A Wind Forecasting Model Using Regression and Genetic Algorithm to Solve Economic Dispatch for Evaluating a Hybrid Power System

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Abstract

This research discusses a problem of finding an evaluator to determine a location to build the stand-alone power system. This research consequently suggests that the problem be solved with Kernels Regression where it receives 2 inputs such as time and wind speed to predict the future wind speed. Afterward, the obtained predicted wind speed is converted into potential electrical energy with maximum and minimum energy. The Genetic Algorithm (GA) is used to solve the Economic Dispatch (EDC) to see the operational cost when it is dispatched into the grid. The data were taken from Baron Techno-Park and PLTH Pantai Baru from September to December in the rainy season. The significant parameters shows that Baron Techno-Park has the least operational cost than PLTH Pantai Baru. Hence, the creation of renewable power plants in Baron Techno-Park are suitable and will have a good operational cost justification.

Keywords: *Economic Dispatch, Genetic Algorithm, Kernels Regression Standalone Power Plant.*

1. Introduction

In developing countries, the supply of electricity is not distributed well to the population. In some cases, small villages in remote areas still lack electricity every day. Conventional power system grid does not work in developing countries because of some factors, such as impossible terrains and dispersed populations. The high cost of supplies to remote areas makes the power company not even beset for this population living in these areas to receive electricity. One solution that can be applied for a village-scale system in remote areas is a stand-alone power system. A stand-alone power system can be a various combination (Hybrid) and the most widely used system are a combination of wind generators, solar panels, diesel generators, and rechargeable batteries. This such system is referred to as the remote hybrid power system (RHPS). The advantage of this system is the cost-effective and ecologically friendly solution. One of the sources for this stand-alone power system is wind. The wind forecasting then is one of important aspects in a stand-alone power system, as it can predict the wind pattern and also see the potential energy of that area to build a stand-alone power system. Therefore, we can conduct a simulated optimization to the stand-alone power system by having a dispatch with the local thermal plant. This procedure that can predict the wind and optimize the system at the same time can help to evaluate the true potential of an optimized state of the area and whether or not a stand-alone power system can be built in these remote areas.

The case study for the data is to gather at two locations in Indonesia. It is conducted on a government research facility that focuses on a stand-alone power system that supplies to local businesses, mostly tourism sites. The data that are gathered can be used as an example to be examined for other remote areas and can be implemented with this specification from these two locations, and that's where the wind forecasting and optimization comes in as an evaluator.

This research uses regression for wind prediction and genetic algorithms to solve the economic dispatch as an optimization control process.

2. Problem Formulation Dynamic Economic Dispatch

The electric supply industry is trying to further the efficiency of the operation in the power system. The problem formulation for Economic Dispatch (EDC) is considered as an optimization problem, which consists of an objective function and some constraints parameter. The traditional EDC problem assumes the amount of power that is supplied by a given set of units by an interval of time and the attempts of minimizing the cost of energy supply subject to the constraints of the generating units [4]. It is enough to determine whether or not such potential of the area can give a cheaper operational cost to the grid.

2.1. *Objective Function*

The objective function can be defined as a regular optimization problem, therefore, the objective is to minimize the cost of the operation:

$$C_T = \sum_{t=1}^{T} \sum_{i \in N} C_i(P_i^t) + C_w(Pw_i^t) \quad (1)$$

$T = The\ number\ of\ time\ interval$
$N = The\ set\ of\ committed\ units$
$C_i(P_i^t) = Cost\ of\ production\ P_i^t$
$P_i^t = The\ set\ of\ generation$
$C_w = Wind\ Curtailment/cost\ Pw_i^t$
$Pw_i^t = Wind\ Power\ Generation$

2.2. *Equality and Inequality Constraints*

The constraints are categorized as two types of constraints, which is the equality and inequality constraints:

- Equality constraint

Load Generation Balance

$$\sum_{i \in N} P_i^t + Pw_i^t = D^t \quad (2)$$

$D^t = demand\ satisfied\ hourly$

- Inequality constraints

Maximum and Minimum Power Generated

$$P_{min}^t \leq P_i^t \leq P_{max}^t \quad (3)$$

$$P_{min}^t \leq Pw_i^t \leq P_{max}^t \quad (4)$$

$P_{min}^t = Minimum\ power\ generated$

$P_{max}^t = Maximum\ power\ generated$

3. Prediction Technique Using Regression

One of the important tasks in mathematical statistics is to find the relationships between a set of independent variables, usually called predictor variables (inputs), and the set of dependent variables called responses (outputs). If at least one of the sets of variables is being subject to random fluctuations, possible measurement noise, or other forms of randomness the problem is known as regression [5].

Regression is a prediction method using statistical data, also known as supervised learning with the functional relationship between quantities. For example, an input could be the temperature and the output is the peak load. The relationship between the temperature and the peak load is seen when the temperature is at high degrees and the peak load will be high. This such example can be predicted as a trained data. The prediction is a constructor function and hopes that the function can predict between input and output well in general.

3.1. *Regression Visualization*

(2. 1)

The visualization of the regression can be categorized into two stages. The first stage is the training stage and the second stage is the validation/application stage. Figure 3.1 illustrates the stages with output/input function.

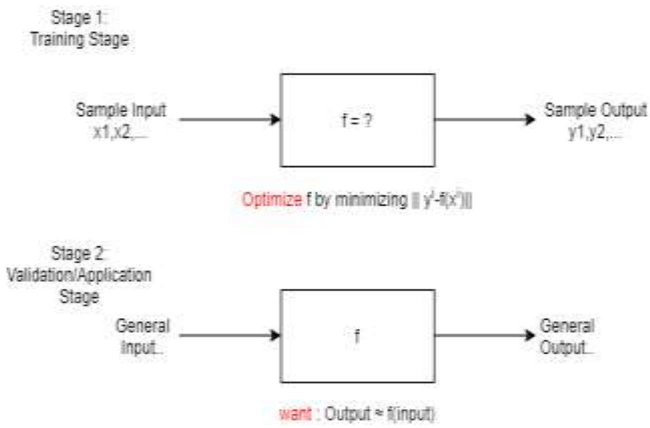

Figure 3.1 Regression Visualization

4. Genetic Algorithm and Regression Method

4.1. *Foundation of the Genetic Algorithm*

The Genetic Algorithm (GA) is a search and optimization algorithm based on the principles of natural evolution, which were first introduced by John Holland in 1970. Genetic Algorithms consist of a population of individuals that is depicted as the search's space, which are explored to find the fittest individuals by producing the next generation iteratively [6]. The Algorithm is divided into five stages, which is illustrated in the flowchart in figure 4.1.

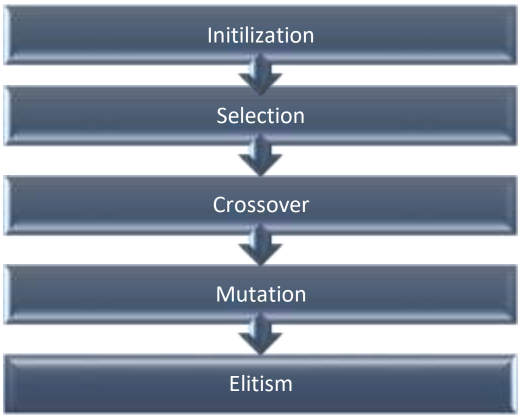

Figure 4. 1 Genetic Algorithms Flowchart Stages

4.2. *Wind Energy Conversion System*

The conversion of mechanical power derived from wind speed can be formulated down below:

$$P = \frac{1}{2}\, \rho C_p A v_w^3 \qquad (5)$$

$$C_p = c_1 \left(\frac{c_2}{\lambda_i} - c_3\beta - c_4\right) e^{-\frac{c_5}{\lambda_i}} + c_6\boldsymbol{\lambda} \quad (6)$$

$$\frac{1}{\lambda_i} = \frac{1}{\boldsymbol{\lambda + 0.08\beta}} - \frac{0.035}{\boldsymbol{\beta^3 + 1}} \qquad (7)$$

$$\boldsymbol{\lambda} = \frac{\mathbf{r}\boldsymbol{\Omega}}{v_w} \qquad (8)$$

$P = Mechanical\ power\ (Mega - watts)$
$\rho = Air\ density\ ({}^{kg}/_{m^3})$
$A = Swept\ Area\ (m^2)$
$v_w = Wind\ speed\ ({}^{m}/_{s})$
$C_p = Nonlinear\ function\ of\ tip\ ratio\ speed$
$(TRS)\ and\ turbine\ pitch\ angle$
$\mathrm{r} = Turbine\ radius\ (m)$
$\Omega = Turbine\ angular\ velocity\ ({}^{Rad}/_{s})$
$\beta = Blade\ pitch\ angle\ (Degrees)$
$\lambda = Tip\ speed\ ratio\ ({}^{m}/_{s})$
$c_1 = 0.5176$
$c_2 = 116$
$c_3 = 0.4$
$c_4 = 5$
$c_5 = 21$
$c_6 = 0.0068$
$c_1 – c_6 = Coefficients\ turbine\ pitch\ angle$

5. Results and Discussion

This section aims to respectively test and confirms the validity of the proposed prediction formulation from section 3 and simulate the optimization method of section 4. Therefore, the solution can be analyzed to find its main goal which is finding the potential power and optimization of a remote power plant through the EDC problem. The method of use is the kernel function as a predictor of wind speed and power conversion formula to include its power potential. The genetic algorithm is used later as the optimization stage.

5.1. *9 Generators Operational Cost Data and Demand for 24 Hours*

To find the optimization of the EDC for the system, the remote power plant is integrated with the conventional grid. In this case, the grid which is used is of the study case for a ten-unit generator. This research is only taking into account operational cost [8].

Table 5. 1 Ten Units Generator Specification

g	a ($/MW^2)	b ($/MW)	c ($)	P_g^{min} (MW)	P_g^{max} (MW)
g1	0.00048	16.19	1000	150	455
g2	0.00031	17.26	970	150	455
g3	0.00200	16.60	700	20	130
g4	0.00211	16.50	680	20	130
g5	0.00398	19.70	450	25	162
g6	0.00712	22.26	370	20	80
g7	0.00079	27.74	480	25	85
g8	0.00413	25.92	660	10	55
g9	0.00222	27.27	665	10	55
g10	0.00173	27.79	670	10	55

The unit 11th generator is the stand-alone power system or the wind power plant whose predicted wind speed is converted into mechanical energy. It takes the average power to obtain the minimum and maximum power to be used as the limit in the inequality constraints that can be seen in table 5.3 and table 5.1 consists of the 10 unit thermal generator which is dispatched with the stand-alone power system.

Table 5. 2 Hourly Demand (24 hours)

Time (Hours)	1	2	3	4	5	6	7	8	9	10	11	12
Demand (MW)	700	750	850	950	1000	1100	1150	1200	1300	1400	1450	1500
Time (Hours)	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Demand (MW)	1400	1300	1200	1050	1000	1100	1200	1400	1300	1100	900	800

Table 5. 3 Wind Turbine Degree Polynomial, Error, Max and Min Power

Months	Number Of Polynomial Degree (N)	Relative Error (%)	Average Wind Speed (m/s)	Maximum Power Baron (MW)	Minimum Power Baron (MW)	Maximum Power Pantai Baru (MW)	Minimum Power Pantai Baru (MW)
September	5	5.7775	2.0260	89.2191	1.7690	76	1
October	5	5.3110	2.1849	83.1941	34.6820	47	0
November	5	3.2116	2.4093	98.2238	65.2174	68	2
December	5	5.4232	2.4285	97.0616	68.7051	71	6

5.2. *Wind Prediction Results Using Kernels Regression*

The wind data were provided by Baron Techno-Park and PLTH (Hydro Power Plant) Pantai Baru. Considering PLTH Pantai Baru only gave us one year of data which was in 2019, therefore we only used the data given from the Baron Techno-Park and PLTH Pantai Baru as a comparison.

As for the wind prediction, we only used the data that is from September, to December and in 2017-2019. These four months are used because it is in the rainy season where mostly the velocity is at its highest. The results for each prediction can be seen in Table 5.3.

As we can see in table 5.3 the maximum average wind speed in September is the lowest speed with 2.0260 m/s, month of October with 2.1849 m/s, month of November with 2.4093 m/s, and month of December with the highest wind speed 2.4285 m/s, during which the predicted data using the polynomial degree of N = 5, accumulated a relative error below 20 %, in our case it’s a small margin error which can be tolerated.

After power conversion using the formula for mechanical power, some variables are given:

Frequency = 60 Hz

$r = 1.3$ (Radius of turbine or length of blade (Meters))

$Omega = 2 * pi * r * frequency$

((Angular speed (Rad/s)) (9)

$\beta = 35.5$ (Blade pitch angle (Degrees))

$\rho = 1.225$ (Air density (Kg/m^3))

$A = pi * r^2$ (Wind turbine swept area (m^2))

Coefficients:

$c1 = 0.5176$

$c2 = 116$

$c3 = 0.4$

$c4 = 5$

$c5 = 21$

$c6 = 0.0068$

The converted power on the table shows that the power produced from relative velocities of 2.4 m/s and blade radius of 1.3 m, can have a maximum power less than 97 MW and a minimum power less than 69 MW.

Table 5. 4 ***Baron Techno-Park and PLTH Pantai Baru Cost for Each Month***

Location	Baron Techno-Park	PLTH **Pantai Baru**
September	687400	680990
October	662200	674880
November	688070	677090
December	687050	679330

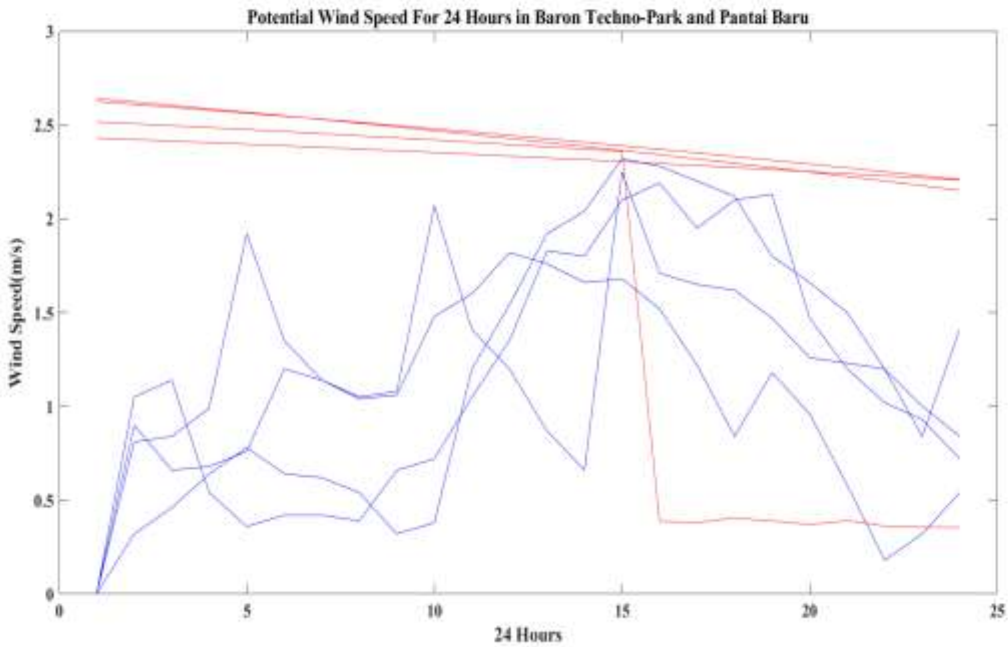

Figure 5. 1 Baron and Pantai Baru Energy per Currency

Figure 5.1 shows the wind speed for both locations, and it shows that PLTH Pantai Baru (in blue) have a random and unpredictable wind speed that shows no pattern, therefore it's hard for a wind turbine to obtain optimal energy. In the other hand Baron Techno-Park (in red) wind is relatively from high velocity to low velocity regarding the time for 24 hours.

5.3 Energy per Currency for 24 Hours

Energy per Currency for each hour tells us how much it costs to produce that much energy to supply to the demand. In our case, Baron Techno-Park and PLTH Pantai Baru, the RHSP is dispatched with a 10 generator thermal plants. Afterward, the minimal operational cost for each hour is found by having the power produced (watt) divided by the total operational cost ($) in our case the power produced for each hour.

$$\frac{Power \quad Produced\ each\ hour\ (24\ Hours)}{Total\ Operational\ Cost} = {watt}/_{\$}. \quad (10)$$

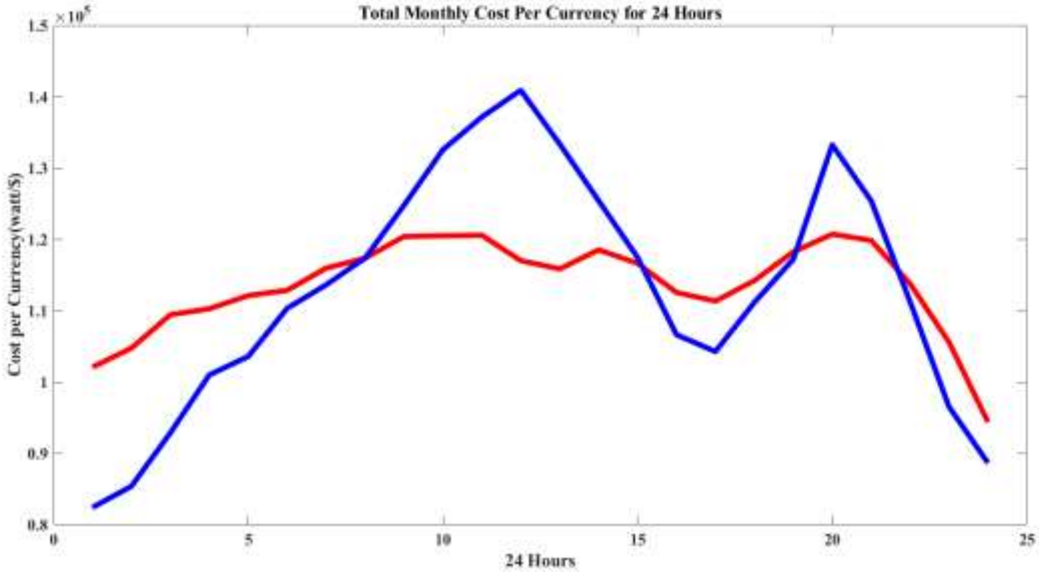

Figure 5. 2 Baron and Pantai Baru Total Monthly Energy per Currency

As shown in figure 5.2 above the energy per currency (watt/$) shows the operational cost for both locations for each hour. In this case, the total operational cost is counted from September to December. The dispatch unit with 10 thermal generators and the stand-alone power plant, Baron Techno-Park (in red) has less operational cost compared to PLTH Pantai Baru (in blue). As seen as well in power generated in table 5.3, the difference between power generated Baron Techno-Park from PLTH Pantai Baru is quite significant. Hence, the power system tends to consider using the cheaper renewable energy where it does not consider fuel cost.

6. Conclusion

6.1. *Conclusion*

After a comprehensive consideration into evaluating the potential area to build an RHPS, this article considers two locations, Baron Techno-Park and PLTH Pantai Baru which are located in Yogyakarta, Indonesia. Concerning suitable wind speed in Baron Techno-Park and PLTH Pantai Baru, using kernel regression save not only PC memory but also computing time. The predicted wind speed from Baron Techno-Park from September to December also has the relative error of, 5.7775 %, 5.3110 %, 3.2116 %, and 5.4232 %, respectively, with the average wind speed, 2.026 m/s, 2.1849 m/s, 2.4093 m/s, and 2.4285 m/s. The specification for power conversion is r = 1.3 meters (Radius of turbine or length of blade) and β = 35.5° (Blade pitch angle), with the coefficients: c1 = 0.5176, c2 = 116, c3 = 0.4, c4 = 5, c5 = 21, c6 = 0.0068. The maximum power limit of Baron Techno-Park for four evaluated months are 89.2191 MW, 83.1941 MW, 98.2238 MW, and 97.0616 MW, and the minimum limit are 1.7690 MW, 34.6820 MW, 65.2174 MW, 68.7051MW. Whereas, the maximum power limit of PLTH Pantai Baru from September to December are 76MW, 47 MW, 68 MW, and 71 MW, and the minimum power limit are 1 MW, 0 MW, 2 MW, and 6 MW.

From the electricity Operational Cost point of view, the amount of electricity production by the stand-alone power plant (wind power) with 10 thermal generators from Baron Techno-Park from September to December equals to 687400 ($/day), 662200 ($/day), 688070 ($/day), and 687050 ($/day).While the amount of electricity production by the stand-alone power plant (wind power) with 10 thermal generators from PLTH Pantai Baru equals to 680990 ($/day), 674880 ($/day), 677090 ($/day), 679330 ($/day). Therefore, the significant parameters show that Baron Techno-Park has less operation cost than PLTH Pantai Baru. Then, the creation of renewable power plants in these areas is suitable and will have a good operational cost justification when connected to the grid.

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