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Genetic Rules Induction Fuzzy Inference System for Classification and Regression Application in Energy Industry

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Abstract: Genetic fuzzy system encompasses genetic algorithm and fuzzy logic. It divulges the advantage of optimization with ease of understanding for classification and regression of energy performance of buildings, transformer, and harmonic current in energy industry. This paper presents development of a new rules induction algorithm namely genetic rules induction fuzzy inference system for classification and regression (GRIFISCnR) that combines genetic algorithm with fuzzy logic to facilitate efficient design of building, transformer and harmonic current filter in energy industry using Pittsburgh approach. GRIFISCnR possesses the rules induction capability over other algorithms for multi-class classification and regression problems without compromising on interpretability and accuracy. It manages to strike a balance between interpretability and accuracy, and yield better accuracy with lesser number of rules. It is easier to interpret and understand fuzzy rules as compared to numerical numbers.

Keywords: Fuzzy Inference System; Genetic Algorithm, Harmonic Current

I.INTRODUCTION

Computational intelligence research remains as an interesting topic to deal with complex engineering problems that are difficult to be solved by conventional methods [9][13][14][27]. This paper presents a new hybrid computational intelligence algorithm namely genetic rules induction fuzzy inference system for multi-class classification and regression (GRIFISCnR) that combines genetic algorithm and fuzzy logic for harmonic current, transformer and energy performance of buildings classification. Genetic fuzzy system using Pittsburgh approach is chosen as the methodology for rules learning and induction. It is difficult to predict characteristic of harmonic current as magnitudes of harmonic current are random in nature and nonlinear [20]. Harmonics distortion can cause substantial harm to power system and instability in distribution network.

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Hence, classifications of harmonic current using computational intelligence techniques is vital as it can help planners or distribution planning engineers to identify the composition and types of nonlinear loads in a power system and design suitable harmonic filters to minimize the impact of harmonics.

Transformer is one of the main components in power system. Regular inspection and assessment of transformer condition needs to be carried out periodically in order to detect early faults in distribution network. Dissolved gas analysis (DGA) is the method that is widely used by power utility companies [11] [21] [23] [31] for transformer fault diagnosis. Classification of transformer faults with fuzzy rules by computational intelligence techniques enables the power utilities engineers to detect early transformer faults. It will definitely minimize the risk of transformer breakdown by continuous monitoring of transformer health to prevent it from deterioration.

There is a rising concern for energy performance of buildings (EPB) in energy industry especially about energy waste and its recurrent adverse effect on environment [12] [40]. Computation of heating load (HL) and cooling load (CL) is crucial in efficient building design [4]. Classification of HL and CL with fuzzy rules enables the civil engineers to design the building in a more efficient manner. It will facilitate a more comfortable indoor air conditions to reduce energy waste and maintain efficient usage of energy.

The paper is formatted with an introduction of motivation of the research work, followed by related works on fuzzy rule based system and genetic fuzzy system. Proposed method and algorithm is presented, followed by elaboration of GRIFISCnR details. In result and discussion section, three components of energy industry, i.e.: harmonic current, transformer, and energy performance of buildings are presented. These energy industry case study results are then discussed, analyzed and benchmarked against other models. It is concluded with reemphasis on importance of rules induction in energy industry.

II.RELATED WORKS

A fuzzy rule-based system (FRBS), which is also known as a inference system, consists of fuzzification and defuzzification modules, a knowledge base, and a decision making unit [9][13][16][25][26] [42]. As shown in Figure 1, a knowledge base is composed by a database (DB) and a rule base (RB).

A rule base (RB) contains of a number of fuzzy rules. A data base (DB) defines membership functions of fuzzy sets used in fuzzy rules. Fuzzy sets in fuzzy rule usually have linguistic labels such as "*low*" and "*high*". As a result, fuzzy rules are usually linguistically interpretable such as "If x_1 is *low* and x_2 is *high* then y is *high*". A decision making unit is characterized by a fuzzy reasoning method, which is used to calculate an output value for an input vector using fuzzy rules. A fuzzification module performs the calculation of compatibilities (i.e., membership values) of input values with antecedent fuzzy sets. A defuzzification module transforms a fuzzy reasoning result to the final output[9][13][16]. The derivation of fuzzy rules in the rule base (RB) and the specification of membership functions in the data base (DB) are main tasks in fuzzy rule-based system (FRBS) design [22].

There are different categories in genetic knowledge base (KB) learning [13] [43]. A typical genetic KB learning involves genetic rules learning, selection, database (DB) learning and simultaneous learning of KB components. In this research, it focuses on genetic rules learning where it capitalizes on genetic RB learning for prediction in classification and regression problem.

Genetic learning deals with learning existing RB in FRBS [13][27][32], it might cause the RB and/or DB to be changed after the adaptive learning process. It is reported in[8][10][17][28][29][38][39]that genetic learning deals with RB learning and application to derive a set of rules from predefined DB.

A typical genetic fuzzy inference system normally involves learning and tuning process [13][27][32]. It is hard to differentiate between the two [13][27][32] since most of the time they are overlapping with each other in evolutionary learning and tuning for optimization process.

In this research, the knowledge discovery process involves evolutionary learning and tuning of the RB. The process does not change the DB. It only induces the rules from existing KB after the optimization process.

III.PROPOSED METHOD AND ALGORITHM

A typical genetic KB learning involves genetic rules learning, selection, DB learning and simultaneous learning of KB components [13][14][27]. In this research, it focused on genetic fuzzy rules extraction where it capitalized on genetic RB learning and induction in energy industry dataset pattern recognition.

Thrift is the pioneer that applied Pittsburgh approach in his research for rules based learning [13][14]. It is reported that the method works by using a decision table to antecedents and consequents [33]. This approach codified each fuzzy set with an integer including null value with 0[13][33].

The genetic learning and tuning of KB learning in this research follows "Chromosome = Set of Rules" or Pittsburgh approach [9][13][14][27][33], each chromosome represents a set of rules. There is a slight difference from Thrift approach that there is no lookup table used. Binary coding scheme is applied in this research; a constant variable is applied to each linguistic term of antecedents [9].

Before the evolutionary process begins, parameters such as number of populations, generations, mutation rate, crossover fractions and number of rules are defined. Crossover fraction and mutation probability is predefined at 0.85 and 0.02 respectively.

Table. 1 Genetic algorithm setting and parameters

Parameter	Value
Generations	**800**
Populations	**200**
Crossover fraction	**0.85**
Mutation probability	**0.02**

During evolutionary process, binary string is applied to each of the antecedents of the rules. Training data are then fetched and fuzzy predicted outputs of each data are derived. The predicted value, ypredict, is derived using weighted average defuzzification method. The derivation of fuzzy predicted output of each data is based on the linguistic terms for each antecedents and consequents of rule determined by genetic optimization process. If binary 0 is assigned for an antecedent of a linguistic variable, then the linguistic variable will not be used in defuzzification process vice versa. The individuals evolve as a complete rule base to compete among each other in each generation to come out with the least minimum classification error (fitness function for classification) or root mean square error (fitness function for regression) among all runs.

When generations are completed, the best offspring derived from evolutionary process is applied. If all antecedents for a particular variable binary value are 0, then the variable will not be used in output derivation. Validation data are then fetched and evaluated. Original targeted class and predicted class value is compared and calculated. After 50 runs of validation, the best offspring derived from evolutionary process is applied. Testing data is then fetched and evaluated. Original targeted class and predicted class value is compared and calculated. Accuracy is calculated and stored for benchmarking. Details of the GRIFISCnR algorithm are elucidated in Figure1. A flowchart is demonstrated to explain the flow of the algorithm in Figure2.

The process of defining fitness measurement function in genetic fuzzy inference system is problem dependent. In this research, minimum classification error is chosen as the fitness function for classification while root mean square error is chosen as fitness function for regression during the evolutionary process. In the process of rules induction, the objective is to minimize the error of the consequent. Minimum classification error is an estimation parameter used to quantify the difference between the original targeted value and estimated value. It is illustrated in (1), i.e. S is the number of correctly classified samples and $N$is the size of samples. On the other hand, root mean square error is depicted in (2), i.e. N is the size of samples, yt is the targeted output, and yp is the predicted output.

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$$f = 1 - \frac{\sum_{i=1}^{N} s_{TP}}{\sum_{i=1}^{N} s_i} \quad (1)$$

$$f = \text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(yt^i - yp^i)^2} \quad (2)$$

IV.RESULTS AND DISCUSSION

The GRIFISCnR algorithm is evaluated against IGART-FIS, FAM-FIS and MLP neural network respectively for three different experiments. There are three performance indicators reported in [7] that are commonly used in computational intelligence research result analysis. They are illustrated in (3), (4) and (5) respectively. Accuracy is referred to percentage of correctly classified cases against total number of cases. Sensitivity is referred to percentage of correctly classified positive cases against total number of positive cases while specificity is referred to percentage of correctly classified negative cases against total number of negative cases.

Another nonparametric statistical parameter used for estimation is bootstrap method where the underlying sampling distribution is unknown or difficult to estimate [6]. In this research, instead of a single run, the experiment is repeated 50 times with different combinations of training and test samples. After obtaining all 50 accuracy rates, the bootstrap method [6] [7] with 1000 resamplings is then applied to obtain the bootstrap mean of the accuracy rates. Bootstrap mean is applied to all three energy industry datasets for accuracy comparison. Besides, average, best and standard deviation [3] for testing classification accuracy are reported separately in respective tables for each experiment.

$$accuracy(\%) = 100 \text{ x } \frac{\sum_{i=1}^{N} TP+TN}{\sum_{i=1}^{N} TP+FP+TN+FN} \quad (3)$$

$$sensitivity(\%) = 100 \text{ x } \frac{\sum_{i=1}^{N} TP}{\sum_{i=1}^{N} TP+FN} \quad (4)$$

$$\text{specificity } (\%) = 100 \text{ x } \frac{\sum_{i=1}^{N} TN}{\sum_{i=1}^{N} FP+TN} \quad (5)$$

Harmonic current distortion is usually caused by nonlinear loads or devices in the power system [15]. Due to the rapid advancement in power electronics technology and higher energy efficiency achieved from power electronic driven loads, the use of power electronic loads has become very common in all industry of electricity consumers. Examples of nonlinear or power electronic loads are compact fluorescent lamps, television, computers, inverters air-conditioner, and motor adjustable speed drives.

Some of the adverse effects of harmonic current on power system are: additional heating (energy loss) in distribution power system, malfunctioning of electronic devices, harmonic resonance, and de-rating of transformers. Magnitudes of harmonic current of aggregate loads are random in nature and therefore difficult to predict. However, characteristic harmonic current can be associated with the types of nonlinear loads. For instance, classifications of harmonic current using artificial intelligence techniques can help planners or distribution planning engineers identify the composition and types of nonlinear loads in a power system and design suitable harmonic filters to minimize the impact of harmonics. It can also be a source of input to forecast the growth on nonlinear loads in a power system.

According to the experimental procedure reported in [20], the dataset is divided equally for training, validation, and testing respectively. The real harmonic current dataset is collected in Malaysia and each subset contained 2312 samples with 313, 670, 345, 669 and 315 samples for classes 1–5 respectively. The classification result shows a comparative better accuracy as compared to result gathered from IGART-FIS [20] as illustrated in Table 2. It is reported with the best testing accuracy of 96.58% with 5 rules among 50 runs as depicted in Table 3 together with sensitivity and specificity.

Table. 2 Rules induction accuracy comparison

Model	No. of Rules	Average Testing Accuracy (%)	Standard Deviation
GRIFISCnR (bootstrap mean)	**5**	**96.53**	**0.39**
IGART -FIS	**6**	**90.4**	**-**

Table. 3 Accuracy, sensitivity and specificity parameters

Parameter	Best Testing Accuracy (%)
Accuracy	**96.58**
Sensitivity	**95.36**
Specificity	**84.6**

```
Initialize population, generation, crossover, mutation rate and number of rules

While generation not exceeded
While population not exceeded
        Fetch training data
                While number of rules not exceeded
                        Apply binary value to each of the antecedents of the rules
                End while

        While number of rules not exceeded
                Derive the output, ypredict(fuzzy predicted output of each data)
based on the linguistic terms for each antecedents of rule determined by genetic
algorithm (if the bit is 0, then the respective linguistic term will not be used)

        Evaluate the fitness function (minimum classification error/root mean square
error)
        End while
End while

Perform crossover and mutation
End while

Apply the best offspring returned from genetic algorithm process to each linguistic
term of antecedents of the rules

Fetch training data
While number of rules not exceeded
        Derive ypredict based on the generated rules returned from genetic algorithm
process (if all linguistic terms for an antecedent binary value are 0, then the antecedents
will not be used)
        Evaluate minimum classification error/root mean square error for the training
data
        Evaluate accuracy for the training data
End while

Fetch validation data
While number of rules not exceeded
        Derive ypredict based on the generated rules returned from genetic algorithm
process
        Evaluate minimum classification error/root mean square error for the
validation data
        Evaluate accuracy for the validation data
End while

After 50 runs of validation, apply the best offspring returned, then, fetch testing data.

While number of rules not exceeded
        Derive ypredict based on the generated rules returned from genetic algorithm
process
        Evaluate minimum classification error/root mean square error for the testing
data
        Evaluate and store accuracy for the testing data

End while
```

Fig. 1 Pseudo-code for GRIFISCnR

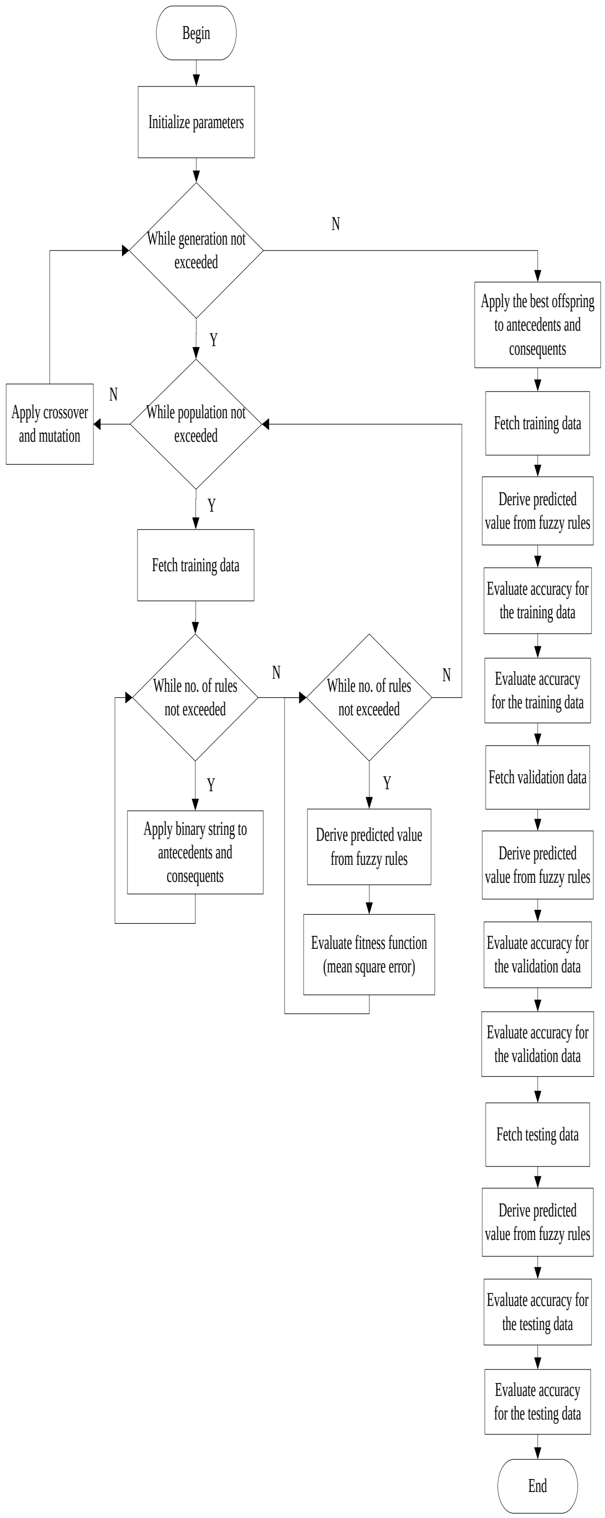

Fig. 2 Flowchart for GRIFISCnR

Early detection of transformer faults can prevent the health condition of transformer from deterioration. Thus, regular inspection of transformer condition needs to be carried out periodically. Dissolved gas analysis (DGA) is the method that is widely used by researchers and power utility companies [11][21][23] [31] for transformer fault diagnosis.

It starts with observation of the combustible gases' evolution rate. If the evolution rate is greater than a predetermined threshold, then the transformer may have internal problems. Thus, DGA is used to further identify the type of transformer faults. The general procedure to detect faults in a transformer can be found in [1] and [2]. In this research, GRIFISCnR is used to detect and classify faults in transformers. Apart from that, GRIFISCnR can induce fuzzy rules from the classification result. It is easier to understand the extracted fuzzy rules as there are five likert scales from very low to very high.

The extracted transformer dataset from [24]is used to evaluate the classification accuracy of GRIFISCnR. The dataset consists of 117 samples, each with seven attributes, i.e.: concentration of H2, CH4, C2H2, C2H4, C2H6, CO and CO2. In this research, three main types of transformer faults are investigated, i.e.: thermal fault, partial discharge and discharge fault. A total of 34 samples are labeled as thermal fault (class 1), 9 samples as partial discharges (class 2) and the remaining 74 samples as discharges fault (class 3).

The experimental set up follows exactly what is reported in [20]. In this research, instead of a single run, the experiment is repeated 50 times with different combinations of training and test samples. After obtaining all 50 accuracy rates, the bootstrap method [6][7] with 1000 resamplings is then applied to obtain the bootstrap mean of the accuracy rates. The results of GRIFISCnR against other models are shown in Table 4.The best testing accuracy among 50 runs is reported in Table 5 together with sensitivity and specificity.

Table. 4 Rules induction accuracy comparison

Model	No. of Rules	Average Testing Accuracy (%)	Standard Deviation
GRIFISCnR (bootstrap mean)	**3**	**99.65**	**0.16**
IGART-FIS	**3**	**89.7**	**-**
FAM-FIS	**6**	**89.7**	**-**

Table. 5Accuracy, sensitivity and specificity parameters

Parameter	Best Testing Accuracy (%)
Accuracy	**100**
Sensitivity	**95.45**
Specificity	**88.24**

Energy performance of buildings (EPB) is a rising concern in energy industry especially about energy waste and its recurrent adverse effect on environment [12][40].The computation of heating load (HL) and cooling load (CL) is crucial in efficient building design [4]. It is required to determine the heating and cooling equipments' specifications in order to maintain comfortable indoor air conditions to reduce energy waste and maintain efficient usage of energy.

There are various machine learning tools that are explicitly used to predict HL and CL [4] with respective techniques such as polynomial regression [36], support vector machines [5][30] artificial neural networks [18][34] and decision trees [40].

In this research, HL and CL are associated with variables such as relative compactness [37], climate [19], surface area, wall area, and roof area [35][37], orientation [35][37], and glazing [37]. These variables are found to be correlated with energy performance of building design, HL and CL in particular.

The dataset is obtained from 768 building shapes which comprises eight attributes, i.e.: relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area and glazing area distribution. They are used to determine the output variables HL and CL of residential buildings. These eight variables are frequently used in EPB literature to investigate the effect of HL on energy related topics [37]. The dataset is partitioned into 10 subsets and executed based on 10-fold cross validation approach. Nine subsets are combined to form the training set in each run, and the remaining subset is used for testing. The same process is repeated 10 times so that different subset of data is used for testing in each run. GRIFISCnR is benchmarked against multilayer perceptron feedforward neural network and root mean square error, as depicted in (8) is selected as error measurement parameter. The average testing root mean square error for HL and CL is illustrated in Table6 and 7 respectively.

The GRIFISCnR possesses advantage over neural network as rules induction for multilayer perceptron feedforward neural network is not easy. The possible number of rules extracted from hidden neuron in neural network are huge and it may not be able to be converted to meaningful explicit rules set. In this research, there are 512 rules extracted from MLP neural network. The calculation of rules is based on assumptions that 2 ^ number of inputs multiplied with number of outputs [41].

Although the proposed GRIFISCnR has several advantages as compared to other approaches, but it has one limitation that required attention. i.e., not able to extract the rules of the application in real times. However, such limitation is not crucial in application that doesn’t required response in real time.

Table. 6 Heating load error comparison

Model	No. of Rules	Average Testing Root Mean Square Error
GRIFISCnR (bootstrap mean)	**10**	**0.0639**
MLP Neural Network	**512**	**0.0694**

Table. 7 Cooling load error comparison

Model	No. of Rules	Average Testing Root Mean Square Error
GRIFISCnR(bootstrap mean)	**10**	**0.0686**
MLP Neural Network	**512**	**0.0812**

V.CONCLUSION

All in all, this research manages to exemplify the combined usage of genetic algorithm and fuzzy logic in genetic fuzzy system. Genetic fuzzy rules learning and induction using Pittsburgh approach is attained. The experimental result is analyzed and benchmarked with existing reported result. The proposed genetic fuzzy rule base learning and induction algorithm for classification and regression, GRIFISCnR reports higher accuracy with lesser number of rules against other models to facilitate the design of harmonic current filter, early detection of transformer faults, and efficient energy performance design of buildings in energy industry.

This research demonstrates an improved genetic fuzzy rules inference system for multi-class classification and regression that contributes to reasonably high accuracy without compromising on interpretability. Normally, there are always different tradeoffs between accuracy and interpretability, however, GRIFISCnR manages to strike a balance between accuracy and interpretability. The GRIFISCnR, with simplistic binary coding scheme manages to exploit the potential of genetic fuzzy inference system with ease of understanding to facilitate the rules induction in knowledge pattern recognition for multi-class classification and regression problem. It manages to reduce the number of rules as compared to other models and yet achieve higher accuracy while maintaining ease of understanding.

The GRIFISCnR possesses advantage of fuzzy rules extraction feature apart from conventional multi-class classification and regression models which are lacking of fuzzy interpretation. It is easier to interpret and understand fuzzy value in contrast to continuous or range value especially in multi-class classification and regression pattern recognition. Although this research is focusing on energy industry rules induction and pattern recognition, it is believed that GRIFISCnR can be applied to other areas of interest for pattern classification and rules extraction.

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