www.rericjournal.ait.ac.th

Modeling of Power Characteristic Curve on Small Scale Compressed Air Energy Storage using Regression Analysis

Widjonarko*[,1], Rudy Soenoko[+], Slamet Wahyudi[+], and Eko Siswanto[+]

Abstract – *The research on small scale compressed air energy storage (SS-CAES) becomes an interesting topic especially in optimizing the performance of the system. In this topic, the characteristic curve of the energy storage system is the key to control the system to reach optimum power to the load. In previous research, mathematical equations were used to get the characteristic curve. This paper proposes the polynomial regression based on the actual output data from the prototype to model the characteristic curve of the SS-CAES prototype. The authors have compared the use of mathematical models and polynomial regression in modeling the power curve with actual observational data and determining the level of accuracy of modeling. The results showed that by using polynomial regression, the characteristics of the SS-CAES prototype power curve could only be obtained by using the sample data from the system output with accuracy value 0.967 for R-square. Thus, an approach using this method would facilitate researchers to obtain the characteristics of the curve of the system.*

Keywords – *modeling, optimization, polynomial regression, power curve, small scale compressed air energy storage (SS-CAES).*

1. INTRODUCTION

Energy development in this era began to become a very crucial topic to discuss. This problem comes due to the high use of fossil energy in several countries, which results in climate change on earth [1]. Therefore, several studies are focused on solving this topic and one of which is by utilizing renewable energy combined with storage technology [2],[3]. By using energy storage, high energy requirements can be backed up with other energy sources that have been stored in the past [4]. This stored energy is then discharged to support the load peak shaving on the power grid [5]–[12]. One of the technologies used is compressed air energy storage (CAES). CAES was chosen because it promises high reliability with low environmental impact compared to other energy storage technologies because it does not produce waste in the process of its utilization [13]–[15]. Besides, CAES also does not degrade over time and is relatively cheap on an energy base [14],[16],[17]. Another advantage is CAES can also be combined to support other renewable energy sources to solve problems such as low power density and an unpredictable nature [18]–[21]. CAES technology consists of two storage tank constructions: namely construction for large-scale and small scale technology. The constructions of large-scale CAES technologies are A-CAES, D-CAES, and I-CAES [22],[23]. This large scale system has a weakness; it has dependence on geological formations because it requires a large air storage space to store energy. Therefore, the small scale-CAES (SS-CAES) system is an alternative solution with more compact storage tanks, higher system portability, and higher adaptability even with distributed or self-directed energy production [24], [25].

One topic related to the development of SS-CAES technology researches is optimizing the system performance during the process of air discharge from the stored tank [25]–[27], which in this case is also a topic that continues to be developed in various applications, especially in the optimization of a system at other plants such as renewable energy [28]–[30]. One of them is the research conducted by Lydia, *et al.* [31] where the modeling techniques to determine the performance curves of wind turbines installed in wind farms was used as a reference in controlling wind turbines.

In a research using optimization topic, to transfer the maximum energy at the load which will be provided, the researcher must know the characteristics of the operating point of the system. The characteristics of the point operation are in the form of a 3D curve with three variables, which are power, pressure and speed of airmotor. By knowing the characteristic curves, the system can be optimized to achieve its maximum power transfer. The way to do it is by referring to the controls on the variables of the air pressure and the air motor speed according to the power curve to get the maximum power transfer. One of the studies utilizing this technique was carried out by Lemofouet, *et al.* [32]. In this study, SS-CAES was controlled to achieve maximum efficiency from the air discharge process in the air tank. The power curve variable used to achieve maximum efficiency were air pressure and air motor speed. In other studies such as by Martinez, *et al.* [33], the SS-CAES power curve were also used. In this study, SS-CAES was controlled to reach the maximum power point. The variables used for control were air pressure and air motor speed. Also, Kokaew *et al.* research used the power curve as a reference for his control [25], [26],

*Electrical Engineering Department, Universitas Jember, Jalan Kalimantan No. 37, Jember, East Java, Indonesia.

[+]Mechanical Engineering Department, Universitas Brawijaya, Jalan Mayjend Haryono No. 167, Malang, East Java, Indonesia.

[1]Corresponding author;
Tel: + 62 813 5822 3843, Fax: + 12 345 678 980 10.
E-mail: widjonarko.teknik@unej.ac.id.

[34]. In their study, Kokaew *et al.* used the characteristic curves of the SS-CAES formed to obtain optimal and maximum power transfer. The parameters used were air pressure and air motor speed. From several studies that have been mentioned, it shows that the characteristics of SS-CAES are essential for system control optimization.

To know the characteristics of SS-CAES, it can be obtained by formulating a mathematical equation of the installed components. Then, some parameters needed to form a power curve in the mathematical equation of the system built [25]–[27] are entered in that mathematical equation. Some of the parameters are certain coefficient variables or certain constants of component that have been installed. Unfortunately, this will undoubtedly take a long time to know if the coefficients and constants are unknown and need to be measured first. Therefore, this paper described an alternative method to obtain the model of characteristic the power curve on SS-CAES based on empirical data derived from the prototype and polynomial regression instead of modeling mathematics from the SS-CAES system. By using this technique, the relationship between variables that enter the regression process will be found without needing to enter the coefficient and constants needed in mathematical techniques. Thus, it will make it easier to know the power curve by ignoring these values [35]–[37].

In other studies, there have been several studies that discussed the use of polynomial regression, to be able to predict the characteristics of data. Some of the studies included [37] used polynomial regression to analyze transient responses from PEM fuel cells. In other research carried out by Fumo *et al.* [38], this regression technique was used to predict the energy consumption in residential buildings. In Lydia *et al.* [31] research, this technique was also used to model the characteristics of wind turbine generators in certain wind farms. However, there has never been a study of the use of polynomial regression to know the characteristics of the curve in the SS-CAES. Therefore, this study focused on exploring the use of regression techniques in the SS-CAES to model the power curve. The regression polynomial technique that was used in this study is to utilize the empirical output data from the SS-CAES. The output data were taken using a sampling technique, which were then regressed and produced an equation that represented the entire SS-CAES power curve.

In this paper, the researcher had modeled the power curve on SS-CAES prototype with a power capacity 50W by using empirical sampling data output. By using these data, the modeling of the power curve was formed using the regression process, then an equation that represented the power curve was obtained [39]. For validating the results of the power curve modeling in this paper, the modeled data were compared using conventional ways, which was by using mathematical equations and observed data obtained directly from the prototype to determine the accuracy of the proposed method.

2. DATA GATHERING

The data used in this study come from observational data taken on a prototype that had been designed. In the data retrieval process, fifteen (15) data were taken to get the power curve parameters of SS-CAES by installing different load values for each sampling data. The load used was a resistor with several values: 9.6, 56, 100, 122, 270, 313, 330, 364, 430, 440, 560, 600, 920, 1000, 2200Ω. The parameters were the air pressure parameters passing through the air motor (*pAir*), the speed of the air motor (ω) and the power generated by the DC (P) generator [23]. The process of taking these parameters was carried out by running the prototype at the discharge stage of the air tank and installing different loads on each of its data retrieval [21] with the range of air pressure from 0.2 to 3 bar.

The designed prototype is shown in Figure 1. There were several sensors installed in it to extract the power curve forming parameters from the SS-CAES. The first was a pressure sensor mounted after the air valve to measure the air pressure that passed through the air motor. The second was the speed sensor to measure the rotational speed between the air motor and the DC generator (shaft). The third was a power sensor which was a combination of current and voltage sensors. The results of these two sensors then were multiplied to obtain the power generated by the DC generator. As in the data retrieval process the power parameters on the prototype ran at the discharge stage, the data logger installed to the prototype was to facilitate data retrieval from the four sensors.

There are four types of sensors that were used and implemented in the prototype. First was a voltage sensor which was made by using the principle of the voltage divider. The second was a speed sensor using a hall effect sensor. The third was the air pressure sensor using MPX 5010, and the fourth was the current sensor using ACS712. All sensors used had been calibrated, so the value that appeared in the sensor was the real value of the measured parameter. As to save data from all sensors installed, personal computers were used as dataloggers. The figure of the prototype that had been built can be seen in Figure 2.

The data taken in this session were data when the system was given air with a range of 0.2-3 bar, so that the data obtained were 29 data for each session. Table 1 is an example of data retrieval performed at load 560Ω.

As for the data at the next load, the authors also took them using the same way and the data were saved in the datalogger. So, the total data received was 435 data (15 loads x 29 data per session). For each session, the data taken were the same as the data contained in Table 1. That data were from four sensors, which were in the form of voltage, current, velocity and air pressure. Then, the the power parameter was the result of the voltage and current multiplication.

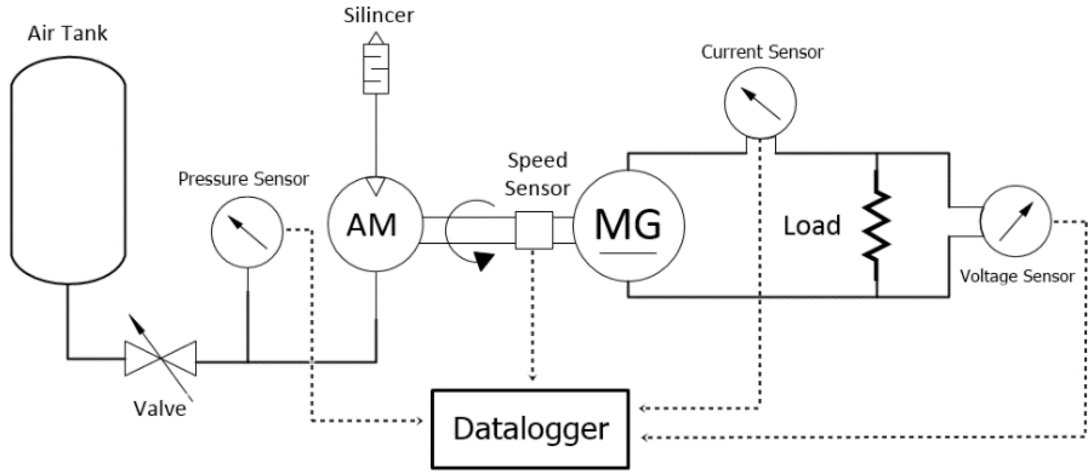

Fig. 1. Prototype scheme.

Fig. 2. The prototype SS-CAES.

Table 1. Examples of data logger at a load of 560 Ω.

Parameter	Data 1	Data 2	Data 3	Data n	Data 29
Voltage (V)	0.1	10.5	15.45	...	59.13
Current (A)	0.1	0.02	0.03	...	0.11
Power (P)	0.01	0.21	0.47	...	6.50
Speed (RPM)	202	1000	1623	...	6522
Pressure (Bar)	0.2	0.3	0.4	...	3

3. METHOD AND EXPERIMENTAL SETUP

3.1 Method

The data processing method in this study can be seen in Figure 2 which consist of two (2) main flow blocks diagram. The first block is a block that is often used in previous research, which is a mathematical block. To be able to find out the power curve in the system, the mathematical equation for each component of the system needed to be found. Then each mathematical equation was connected into the physical relationships between components. After the equation was combined, then several parameters were entered into the formula, and the power curve of the system was formed.

The second block is the method used in this study. It used empirical data derived from observation data taken directly on the SS-CAES prototype. In this study, fifteen (15) sampling data were taken which were then divided into two sub-data. The first sub-data was the data used as a regression process. There are four (4) data from fifteen (15) data sampling data. Those data were two load data with small resistive values (9.6 Ω, 56 Ω) and two load data with big resistive values (1000 Ω, 2200 Ω). The reason for using the sampling data on that load was to model the power data that passed between the highest and the lowest power, that occured due to the load by using on the resistive load. The power data between the highest and the lowest power could be predicted and known by using polynomial regression so that the overall power curve of the SS-CAES prototype can be modeled and known.

The third block was the measured data block. This block was the data (11 data) that had been obtained in the data observation process. These eleven data were gotten by dividing the total of the observation data used in this study. The observation data were fifteen (15) data with four (4) of which were used for the regression process, so the eleven (11) data were obtained from this. These measured data were used as comparative parameter data from the success of this method, or it can be known as the data test from the predicted output from the regression process. The use of this data (measured data) will be used to compare output data from the two previous methods. So, after each power curve results are known in each method, the next step is to compare data on each result obtained with the measured data to determine the degree of accuracy. For more details, the flow of research methods in this study can be seen in Figure 3.

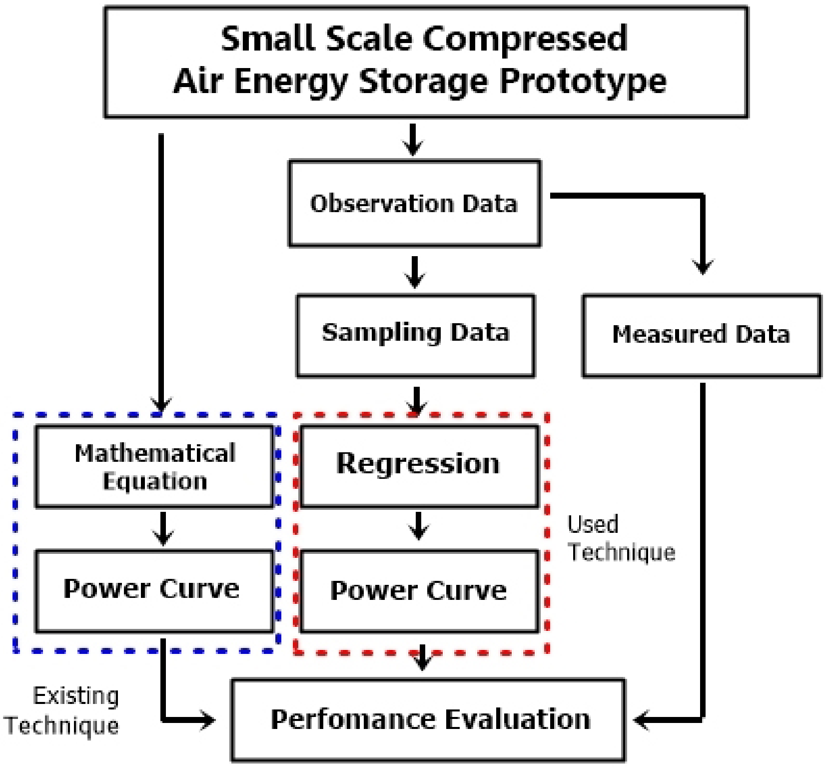

Fig. 3. Data processing block.

Figure 4 is the flow of the regression method process used. After the data were obtained, the sampling data used to form the modelling of characteristic curves (four (4) data from fifteen (15) sampling data taken) were selected. Next, the polynomial degree was set to obtain an appropriate equation to represent the modelling curve. When the value of the degree set was completed, the result of the equation was evaluated using statistical parameters to determine the resulting error rate and suitability. If the results obtained when changing the polynomial degree were not the best results, then the polynomial degree was changed, and the process continued until it found the best parameters of this regression process. The parameters used were R-square, RMSE (root mean square error) and SSE (sum of square due error) [40].

3.2. Experimental Setup

Determining the power curve it was done in two ways. The first was by using a mathematical equation and the second was by modeling the power curve by using the polynomial regression approach.

3.2.1. Mathematical Approach

3.2.1.1. Air Motor

The air motor used was manufactured by Prona. To be able to know the characteristics of the air motor, the researcher must first know the characteristics of the air motor used by looking at the performance curve on the datasheet issued by the factory. The following equation was used to know the motor torque (M) [41].

$$M = \frac{1}{2\pi}.Vg.p_{it}\eta_p.\eta_m \tag{1}$$

where M is air motor torque, Vg is the displacement of the motor, $Ƥ_{it}$ is theoretically shown pressure, η_p filling efficiency and η_m mechanical efficiency by having value for the piston motor with the connecting rod mechanism $\eta_p = 0.85 \div 0.9$ and for the motor with the shear mechanism, $\eta_m = 0.9 \div 0.92$. While to know the motor power of the air, Equation 2 can be used [41], [42].

$$Ps = Vg.n.p_{it}.\eta_p.\eta_m \tag{2}$$

where Ps is the power of the air motor, the ηp filling efficiency depends on the linearly variable velocity where $\eta_p = 1 - \alpha.n$, α expresses the inclination line, so it could be substituted into Equation 3 [41],[42].

$$Ps = Vg.n.p_{it}.\eta_m - Vg.n^2.p_{it}.a.\eta_m \tag{3}$$

Air consumption (*Qn*) calculated for normal atmospheric conditions could be approximately calculated from Equation 4 [41],[42].

$$Qn = Vg.n.\frac{p1}{pN}.\delta.\frac{1}{\eta_Q} \tag{4}$$

where η_Q flow efficiency has a value between 0.85 to 0.95 depending on the design and motor used. δ is called coefficient of filling, it ranges from 0.45 to 0.7, $p1$ is true value of indicated pressure and pN is the number of vane.

3.2.1.2 DC Motor Generator

For permanent DC motors, the dynamic behavior generator is driven by a prime mover (an air motor) obtained by Newton's second law [25], as follows.

$$T_{am} - (B_{mam} - B_{mg})\omega_{ram} - T_{eg} = (J_{am} + J_g)\frac{d\omega_{ram}}{dt} \tag{5}$$

where T_{am} is airmotor torque, while the back emf / torque (E_{ag}) constant of the generator could be calculated by Equation 6 [25] as follows:

$$E_{ag} = K_m\omega_{ram} \tag{6}$$

The load torque (T_{eg}) for an air motor was the electromagnetic torque generator, that was:

$$T_{eg} = K_e i_{ag} \tag{7}$$

Where i_{ag} is an armature current generator, ω_{ram} is the angular velocity of the air motor and the generator incorporated in one shaft, the rag is armature resistance, Lag is the inductance value of the generator winding rotor, V_t is the voltage terminal; K_e is the constant torque; K_m is the constant velocity, B_{mam} and B_{mg} are the viscous friction coefficient of the air motor and the respective generator and J_{am} and J_g are the moments of inertia of the air motor and generator.

3.2.2. Regression Approach

For modeling the power curves of SS-CAES, curve analysis using the linear regression technique was applied. Because the parameters in SS-CAES power curve are formed based on three variables; two independent variables (pressure air pressure through air motor (*p*Air) and air motor rotation speed (ω), and one dependent variable is power (P)). Then multiple linear regression was used [43].

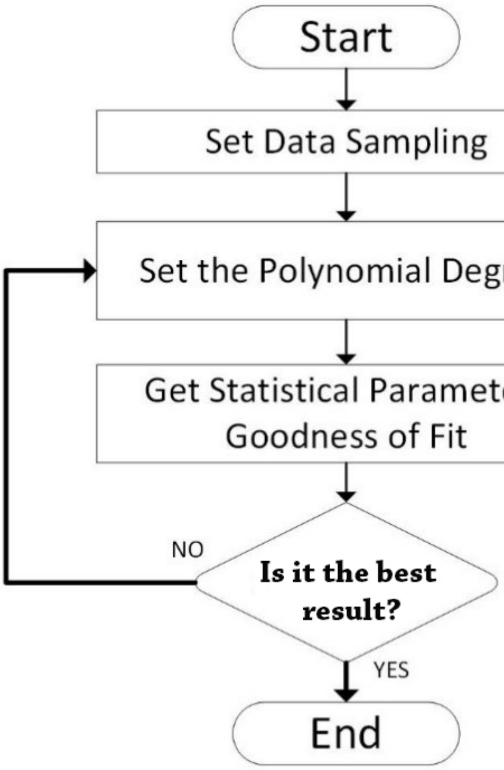

Fig. 3. Data processing block.

3.2.2.1 Multiple Linear Regression Analysis

Multiple linear regression is one of the multivariate techniques used to estimate the relationship between one dependent variable metric with a set of independent variables of metric or non-metric. By multiple regression analysis, the researcher can estimate and/or model the average value (population) of one dependent variable based on two or more independent variables. Regression analysis will produce an equation / regression model [43], [44]. Multiple regression analysis is different from correlation analysis which only yields correlation value. In the correlation analysis, what is being analyzed is the existence of a relationship between two variables and how strong the relationship. Whereas in the analysis of multiple regression, it is how big the influence of a variable (hereinafter referred to as independent variable) to other variables (hereinafter referred as the dependent variable) that is being analyzed.

$$Y_j = b_0 + b_1X_{1j} + b_2X_{2j} + ... b_kX_{kj} + e_j \quad (8)$$

More complex can be represented as an equation:

$$Yj \;= \sum_{i=1}^{k} b_i X_{ij} + \; e_j \quad (9)$$

where Yj is the predicted value of the dependent variable, bi is the regression coefficient for the predictor variable Xi, Xij is the case measurement j on the predictor variable i, k is the slope of the regression surface against the variable Xj and ej is the random error component for the i-th case [43], [44].

In order to know the accuracy of this technique, there are several statistical parameters that can be used as a reference in this regression process.

3.2.3. Performance Analysis

3.2.3.1 SSE (Sum of Squares Due Error)

SSE is the sum of the values of the overall quadratic difference between each observed value and the value of the group average. This parameter represents the size of the variation in a cluster. If all cases in the cluster are the same or have a small error value, then SSE will be equal to zero (0) [45].

$$SSE = \sum_{i=1}^{n} (yi - \hat{y})^2 \quad (10)$$

where n is the number of data, the i is the i-th value and ŷ is the overall mean value.

3.2.3.2 RMSE (Root Mean Square Error)

RMSE is the average value of the sum of the squares error, it can also state the size of the error generated by a forecast model. The low RMSE score indicates that the variation of the value generated by a forecast model approaches the variation in its observed value or can be said to have a higher degree of accuracy [45].

$$RMSE = \sqrt{\frac{SSE}{n}} \quad (11)$$

3.2.3.3 R-square

R-square is the parameter used to measure the goodness of the regression equation or it can be said that R-square is the ratio between the value of the amount of error value predicted by the regression process (SSRegression, sum of squares regression error) with the total error or SSE. So it can be said that R-square gives the proportion or percentage of total variation in the dependent variable described by the independent variable. The value of this R-square is in the range between 0 - 1, and the model match is represented when R-square is closer to 1 [45].

$$SSRegression = \sum_{i=1}^{n} (yi - yRegression)^2 \quad (12)$$

$$R - Square = 1 - \frac{SSRegression}{SSE} \quad (13)$$

where, yRegression is the value generated from the regression.

4. RESULT AND DISCUSSION

By using the flowchart in Figure 4, the polynomial regression process will be carried out. After four (4) data are selected, then the regression process is carried out. In this case (regression analysis), the best degree is obtained by using fifth-degree equations. For the best statistical parameters obtained from this regression process, it can be seen in Table 2. It is important to note that there are two results obtained from the method which uses the regression process algorithm flow. The first one is the result of fit regression data using statistical parameters and the second one is the equation which represents the modeling curve.

Table 2. Statistical performance of the curve fitting.

R-square	RMSE	SSE
0.998	1.03	13.79

From this statistical performance parameter, the regression accuracy can be determined by referring to parameters R-square (from Equations 12 to 13) which value is 0.998 or 99.8%. The square error or RMSE is 1.03 (from Equation 11) and the total error of SSE is 13.79 (from Equation 10). However, this parameter is not related to the level of accuracy that will be compared with all observation data (that process will be performed on performance evaluation), because this statistical performance parameter (Table 2) is a statistical parameter that compares the data used for the regression process with the data generated through the regression approach, the parameter in Table 2 is a parameter that represents the suitability of the four (4) data used to form a polynomial regression equation, so the data in Table 2 cannot describe the predicted accuracy of the overall power curve to be searched for in this study. Therefore, the next step needs to be done. The next step is to enter the values of the speed (ω') and air pressure ($pAir'$) parameters in the equation that comes from the polynomial regression process.

For the equation obtained from the regression process it can be seen in the Equation 14, where the equation consists of variable ω' which is the speed rotation of the air motor angle after through the process of centering and scaling, variable pAir' which is the pressure through the air motor after through the process of centering and scaling and with f (ω', pAir') is P which is the power generated by the generator.

$$f(\omega',pAir') = 25.79 - 9.616\omega' + 15.97pAir' + 12.8\,\omega'^2 + 2.227\omega' pAir' - 3.084pAir'^2 - 3.332\,\omega'^2 pAir' - 1.347\omega' pAir'^2 + 4.834pAir'^3 + 0.8784\omega'^2 pAir'^2 -0.08372\omega' pAir'^3 + 0.8799pAir'^4 - 0.7256\omega'^2 pAir'^3 + 1.343\omega' pAir'^4 - 1.751pAir'^5 \quad (14)$$

with center and scale for ω is normalized by mean 3661 and std 2046 and pAir is normalized by mean 2 and std 1.018.

Where:

$$\omega' = \frac{(\omega - \text{mean})}{std} \quad (15)$$

$$pAir' = \frac{(pAir - \text{mean})}{std} \quad (16)$$

From that equation, the modeling curve can be formed and can be seen in Figure 5 which is a representation of the SS-CAES modeling curve generated by the regression process.

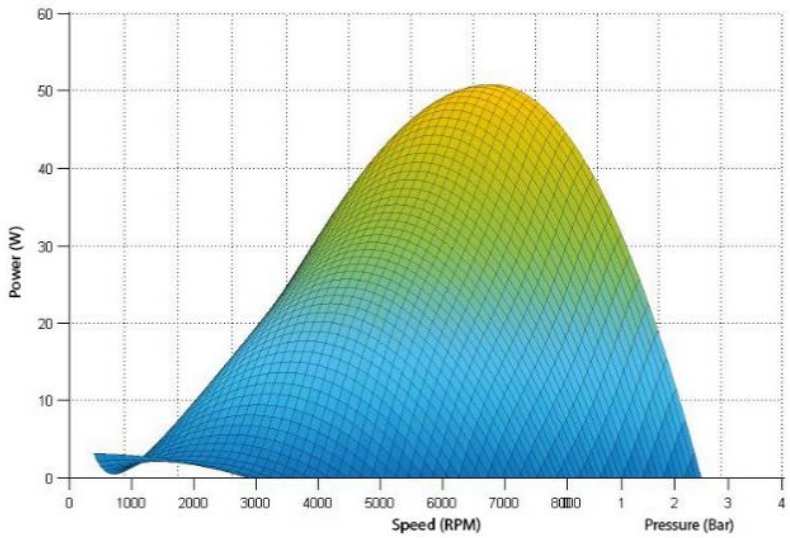

Fig. 5. Curve characteristic modeling.

Table 3. Statistical performance on both methods.

Parameter	Mathematical	Regression
SSE	219.401	845.746
RMSE	0.736	1.445
R-square	0.997	0.967

In Figure 5, three axes are representing the SS-CAES curve. The X-axis represents the speed (RPM) of the shaft, the Z-axis represents the pressure (bar), and the Y-axis represents power (W). In Figure 5 there are color differences. The color difference is based on the energy produced. Blue represents low power (0-20W), green represents middle power (21-40W), and orange represents high power (40-50W).

For analyzing the accuracy of the curve which is produced by two different processes (mathematical and regression), a performance evaluation will be done on both methods. This comparing process will be done with all observed data that have been obtained in two ways. The first way is to use statistical parameters to know the accuracy of the techniques used based on SSE, RMSE, and R-square statistical parameters. The second way is to use the graphs in the data load to know the accuracy in the trend line form. For the first evaluation, the statistical performance was obtained from both approaches as shown in Table 3.

In Table 3, there are parameters of information related to SSE, RMSE and R-square. In the mathematical curve approach, the resulting SSE is 219.401 (from Equation 10) with RMSE is 0.736 (from

Equation 11) and accuracy or R-square is 0.997 (from Equations 12 to 13) from actual measurement. Meanwhile, the regression approach using polynomial with SSE 845.746 (from Equation 10), with RMSE is 1.445 (from Equation 11) and the R-square value is 0.967 (from Equations 12 to 13). From the results obtained show that the accumulated error (SSE) occurs in the regression approach is higher than the mathematical method. This is because the polynomial regression is the approximation of the model by using the polynomial curve function, so the value appears to have a curve-shaped approach. These can be seen and analyzed in the form of trend graphs at each load to be performed on the second test.

For the second test is to compare the four power data generated by the polynomial regression technique and the mathematical approach with measured data on observation by using the graphic. In this test, the data obtained from two ways of approach (regression and mathematical) will be tested with two types of load data. The first data is the load data which is used for the regression process and the second data is the load data outside the data used for the regression. The reason why we should test the load data outside the data used for this regression process is to determine the ability of this regression technique to model the power curve outside that data. The load data used in the first type are 9.6 and 1000 Ω, and for the second load data is 100 and 560 Ω. In this test, the SS-CAES parameter (the air motor speed rotation parameter (ω) and the pressure passing through the air motor (pAir)) which obtained from the observation process will be included in Equation 14 to obtain the predictive model of the power value. Then those data will be compared to the power data obtained from the observation process. The results of the comparison can be seen in the graphic shown in Figures 6 to 9.

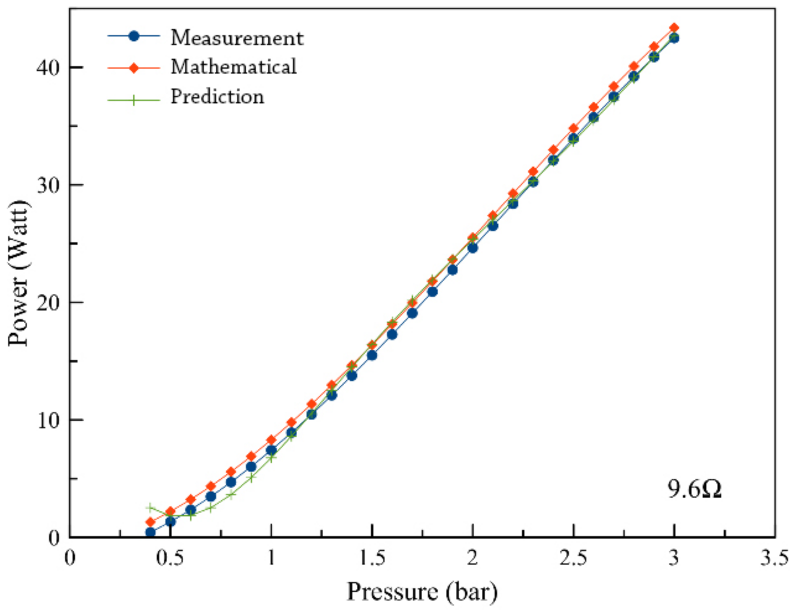

Fig. 6. The curve approach for the load is used to form the modeling curve for 9.6Ω.

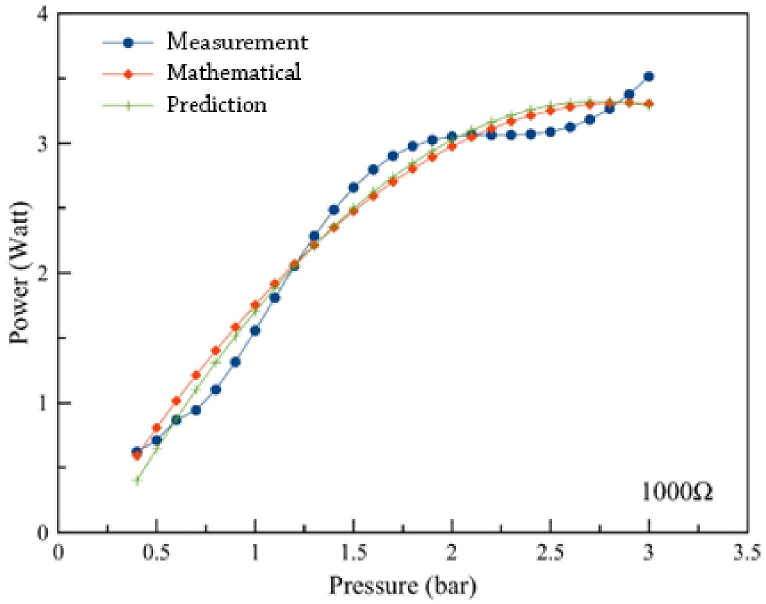

Fig. 7. The curve approach for the load is used to form the modeling curve for 1000Ω.

In Figures 6 and 7, the evaluation of the curve on the load used as the data for the regression process indicates that in both loads, both methods have a good trend-line although the predicted results has an oscillating value at the modeling of power with low pressure which can be seen in Figure 5. While in Figure 6, the oscillation value is seen at almost every pressure.

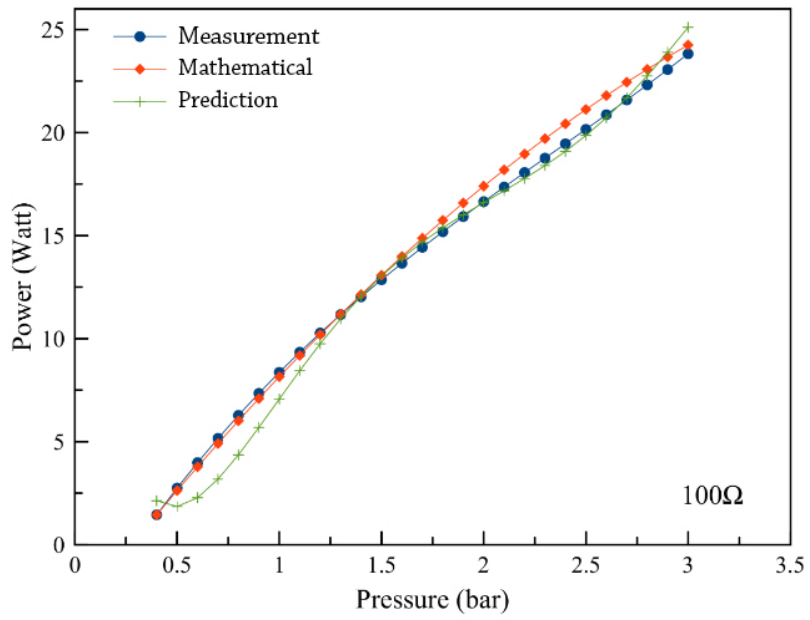

Fig. 8. Curve approach for the load 100Ω.

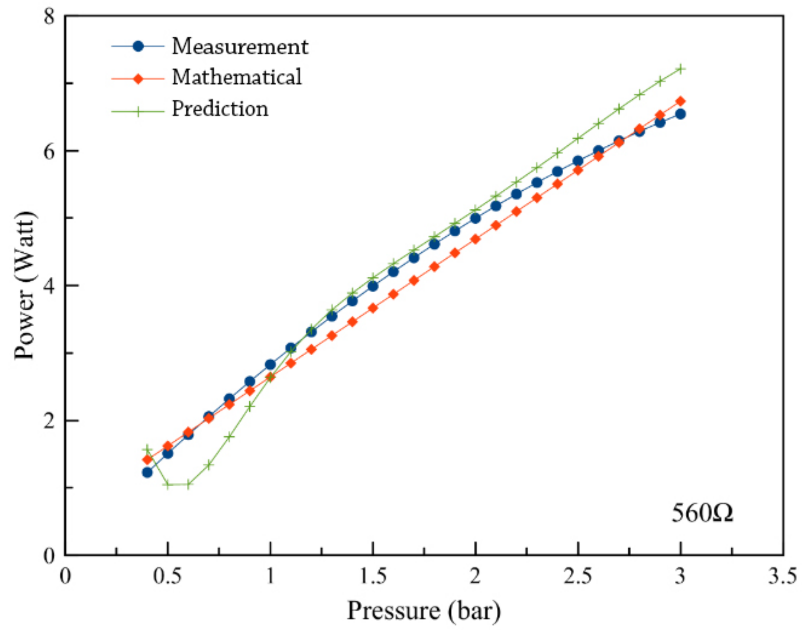

Fig. 9. Curve approach for the load 560Ω.

In Figures 8 and 9, the evaluation of the curve on another load that used as data for the regression process shows that both methods have a good enough trends-line difference. Meanwhile, the model using regression has characteristics that are still the same as the previous result that has values that oscillate on the low-pressure power modeling seen in both Figures 8 and 9.

As explained in the previous discussion on the first test of performance evaluation, the significant value of the SSE parameter contained in the regression approach is due to the use of polynomial regression. It is because the base of this approach is the approximation of a model by using curves. As the result, there is an oscillation of value in the curve form. These phenomena can be seen in Figure 7, where the oscillation values in the load data are very clearly visible and almost occur at any given pressure. It is reasonable that the RMSE value also has a lower value than the data generated through the mathematical approach.

However, such oscillations occur only in low load data as in Figure 7, whereas in high load data as in Figure 6 (load data not used as data in the regression process) the value oscillation tends to be smaller compared to the Figure 7.

For the accuracy level or R-square, both approaches have different values. The mathematical approach has a value of 0.997, while for an approach using regression value is 0.967.

5. CONCLUSION

The modeling to characterize the power curves in SS-CAES is an essential analysis tool because by knowing the characteristics of the curve, the operation of the SS-CAES system can be optimized in specific power loads. This paper has reported how to model the power curve at SS-CAES using two different methods. The first method is using the mathematical approach and the second one is using the polynomial regression approach. Both results from each approach then will be compared with the measurement data directly on the SS-CAES prototype.

Based on the results obtained in the performance evaluation step of the SS-CAES characteristic power curve, it is found that the polynomial regression approach to model the power curve has good potential. However, there are still problems in the oscillation of the curve that occurs in the specific load value. Level of accuracy obtained by using the regression technique is good enough, that is with the value of 0.967 or 96.7% to the observed data obtained. Thus, it can be said that by using this regression, the SS-CAES curve can be predicted and known, although the results obtained using this technique are still no better than using a mathematical approach. It happens because in the polynomial regression approach, there is a value oscillation in the form of the curve, so that the accumulation of errors due to the approach using regression is higher than the mathematical model. However, the use of this technique, problems to find out the power curve can be resolved without the need to go through a long process (compiling mathematical equations on each component and knowing the parameter values for each component installed). Therefore, the accuracy of using this polynomial regression technique can be developed to be able to produce a better level of accuracy.

ACKNOWLEDGEMENT

This research is supported by the LPDP scholarships under grant No. 20161141011767. The authors gratefully acknowledge Universitas Brawijaya for the support for this research.

NOMENCLATURE

A	Inclination line
B_{mam} and B_{mg}	viscous friction coefficients of the air motor and the generator, respectively.
E_{ag}	Back emf
i_{ag}	Generator armature current, ampere
J_{am} and J_g	moment of inertia of air motor and generator, kg.m^2
K_m	Constant speed, Rad/m
K_e	Constants torque, N/m
N	Value to n, n > 0
P	Power, watt
pAir’	Air pressure after centering and scalling, bar
pN	The number of vane
$\mathcal{P}_{it}$	The pressure has shown theoretically, bar
P_s	Power from the air motor, watt
$p1$	True value of indicated pressure, bar
Q_n	Air consumption
r_{ag}	Armature resistance, ohm
T_{am}	Air motor torque, N/m
Vg	Displacement of motor
V_t	Terminal voltage, volt
Ω	Electrical resistance, ohm

Greek Symbols

ω	Angular velocity, Rad/m
ω’	Angular velocity after centering and scalling, Rad/m
ω_{ram}	The angular velocity of the air motor and the generator, Rad/m
η_p	Filling efficiency
η_m	Mechanical efficiency
η_Q	Flow efficiency
δ	Coefficient of filling

Latin Symbols

Yi	value of i
$\hat{Y}$	mean of groups

Abbreviations

Mean	Average
RMSE	Root mean square relative error
SSE	Sum of squares error
SSRegression	Sum of squares regression error
Std	Standard deviation

REFERENCES

[1] Heryadi M.D. and D. Hartono. 2016. Energy efficiency, utilization of renewable energies, and carbon dioxide emission: Case study of G20 countries. *International Energy Journal* 16(4): 143–152.

[2] Lal A., Kumar R., and Mehta, U., 2014. Energy dispatch fuzzy model in hybrid power system. *International Energy Journal* 14(4): 133–142.

[3] Ellabban O., Abu-Rub H., and Blaabjerg F., 2014. Renewable energy resources: Current status, future prospects and their enabling technology. *Renewable Sustainable Energy Review* 39: 748–764.

[4] Atmaja T.D. and Amin. 2015. Energy storage system using battery and ultracapacitor on mobile charging station for electric vehicle. *Energy Procedia*. 68: 429–437.

[5] Luo X., Wang J., Dooner M., Clarke J. and Krupke C., 2014. Overview of current development in compressed air energy storage technology. *Energy Procedia*. 62: 603–611.

[6] Akinyele D.O. and R.K. Rayudu. 2014. Review of energy storage technologies for sustainable power networks. *Sustainable Energy Technology Assessments* 8: 74–91.

[7] Hussain H., Javaid N., Iqbal S., Hasan Q., Aurangzeb K., and Alhussein M., 2018. An efficient demand side management system with a new optimized home energy management controller in smart grid. *Energies* 11: 190.

[8] Lv S., He W., Zhang A., Li G., Luo B., and Liu X., 2016. Modelling and analysis of a novel compressed air energy storage system for trigeneration based on electrical energy peak load shifting. *Energy Convers.ion Management* 135: 394–401.

[9] Khamis A., Shahrieel M., Aras M., Nizam H., Shah M., Zamzuri M., and Rashid A., 2017. Design and analysis of diesel generator with battery storage for microgrid system. *International Journal of Advanced Engineering Research Technology* 5: 26–32.

[10] Lim Y., Al-Atabi M., and Williams R.A., 2016. Liquid air as an energy storage: A review. *Journal of Engineering Science and Technology* 11: 496–515.

[11] Kassim A.H., Miskon M.T., Rustam I., Mat Zain M.Y., Mod Arifin A.I., and Rizman Z.I., 2017. Optimum storage size for thermal energy storage system. *ARPN Journal of Engineering Applied Sciences* 12: 3304–3307.

[12] Han X., Liao S., Ai X., Yao W., and Wen J., 2017. Determining the minimal power capacity of energy storage to accommodate renewable generation. *Energies* 10: 468.

[13] Baqari F. and B. Vahidi. 2013. Small-compressed air energy storage system integrated with induction generator for metropolises: A case study. *Renewable Sustainable Energy Reviews* 21: 365–370.

[14] Wang J.., Lu K., Ma L., Wang J., Dooner M., Miao S., Li J., and Wang D., 2017. Overview of compressed air energy storage and technology development. *Energies* 10: 991.

[15] Chen H., Zhang X., Liu J., Tan C., 2013. Compressed air energy storage. In *Energy Storage - Technology Application*, Ahmed Faheem Zobaa, Ed., pp 101–112. doi:10.5772/52221.

[16] Aneke M. and M. Wang. 2016. Energy storage technologies and real life applications – A state of the art review. *Applied Energy*. 179: 350–377.

[17] Hadjipaschalis I., Poullikkas A., and Efthimiou V., 2009. Overview of current and future energy storage technologies for electric power applications. *Renewable Sustainable Energy Reviews* 13: 1513–1522.

[18] Sun H., Luo X., and Wang J., 2015. Feasibility study of a hybrid wind turbine system - Integration with compressed air energy storage. *Applied Energy* 137: 617–628.

[19] Li S. and Y. Dai. 2015. Design and simulation analysis of a small-scale compressed air energy storage system directly driven by vertical axis wind turbine for isolated areas. *Journal of Energy Engineering* 141:1–11.

[20] Krupke C., Wang J., Clarke J., and Luo X., 2017. Modeling and Experimental study of a wind turbine system in hybrid connection with compressed air energy storage. *IEEE Transactions on Energy Conversion* 32: 137–145.

[21] Saadat M., Shirazi F.A., and Li P.Y., 2015. Modeling and control of an open accumulator compressed air energy storage (CAES) system for wind turbines. *Applied Energy* 137: 603–616.

[22] Budt M., Wolf D., Span R., and Yan J., 2016. A review on compressed air energy storage: Basic principles, past milestones and recent developments. *Applied Energy* 170: 250–268.

[23] Salvini C., 2018. CAES systems integrated into a gas-steam combined plant: Design point performance assessment. *Energies* 11: 415.

[24] De Lieto Vollaro R., Faga F., Tallini A., Cedola L., and Vallati A., 2015. Energy and thermodynamical study of a small innovative compressed air energy storage system (micro-CAES). *Energy Procedia* 82: 645–651.

[25] Widjonarko, Soenoko R., Wahyudi S., and Siswanto E., 2019. Comparison of intelligence control systems for voltage controlling on small scale compressed air energy storage. *Energies* 12: 803.

[26] Kokaew V., Sharkh S.M., and Moshrefi-torbati M., 2016. Maximum Power point tracking of a small-scale compressed air energy storage system. *IEEE Transactions Industrial Electronics* 63: 985–994.

[27] Proczka J.J., Muralidharan K., Villela D., Simmons J.H., and Frantziskonis G., 2013. Guidelines for the pressure and efficient sizing of pressure vessels for compressed air energy storage. *Energy Conversion Management* 65: 597–605.

[28] Isaloo B.A. and P. Amiri. 2016. Improved variable step size incremental conductance MPPT method with high convergence speed for PV systems. *Journal of Engineering Science and Technology* 11: 516–528.

[29] El Hammoumi A., Motahhir S., Chalh A., El Ghzizal A., and Derouich A., 2018. Low-cost virtual instrumentation of PV panel characteristics using Excel and Arduino in comparison with traditional instrumentation. *Renewables: Wind. Water, Solar* 5: 3.

[30] Babu R.N., and P. Arulmozhivarman. 2013. Wind energy conversion systems - A technical review. *Journal of Engineering Science and Technology* 8: 493–507.

[31] Lydia M., Kumar S.S., Selvakumar A.I., and Prem G.E., 2014. A comprehensive review on wind turbine power curve modeling techniques. *Renewable Sustainable Energy Review* 30: 452–460.

[32] Lemofouet A.R., 2005. Hybrid energy storage systems based on compressed air and supercapacitors with maximum efficiency point tracking. In *2005 European Conference on Power Electronics and Applications.* Dresden, Germany, 11-14 September.

[33] Martínez M., Molina M.G., and Mercado P.E., 2010. Dynamic Performance of compressed air energy storage (CAES) plant for applications in power systems. In *2010 IEEE/PES Transmission and Distribution Conference and Exposition: Latin America (T&D-LA)*, 8-10 November 2010, Sao Paulo, Brazil, pages 496–503.

[34] Kokaew V. and S.M. Sharkh. 2014. A hybrid method for maximum power tracking of a small scale CAES system. *International Symposium on Communication System, Networks Digital Sign (CSNDSP)* 9: 61–66.

[35] Niu F., Yu Y., Yu D., and Li H., 2015. Heat and mass transfer performance analysis and cooling capacity prediction of earth to air heat exchanger. *Applied Energy* 137: 211–221.

[36] Ostertagová E., 2012. Modelling using polynomial regression. *Procedia Engineering* 48: 500–506.

[37] Edwards R.L. and A. Demuren. 2016. Regression analysis of PEM fuel cell transient response. *International Journal Energy Environment Engineering* 7: 329–341.

[38] Fumo N. and M.A.R. Biswas. 2015. Regression analysis for prediction of residential energy consumption. *Renewable Sustainable Energy Reviews* 47: 332–343.

[39] Soni B.P., Saxena A., and Gupta V., 2015. A minimax polynomial approximation objective function approach for optimal design of power system stabilizer by embedding particle swarm optimization. *TELKOMNIKA Indonesia Journal of Electrical Engineering* 14: 191–198.

[40] Chin H.C., Haur K.F., and Tan M.L.P., 2015. Empirical modeling of a graphene field-effect transistor sensor. *Journal of Computational and Theoretical Nanoscience* 12: 161–167.

[41] Dvoĝák L. and K. Fojtášek. 2017. Calculations of parameters and mathematical model of rotary air. *EPJ Web of Conferences* 143: 2016–2019.

[42] Luo X., Wang J., Shpanin L., Jia N., Liu G., and Zinober A.S.I., 2008. Development of a mathematical model for vane-type air motors with arbitrary n vanes. *Proceedings of World Congress Engineering 2008* I:1–6.

[43] Hayes A.F., 2013. *Introduction to Mediation, Moderation, And Conditional Process Analysis.* 2nd Edition. New York : The Guilford Press.

[44] Wang Z., Yi D., Duan X., Yao J., and Gu D., 2012. *Measurement Data Modeling and Parameter Estimation*. CRC Press, Boca Raton.

[45] Darlington R.B. And AF. Hayes. 2016. *Regression Analysis and Linear Models: Concepts, Application and Implementation*. New York: Guilford Press.