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HYBRID SARIMA SUPPORT VECTOR REGRESSION FIREFLY ALGORITHM IN ELECTRICAL LOAD FORECASTING

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ABSTRACT

Analysis of electricity consumption is important because it concerns the resilience of a country. Data mining techniques are needed that can handle fluctuations in these data, one of which uses SVR. The best parameter search for SVR is the most important for forming the model. In this paper, we will discuss in detail the combination of SARIMA-SVR and Firefly algorithms. The firefly algorithm is one of the metaheuristic techniques that provides accuracy which proven by the value of MAPE and RMSE.

Keywords: electrical load, SVR, Firefly, Metaheuristics, Forecasting.

1. INTRODUCTION

Sumatra Island as the island with the second largest population in Indonesia and covers 20% of the total population, so projections of electricity needs are very necessary. Electrical energy needs in Indonesia always increase every year. The projected average annual growth in electricity demand for the 2018-2027 period is lower compared to the 2017-2026 period from 8.3 percent to 6.86 percent.

The household sector uses energy for lighting, cooking, electronic equipment, refrigeration, and heating. The problem that often arises related to energy consumption from the household sector is the difference in energy consumption from the lower middle-class community with the upper middle class. The industrial sector uses energy to run industrial machinery. High energy needs in this sector make some industrial sector customers generate electricity for their purposes, known as captive power. The business, social and public sectors use electrical energy with different objectives and with different intensity of energy use. Generally, the largest number of customers is electricity customers from the household sector, but the greatest intensity of energy use is the intensity of electricity consumption by the industrial sector. Energy intensity per sector such as the household, industrial, business, social and public sectors. Electricity intensity is calculated based on the use of electricity in each sector.

Also, The highest electrical energy needs in the household sector. This is due to a large number of household customers even though the intensity of energy usage is not too high. Electricity needs are calculated as a result of the activity level with energy per activity. The activity level in this projection is the number of electricity customers divided into five sectors, namely the household, industrial, business, social and public sectors. Energy per activity is the average energy used by one sector customer for one year.

In other words, electric power has unique characteristics that are different from other "commodities". Distribution or distribution of electric power to date has to go through a specific network, then the level of production or energy produced by the power plant needs to be in accordance with the level of need or the amount of burden that must be served.

Adjustment or control between production and the need for electric load is very important to do to memningat the typical nature of electric power which cannot be stored on a large scale, thus this energy must be provided when needed. As a result, problems will arise in the face of electrical power requirements that are not fixed or always change from time to time. So there must be scheduling to operate an electric power so

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that it can always meet the demand for power at any time with good quality and efficiency. If the power sent from a power plant is far greater than the demand for power at the load, there will be energy waste. Conversely, if the power generated or provided by a lower power plant, over load will occur which will have an impact on blackouts. So far the estimated period is grouped into:

1. Long term: Estimated demand for loads with a period of> 1 year
2. Medium term: Estimated load demand with a period of> 1 month
3. Short term: Estimated demand for loads with a period of several hours in a day up to a week

In this paper, forecasting will be using support vector regression and firefly heuristic optimization [1]. The combination of SVR and FA will produce the best parameters for SVR forecasting. Moreover, Moazenzadeh et al. [2] provide the SVR and SVR-FA models more relevant results when predicting evaporation amounts lower than the threshold.

2. SUPPORT VECTOR REGRESSION – FIREFLY ALGORITHM

In this section, we are not explain the basic concept of SVR. However, the complete SVR theory can be seen at [3], [4],[5]. The first thing that needs to do is to get the lag used as input for the SVR from the ARIMA method whose parameters have a significant effect. The lag is obtained by describing the ARIMA model [6]. After finding a significant lag in the ARIMA model, a Support Vector Regression which is formed from the lag. Then some of the first data will be deleted according to the most considerable amount of lag. To obtain optimal parameter values on the SVR method cannot be done easily. The technique that is usually used to get the optimum method is the grid search method [7]. In this study optimization of the firefly algorithm will be carried out to obtain the optimum parameters in the SVR model so that the optimum accuracy value is obtained. Firefly algorithm [8] is a metaheuristic algorithm inspired by the flashing behavior of fireflies. The main purpose of the flicker of fireflies is to attract other fireflies. Dr. Xin-She Yang first discovered this algorithm at the University of Cambridge in 2007 [9]. There are three basic formulations in this algorithm:

1. All fireflies are unisex so that Firefly will be attracted to other fireflies regardless of their gender.

2. Attractiveness is proportional to brightness, so fireflies with lower light will move towards fireflies with brighter brightness and brightness decreases with increasing distance. If there are no fireflies that have the intensity, fireflies will move randomly.

3. The brightness level of fireflies is determined by the location of the objective function of fireflies.

The intensity of light at a certain distance from the light source obeys the inverse square law. Means, the intensity of light decreases with increasing *r* distance. In addition, the air absorbs light so that light becomes weaker as distance increases. These two combined factors make most visual fireflies have a boundary distance. Blinking fireflies can be formulated in such a way that an optimized objective function is formed.

In the process of optimization problems, the brightness of a firefly's light is proportional to the value of the objective function. Other forms of brightness can be defined in the same way for fitness functions in genetic algorithms. Based on these three regulations, the necessary steps of the firefly algorithm (FA) can be summarized as the following pseudo-code.

Table 1. Pseudo-code Firefly

Algorithm Firefly

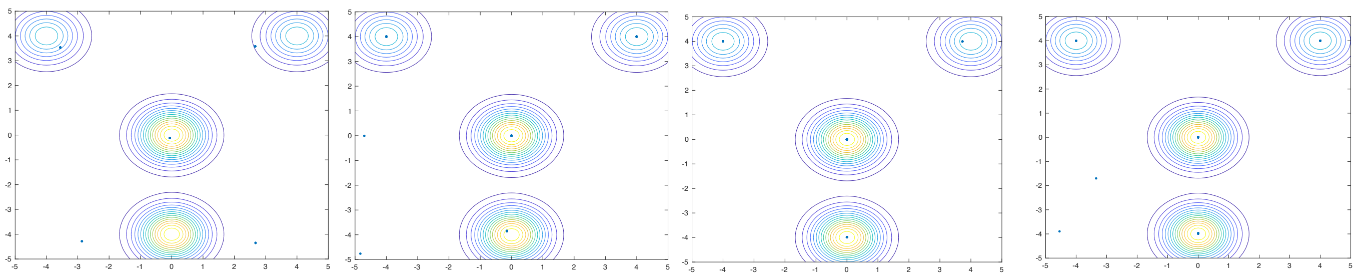
Objective function $f(x), x = (x_1, \dots, x_d)^T$
Initializing firefly populations $x_i, (i = 1,2, \dots, n)$
Determine the light absorption coefficient *γ*
    while (*t* < Max Generation)
    for *i = 1 : n* all of *n* firefly
    for *j = 1 : i* all of *i* firefly
Light intensity *Ii* to xi decided by $f(x_i)$
    if (*Ij* > *Ii*)
Move *I* firefly towards *j* on dimension *d*
    end if
Population attraction with distance *r* in *exp [−γ r]*
Evaluate new solutions and update light intensity
    end for *j*
    end for *i*

In the firefly algorithm[10], two essential things need to be considered, namely variations in light intensity and formulation of attraction. it can be assumed that the attractiveness of a firefly is determined by the brightness intensity that depends on the formulation of the objective function. In a simple case for a maximum optimization problem, the brightness of a firefly in a given location *x* can be formulated as *I(x)αf(x).* The attraction of *β* is relative, it can be obtained from the sight of other fireflies. Attractiveness will vary with the distance of *rij* between *I* fireflies and *j* fireflies. In addition, the intensity of light will decrease with increasing distance of fireflies from light sources, and the surrounding environment also absorbs light.

So, we can vary the attraction to the degree of absorption γ. The parameter γ explains the variation of attraction, and the value of γ is significant in determining the speed of convergence and how the behavior of the FA algorithm. The third term is randomization with α as the randomization parameter, and *εi* is a vector of random values taken from a Gaussian distribution or uniform distribution. For example, the simplest form of *εi* can be generated from random, which is a uniform random number generator between values 0 to 1

3. ANALYSIS

In this paper using firefly algorithm with parameter settings alpha = 0.3 (Randomness 0-1, highly random), gamma = 0.8 (Absorption coefficient), and delta = 0.7 (Randomness reduction). Then the parameters with different parameters will be carried out as seen in figure 1.



(A) (B) (C) (D)

Fig 1 Firefly optimization 500 iteration (A), 700 Iteration (B), 800 iteration (C), 1000 iteration (D)

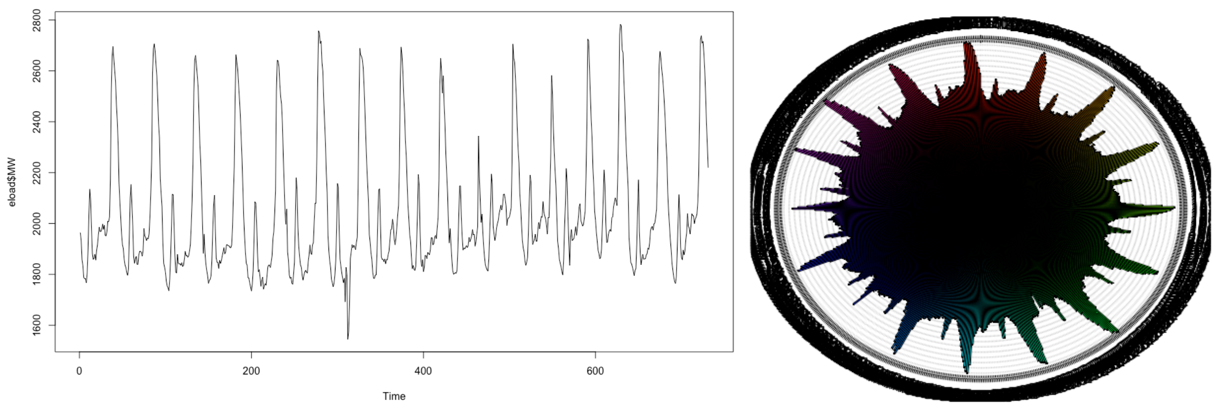


Fig 2 Time series plot (left), and clockplot (right)

Based on Figure 2, it can be seen that there is a seasonal identification of the electrical data. After construction model we get the SARIMA $(0,1,1)(0,1,1)^7$ model has been formed with the following equation

$Z_t = Z_{t-1} + Z_{t-7} - Z_{t-8} - 0.42a_{t-1} - 0.82a_{t-7} + 0.22a_{t-8} + a_t$ Moreover, The model will be used as an input lag, namely Lag 1, Lag 7 and Lag 8 on the SVR model. In research we only use radial basis kernel so that the actual and prediction data can be seen in Figure 3. Actual (Blue) and prediction (red) lines are close together so that it can be said that the SVR Firefly algorithm gives very good results with MAPE values of 0.0243% RMSE 87.417

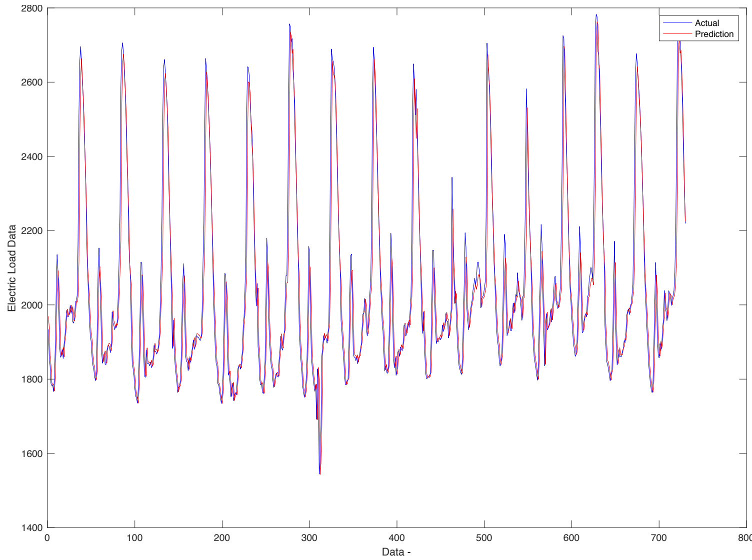


Figure 3. Actual VS Prediction

CONCLUSION

Based on the simulation, the parameters in the SVR are proven to be carried out with the Firefly algorithm. The most important thing is scaling Γ must be following the optimization problem. If Γ is a particular scale for the optimization problemgiven, for the population of fireflies $n >> k$, parameter k itself is the optimum local value, so the initial position of fireflies the number n must be distributed relatively evenly throughout the space Search. Then if the iteration is continued, fireflies will go towards a local optimal (including global ones). With comparing the best solution among all these optimal values, optimal global will be achieved. Recent research shows that the algorithm fireflies will approach global optimal when $n \rightarrow \infty$and $t >> 1$. There are two important things in limiting search cases fireflies, when $\gamma \rightarrow 0$ and $\gamma \rightarrow \infty$. For $\gamma \rightarrow 0$, attraction constant $\beta = 0$ and $\Gamma \rightarrow \infty$, it can be said that the intensity of light is notreduced in ideal space.

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