies for the assignment of membership functions based on the characteristics of the input variables could improve the accuracy and efficiency of the model. Further analysis of the importance of input variables and their interaction will also be crucial to develop better performing energy prediction models.