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Rule Optimization of Fuzzy Inference System Sugeno using Evolution Strategy for Electricity Consumption Forecasting

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ABSTRACT

The need for accurate load forecasts will increase in the future because of the dramatic changes occurring in the electricity consumption. Sugeno fuzzy inference system (FIS) can be used for short-term load forecasting. However, challenges in the electrical load forecasting are the data used the data trend. Therefore, it is difficult to develop appropriate fuzzy rules for Sugeno FIS. This paper proposes Evolution Strategy method to determine appropriate rules for Sugeno FIS that have minimum forecasting error. Root Mean Square Error (RMSE) is used to evaluate the goodness of the forecasting result. The numerical experiments show the effectiveness of the proposed optimized Sugeno FIS for several test-case problems. The optimized Sugeno FIS produce lower RMSE comparable to those achieved by other well-known method in the literature.

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1. INTRODUCTION

Electricity is the key component to modern technology and without it, most of the things that we use every day simply could not work, and would never have been created [1]. Human activities in electrical usage over time will increase. This happened because the electricity has become one of the important aspects of the progress of human civilization in various fields, both regarding economic, technological, social and cultural human. It has huge environmental, social, and economic impacts, such as its influence on climate change, poverty reduction efforts, human culture, industrial and agricultural productivity and environmental and human health [2]. Electric power is used by several factors, like the household sector, industry, commercial businesses, and public services [3]. The increase in demand for electricity requires the electricity provider can deliver the electricity needs of consumers to be stable in every sector of the field in the community can be assured. Large electricity consumption in a period cannot be calculated exactly. Therefore, to do is to predict a large consumption of electrical energy [4]. If large power consumption is not expected, it can affect the readiness of generating units to provide electricity supply to consumers.

There are three types of electrical load forecasting there is long-term load forecasting, middle-term load forecasting, and short-term load forecasting. This paper discusses short-term load forecasting which is a kind of forecasting by using hours period. The short-term load forecasting (STLF) is to predict the load value on the futures days by the characteristics of the power system [5]. Accuracy of short-term load forecasting is important to the power system’s security and economy. Especially in power market, improving the accuracy of STLF is one of the most important means for the management of the power system. Owing to the importance, research in this area in the last 40 years has resulted in the development of numerous forecasting techniques.

Short-term load forecasting techniques can be classified as either traditional or modern models [6]. Time series analysis forecasting model and multiple regression models are representative examples of traditional methods for the short-term forecasting. A modern model such as fuzzy inference system, Genetic Algorithm, Evolution strategies, etc. Historical load data are examined in the former while the relations between load and variation factors are analyzed in the latter. The traditional methods are mature, simple calculation and rapid speed, but they are linear ones. The relationship between the load and its exogenous factors is complex and includes non-linear characteristics, making it purely crucial to model over conventional techniques [7].

The last few years have been a lot of research that discusses the development of a model for prediction of electricity consumption [8],[9],[10]. Many algorithms are applied for forecasting with time series model. One of them is ARIMA modeling which has an edge in predicting the accuracy of the data in the form of time series for short-term periods. One requirement is the regression assumptions must be fulfilled, where data must meet the multivariate normal distribution, and produce the same covariance matrix for each population [11]. To improve the drawbacks regression model, Artificial Intelligence one that is Fuzzy Sugeno can be used. This method has frequently been used to assist in the completion of various kinds of predictions. On ARIMA, the measurement error is obtained from the difference between the actual value and the estimated value, while the fuzzy look of error as a haziness in the model parameters.

Damousis [12], developed a fuzzy model is used to determine the wind speed predictions that generates a very strong correlation with the value of Spearman. Fuzzy Sugeno capable of resolving the problems that have data in the form of time series with a fairly high degree of accuracy [13], [14]. But this method also has drawbacks in the determination rule based on regression function. Therefore, if the data that is used quite a lot of impact on the increasingly complex rule. If the rule is built manually, it will require considerable time and values for the coefficients in the rule is less accurate because there is still uncertainty to determination resulting error level is still high. To correct deficiencies in the methods above, this paper attempts coefficient optimization on Sugeno fuzzy rule where the values of the coefficient rule automatically generated using heuristic algorithms like Evolutionary Strategies. This effort will enable to raise the prediction accuracy on electricity consumption by optimizing Sugeno fuzzy method than using ordinary regression. In its application evolution algorithm optimization strategies proven to finish on fuzzy sets and can improve the performance better than fuzzy method [15].

2. RELATED WORK

Various methods used in the literature to solve the problems will be briefly discussed in this section. The methods include Time series analysis-based approach, heuristic approach, and a hybrid approach.

ARIMA is a method often used for forecasting. Tseng [16], Ediger and Akar [17], He et al [18], Cho, et al [19], applying which proved ARIMA time series data that can predict accurately where the measurement error on ARIMA obtained from the difference between the actual data and data estimation, so that this model requires a lot of trial observation in forecasting. In fact, the reality of data to be rarely predicted reaches the number of observations was assumed as prone to fluctuations in the movement of data. This is causing the error value is still high. ARIMA can also be used in addition to other methods such as Artificial Neural Network (ANN)[20], Genetic Algorithm (Genetic Algorithm) and the most popular method, the Fuzzy Logic (FL). Compared with ANN, Fuzzy Logic offers a clear insight into the model. Fuzzy forecasting system can capture the pattern of past data to project data that will come.

Electrical load time series is very popular and Fuzzy Logic in dealing with the system shaped times series because it is considered a very suitable fuzzy method for forecasting electricity load. Some fuzzy logic has frequently been used to assist in the completion of a wide variety of predictions such as raw material suppliers prediction [21], exchange rate [22], or electricity consumption forecast [23]. Damousis [12], implements fuzzy models are used to determining the wind speed predictions and produce the final result is relevant. Lie et al. [13], calculating electrical energy needs short term by using the approach of grey-based fuzzy that can be used as an operational cost savings and safe conditions that allow utilities to process production resources to optimize energy prices and exchange with producers and consumers. Allahverdi, et al. [24], Talei et al. [25], dan Chang et al. [22] has implemented a forecasting and Sugeno in the case of data that is suitable for time-series.

Fuzzy Sugeno also has a weakness, especially in the rule section THEN, namely the existence of mathematical calculations that can not provide a natural framework for representing human knowledge in truth. The second problem is the lack of freedom to use different principles in fuzzy logic so that the uncertainty of the fuzzy system can not be represented as well.

Heuristic algorithm can help in fixing drawback in Fuzzy Sugeno. Nikdel et al [26], Mariajayaprakash et al [27], Nallasamy and Ratnavelu has implemented optimization on Sugeno can provide the level of accuracy steeper, and optimized fuzzy controller gives better performance than a conventional fuzzy controller also regarding rising and settling time. Evolution Strategies (ES) is an evolutionary algorithm used in this study as an optimization technique. Such as genetic algorithms, this method has a high success rate in solving optimization problems in computer science problems. ES has been stronger and as optimization techniques to the problem of high dimensional search space.

This paper attempts to fill these knowledge gaps by addressing the optimization rule on fuzzy Sugeno using heuristic algorithms that are expected to improve the accuracy of forecasting.

3. RESEARCH METHOD

3.1. Fuzzy Inference System Sugeno

This study uses a model fuzzy inference system Sugeno to overcome the shortcomings that are owned by several other studies in section 2 for forecasting problems. Fuzzy Sugeno is one method in fuzzy logic introduced by Takagi-Sugeno Kang [28]. Fuzzy Sugeno improves the weaknesses possessed by pure fuzzy inference system to add a simple mathematical calculation as rule part THEN. On this change, the fuzzy system has a weighted average value in the rules section fuzzy IF-THEN[29].

One-Order Fuzzy Sugeno model of the form:

$$IF\ (X1\ is\ A1\ ).\dots\dots(XNisAN)THEN\ z\ = p1 * x1\ +\ \dots + pN * XN\ +\ q \qquad (2)$$

Where:

x_{ij} : value weight criteria till- j that relevant work by rules till- i

A_1 : fuzzy set for variable weighting criteria for all relevant rules till-j who relevant until rules till-i

^{o}: operator AND

n : number of criteria

A_i: constanta value till-i

$P1$: constant in the consequent

q : decision

1) Fuzzification

Fuzzification is a process of changing the crips value into membership functions [21]. In the fuzzification, the parameter is represented as a variable input. Parameters used as input variables are presented in Table I. The output variables in this study of the results form as the prediction. This study uses three input variables are shown in Table 1. All five of these variables have the fuzzy sets and same boundaries fuzzy membership. The membership function in the input variables is represented with real numbers.

Figure 1 there is a domain where divided into three fuzzy subsets labeled as “increasing”, “stable” and “decreasing” where fuzzy subsets’ increasing have limited [-1500 - 2100], fuzzy subsets’ constant have limit[-1500 - 1500] and fuzzy subsets' decreasing have limited [1500 - 2100].

Table 1. Parameter description

No	Parameter	Description
1	Y(t-1)	an hour before
2	Y(t-2)	a day before
3	Y(t-3)	a week before

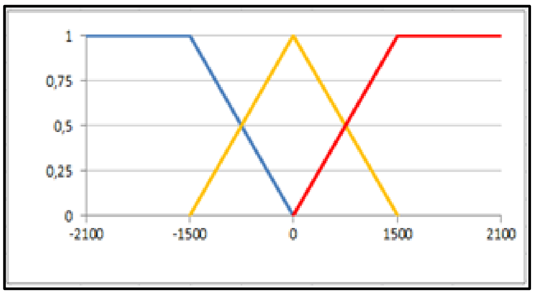

Figure 1. Membership function on Fuzzy Sugeno

For each membership functions, input variable where μ is the degree of membership and x is the value of the input to be converted into a fuzzy set described in Equation 3 and Equation 4.

$$\text{μpmtdecreasing [x]} = \begin{cases} 0 & x \leq -1500 \\ \frac{0-x}{1500} & -1500 \leq x \leq 1500 \\ 1 & x \geq 0 \end{cases} \quad (3)$$

$$\text{μpmtstable [x]} = \begin{cases} 0 & x \leq -1500 \text{ and } x \geq 1500 \\ \frac{x-(-1500)}{1500} & -1500 < x < 1500 \\ \frac{1500-x}{1500} & 0 < x < 2 \\ 1 & x \geq 1500 \end{cases} \quad (4)$$

$$\text{μpmtlincreasing [x]} = \begin{cases} 0 & x \leq 0 \\ \frac{1500-x}{1500} & 0 \leq x \leq 1500 \\ 1 & x \geq 1500 \end{cases} \quad (5)$$

2) Rule Based

This section is the formation of a fuzzy knowledge base (if...then rules). Calculation of the number of rules is by multiplying the number of fuzzy sets (two linguistic variables) as the number of input variables. The establishment of rules on research using any combination of as many as 2 to the power input three which is the sum of many variables resulting in 27 rule [22]. On Fuzzy Sugeno model has output (consequent) system is not in the form of a fuzzy set, but in the form of linear Equations as in Equation 2. Examples of rules the rule of experts to predict the demand for electricity in Table 2.

Table 2. Rule Example

IF Y(t-1) high AND Y(t-2) high AND Y(t-3) high THEN a + b1 * Y(t-1) + b2 * Y(t-2) + b3 * Y(t-3)
IF Y(t-1) high AND Y(t-2) high AND Y(t-3) low THEN c + d1 * Y(t-1) + d2 * Y(t-2) + d3 * Y(t-3)
IF Y(t-1) high AND Y(t-2) low AND Y(t-3) high THEN e + f1 * Y(t-1) + f2 * Y(t-2) + f3 * Y(t-3)
IF Y(t-1) low AND Y(t-2) high AND Y(t-3) low THEN g + h1 * Y(t-1) + h2 * Y(t-2) + h3 * Y(t-3)
IF Y(t-1) low AND Y(t-2) low AND Y(t-3) low THEN i + j1 * Y(t-1) + j2 * Y(t-2) + j3 * Y(t-3)

3) Defuzzification

The method uses is the mean (average) [32]. A-predicate function determination and the determination of α-predicate × output membership functions (Z). Output inference the results of each rule is given explicitly (crips) by α-predicate (fire strength). Having obtained the value of αi, then the next will be the process of calculating the value of each consequent any rules (zi) in accordance with the membership functions are used. Defuzzification Equation model as in Equation 6.

$$Z = \frac{\sum_{i=1}^{n} á_i z_i}{\sum_{i=1}^{n} á_i} \quad (6)$$

The above Equations, αi is the antecedent membership value, and zi is the rule inference system result.

Fuzzy Sugeno suited to fix the times series problems [31]. But, for obtaining optimal system performance, the coefficient by the rules should be determined with precision. Evolution Strategies (ES) algorithms suited to seek coefficient appropriate on the basis of the rules of the fact that in determining the value is still need to test several times beforehand so expect Evolution Strategies able to obtain a solution to the problems of optimal or near-optimal so as to be optimized coefficient values in the rule base that was created earlier. A stochastic component is one of the most successful methods for the global optimization problem; they accept to refuse from local optima and affected premature stagnation. A famous class of global optimization methods is successful evolutionary strategy within the real-valued solutions. For black-box optimization, i.e., for optimization scenarios, Evolution strategies add the most powerful evolutionary methods, where no functional expressions are clearly given, and no derivatives can be computed. In the course of this work, evolution strategies will play an important role. They are adapted to the biological principle of evolution.

Parameter mutation rate or the probability of mutation (pm) is used to determine the number of chromosomes that have mutations in the population. The process carried out by the method of random mutation of genes. The new chromosome generated is described in Equation 7 [32].

$$x' = x + ó\, N(0.1) \tag{7}$$

The formula used to find the value of N (0.1) described in Equation 8.

$$N(0.1) = \sqrt{-2.\ln r_1}\, \sin 2ðr_2 \tag{8}$$

Self-adaptation formed from the measuring step σ in the chromosomes that have a change of variation and selection that is a mutation that is realized by replacing the parent to offspring as in Equation 8.

We propose a method ES (μ + λ) that do not use recombination and selection process involving individuals and the parent where one parent is taken from the regression Equation. ES (μ+ λ) do not use recombination and selection process involving the use of elitism selection of individual offspring and parent. Some notation used by ES as μ (mu) determine the size of the population (as popSize on GAs) and λ (lambda) specifies the number of offspring produced in the reproductive process (same as crossover rate and mutation rate in GAs). Because ES was relying on more mutations, the recombination process is not always used. Recombination and mutation is a genetic carrier. The effectiveness of recombination is very limited when most of the population into homogeneous [33]. Therefore, the mutation being the only method to produce offspring.

At Figure 2, when the establishment of the rule in the Sugeno fuzzy always generate a regression model where “a” “b" coefficient value generated in each rule. To produce optimum accuracy approaching p-value the coefficient is generated automatically by using ES. The process carried out by the method of random mutation of genes. At this mutation process, we enter one of the functions of linear regression were used as one of the individuals with the hope of producing a near-perfect score.

The effectiveness of recombination is very limited when most of the population into a complex that mutation to be the only method to produce offspring. Parameter mutation rate or the probability of mutation (pm) is used to determine the number of chromosomes that have mutations in the population. During the reproductive phase, all the offspring produced by the mutations stored on offspring pool. The selection method is used to determine the chromosomes of the current population and offspring who will be elected to the next generation.

Offspring produced by the mutations will be selected if they have a better fitness value. In the process defuzzification it will produce a constant that will be used to get the z value to be compared with the actual data to get an error resulting in a value of fitness. The larger the fitness value, the better the resulting predictions. The purpose of the use of ES for optimization on Sugeno fuzzy to obtain optimal solutions by optimizing the parameters of the consequent part of the fuzzy Sugeno. Illustration behavior Evolution Strategies is the intelligent algorithms to find a solution as in Figure 3.

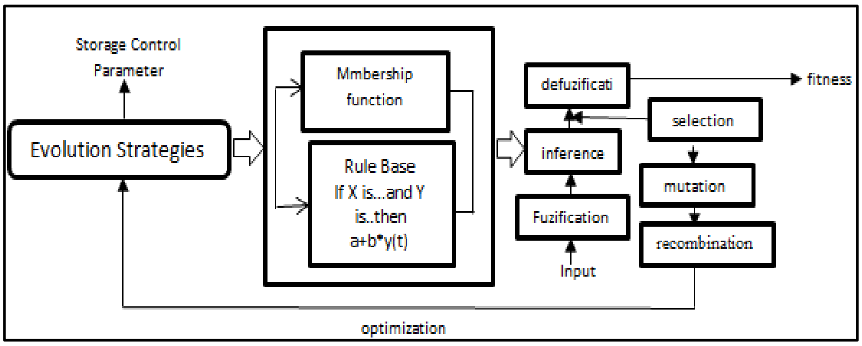

Figure 2. Phase of optimization fuzzy sugeno using Evolution Strategies

In Figure 3 shows the points is representative of the problems to be solved. In the first point of the trouble spots spread across the area of the solution. But over time will accumulate into an area closer to the solution.

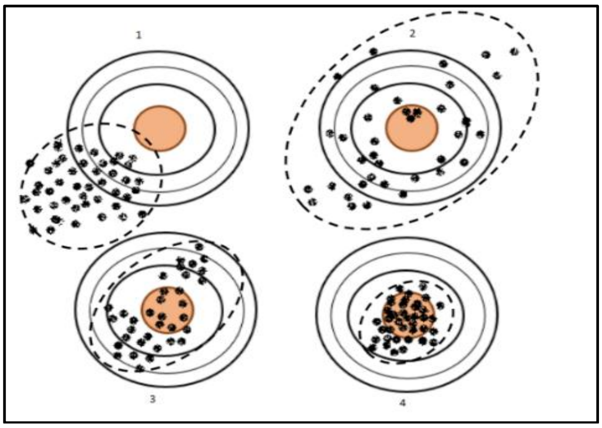

Figure 3. Illustration of Evolution Strategies

4. DATA COLLECTION

Data from IESO Demand Ontario (http://www.ieso.ca/). IESO is an official website Ontario power authority. IESO attempt services, knowledge and reasoning to support Ontario's varied electricity system. The IESO reliably operates the system in real time. The data used in this research consisted of 5809 the daily load data in a period of one year. The examples of the data in one day show in Table 3. We obtained the data from IESO processed into the regression model using three periods. Electric load model has a volatile pattern. The shaped pattern of electricity consumption cycle on historical data previously. The cycle is formed based on the data of the previous hour (y (t-1)), one day ago (y (t-2)), and seven days ago (y (t-3)).

Table 3. The example of generated time series model

Actual(t)	t-1	t-2	t-3
14039	14815	11840	13514
13592	14039	11571	13089
13316	13592	11459	12729
13287	13316	11630	12814
13639	13287	12120	13250
14700	13639	13342	14232
15999	14700	14788	15728
16833	15999	15691	16539
17305	16833	16177	17011
17838	17305	16714	17252
18127	17838	16921	17523
18134	18127	17258	17779
18299	18134	17535	17954
18390	18299	17857	17964
18556	18390	18132	18175
18627	18556	18783	18496
18865	18627	18938	18844
18525	18865	18904	18496
18230	18525	18919	18317
17784	18230	19000	18380
17492	17784	18988	18280
16536	17492	17692	17229
14864	16536	15998	15399
13632	14864	14815	14197
12964	13632	14039	13430

5. NUMERICAL EXAMPLE

5.1. Generation Coefficient Rule Fuzzy Sugeno

Generation IF..THEN rule in one-order on Fuzzy Sugeno, there is time series analysis formula (see Formula 2). In this section, the researcher will generate rule using Evolution Strategies. For regression, calculations like in section 3. The results obtained each hour load value on consumer-owned historical data can be seen in Table 3. Error values are obtained using the Equation 6 generates an error value of 527, 2983. In Table 4, "a" for constants, "b1" is constant for one-hour electricity consumption or load before, "b2" for one day before, “b3” for one week before the load obtained. A simple issue is advanced an example of the problem formulation. The research was conducted using a 64-bit PC. The data sample has tested a total of 100 data. The rule is formed by 27 rule with the same coefficient values in each rule that is formed as follows:

IF *Y(t-1) high* ***AND*** *Y(t-2) high* ***AND*** *Y(t-3) high* ***AND*** *Y(t-4) high* ***THEN*** *z = a+ b1 * Y(t-1) + b2 * Y(t-2) + b3 * Y(t-3) + b4 * Y(t-4).*

Offspring obtained from 10 mains. In Equation 7, the initiation of which the value of σ is raised in the range [0,0.05] Values of N (0,1) is a random number. To get a better fitness, a constant value of regression calculations made as one parent so that the ES can be close to or even better than the results of the regression calculation. The calculation of the value of each coefficient in Table 4.

Table 4. Regression coeficient result using 100 data

constanta	*Coefficients*
a	-128,083
t-1	0,148815
t-2	0,018753
t-3	0,844154

Viewing from Table 4 can be formed following regression:

y’$=-128{,}083 + 0{,}148815x114815\ +\ 0{,}018753x11840\ + 0{,}844154x13514$

This value is applied to a rule that is formed to serve as the error value to search for fitness. Equation 9 is used to calculate fitness.

$$fitness = \frac{1}{error+1} \quad (9)$$

Testing was conducted using 100 data to know how pop size the right to produce the best fitness values to be used in this study. Pop size or λ value used in this study is 7λ according to some previous studies[36] Combination trials using pop size different sizes to produce the best pop size provided in Table 5. As other heuristic methods, Evolution Strategies has the stochastic characteristic that produces the different solution in each run. Thus, the numerical experiment is repeated ten times for each input combination [34], [36]. The results of the fitness test are then plotted for greater ease in understanding the difference pop size used in each test as in Figure 4.

In Figure 4 it can be seen that the average value of fitness continuously increased in pop size 20. The average increase obtained in the best fitness pop size 7000 is 0.02895. Testing pop size pop size dismissed in 7000 due to a stable point in this trial are in pop size to 2000 is shown in the average fitness finest. And if the trial continued on a larger generation, an increase in fitness is not too significant. The number pop size affected the average increase fitness.

In these cases, using the weekly period is therefore determined running time should not be more than one week then on to 7000 pop size trial terminated. Pop size trial is limited to 7000 because the larger the size pop size used, computing time to produce the best solution is also getting old. The size of the fitness pop sizes a situation where if pop size is too small, the exploration area in the search for solutions will be more narrow so that a solution is found not too good. Likewise, the higher the number pop size not very significant increase in value resulting in convergence.

Table 5. Result experimental μ

Multiplier (7)		Fitness average	Execution time average (minutes)
μ	λ		
10	70	0,02033	8,50
15	105	0,01999	8,69
20	140	0,02101	7,21
25	175	0,02197	7,03
30	210	0,02239	8,04
35	245	0,02316	8,55
40	280	0,02337	10,2
45	315	0,02318	10,3
50	350	0,02330	12,1
100	700	0,02429	42,7
150	1050	0,02470	48,3
200	1400	0,02524	49,2
250	1750	0,02566	63
300	2100	0,02601	191,4
500	3500	0,02590	443,8
1000	7000	0,02685	1030,2
1500	10500	0,02759	2079,4
2000	14000	0,02777	1879,1
3000	21000	0,02851	2170,9
5000	35000	0,02882	2775,1
7000	49000	0,02902	3357,6

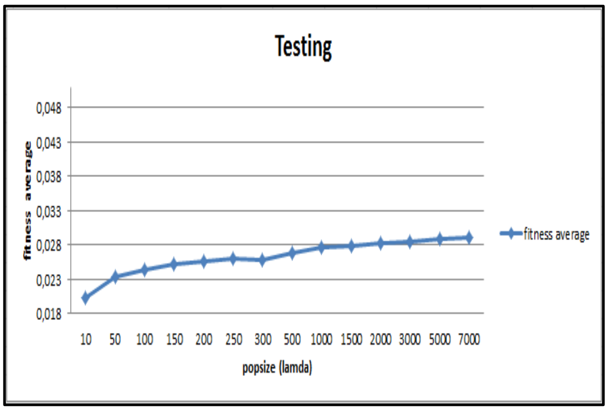

Figure 4. plot trial multiple miu

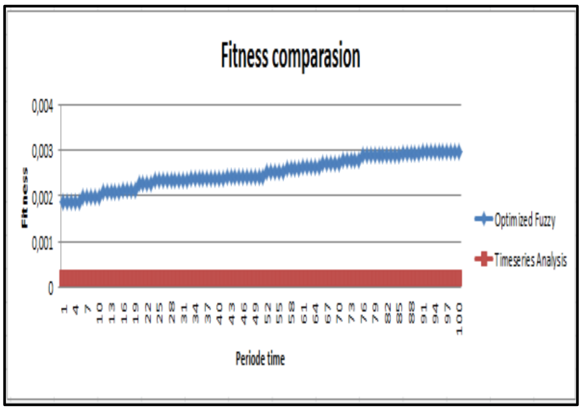

Figure 5. Fitness comparison between Sugeno fuzzy optimization and Time series analysis

The result of this calculation pop size used as guidance in the short-term power load forecasting The results of this calculation is fitness as in Table 5. The results of the forecasting time series analysis are also converted into fitness. It is used to make it easier to compare the final results. The results of this calculation then plotted as in Figure 5. Figure 5 can be seen the red color is the result of fitness time series analysis and the blue is the result of optimized fuzzy fitness. From the results of the comparison between optimized fuzzy with time series analysis where it is clear that the method Sugeno produce greater fitness than using a regression model that his fitness values tend ramps.

6. RESULT AND DISCUSSION

The study compared the results of forecasting using "time series Analysis" with our proposed method, electricity forecasting using optimization fuzzy Sugeno on the coefficient rule. The results of the comparison are presented in Table 6. Evolution Strategy algorithm is one of the heuristic algorithms can find a better solution and suitable for optimization algorithm [35]. Electricity consumption in the city of Ontario has fluctuated pattern as in Figure 6. The pattern is based on historical data from today until one months backward is represented by y (t), y (t-1), y (t-2), and y (t-3) for a month. Results of experiments with 5809 data by using regression forecasting and FIS Sugeno each value is given a value close to the actual data as in Figure 7.

Forecasting results proved that our proposed method has a better performance than in the time series analysis of the problem of electric load forecasting. This happens because of the weakness is most prominent in the time series are not able to process the data fluctuated. Different from the fuzzy which tend to receive various types of data [36].

Table 6. Comparison forecasting result

Date	Hour	Actual (t)	Sugeno ES	Timeseries Analysis
31 – Des-2014	1	14039	13695,74	14005,47
31 – Des-2014	2	13592	13218,89	13520,81
31 – Des-2014	3	13316	12850,93	13147,38
31 – Des-2014	4	13287	12887,92	13179,35
31 – Des-2014	5	13639	13264,24	13553,37
31 – Des-2014	6	14700	14174,91	14466,52
31 – Des-2014	7	15999	15624,70	15922,41
31 – Des-2014	8	16833	16524,22	16827,07
31 – Des-2014	9	17305	17057,58	17363,66
31 – Des-2014	10	17838	17343,75	17656,53
31 – Des-2014	11	18127	17651,83	17973,6
31 – Des-2014	12	18134	17913,87	18244,85
31 – Des-2014	13	18299	18068,01	18400,9
31 – Des-2014	14	18390	18111,64	18444,37
31 – Des-2014	15	18556	18309,84	18640,95
31 – Des-2014	16	18627	18620,53	18956,9
31 – Des-2014	17	18865	18916,61	19270,27
31 – Des-2014	18	18525	18649,39	19030,53
31 – Des-2014	19	18230	18451,65	18830,59
31 – Des-2014	20	17784	18468,3	18838,84
31 – Des-2014	21	17492	18318,21	18683,06
31 – Des-2014	22	16536	17360,83	17717,68
31 – Des-2014	23	14864	15645,73	15987,05
31 – Des-2014	24	13632	14361,49	14682,86
......	.....	......	......	......
31 - Jan- 2014	24	16568	17860,21	17030,44

According to the forecasting results shown in Table 6, there are no a unique and more appropriate unbiased estimators that can be applied to see how far the model is able to forecast the values of electricity load, and thus error measure of accuracy are employed. For this reason, the models are evaluated by the square root of the mean square error (RMSE).The Mean Square Error (MSE) is another method to evaluate forecasting methods. Each error or residual squared. Then calculated and apart by the number of estimates. This approach set the forecasting error is large because it is squared errors. A technique that produces moderate errors may be better for one that has a small mistake but sometimes produce very large [37].
Here's the formula RMSE:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Yi_{observed} - Yi_{predicted})^2} \quad (10)$$

With :
N : number of data
$Yi_{predicted}$: observation value models, and
$Yi_{observed}$: the estimated value of the models

In forecasting using time series analysis and Sugeno fuzzy optimization ES, RMSE testing is required to determine the error rate is generated and then made a comparison with the calculation of Sugeno fuzzy optimization ES. Results from each RMSE calculation method for electricity load forecasting Ontario provided in Table 7.

In Table 7, optimized fuzzy proven performance better than time series analysis with RMSE values smaller than the RMSE time series analysis. The smaller the error rate, the better the results of the algorithm work in overcoming the existing problems. This proves that for forecasting electricity load with complex data, the proposed method can provide better results and actual approach.

Table 7. RMSE result

Model	RMSE	% RMSE
Timeseries Analysis	0,00192	0,192%
Sugeno fuzzy optimization ES	0,000957	0,0957%

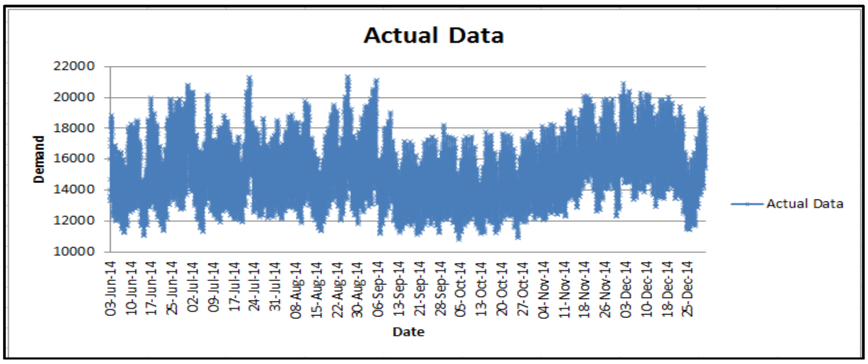

Figure 6. Actual data of demand

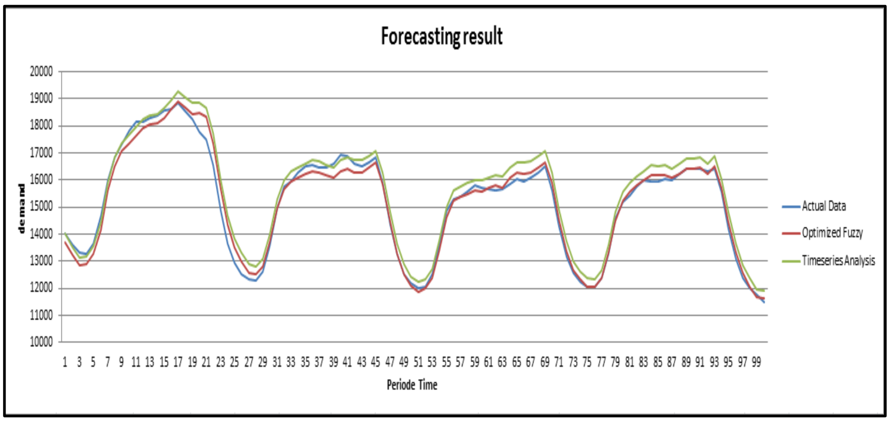

Figure 7. Comparison result of forecasting

7. CONCLUSION

In this paper, has discussed the problem of short-term power load forecasting. Sugeno fuzzy method with Evolution Strategies provides optimum approach problem-solving solution than using traditional forecasting namely linear regression. Pop size testing is done to obtain the best combination to get optimal performance. Pop size selected is 7000 with a multiplier 7. Calculation of optimized-fuzzy RMSE generates value 0,095%. This indicates optimized-fuzzy method goes well when compared with the results of time series analysis of 0.192%. The next study will consider the hybridization of Evolution Strategy with other heuristic method and ANFIS [38] to obtain lower RMSE.

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