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Analyzing the Relationship Between Meteorological Parameters and Electric Energy Consumption Using Support Vector Machine and Cooling Degree Days Algorithm

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Abstract

Nowadays, electricity is increasing rapidly. This increase is caused by several factors, one of which is meteorological factors. Meteorological parameters have various types, but this research uses three types in the form of temperature, humidity, and wind speed. The selection of these three types is due to the fact that they have a very close relationship with human life. In line with that, this research uses datasets obtained from the official websites of BMKG (Meteorology, Climatology and Geophysics Agency) and PLN (State Electricity Company). On this occasion, researchers used several methods, namely Cross-Industry Standard Process for Data Mining (CRISP-DM), Cooling Degree Days (CDD), and Support Vector Machine (SVM). The CRISP-DM method is useful for describing the data mining cycle so that the process can be more organized. The SVM algorithm is useful for predicting electricity consumption based on meteorological parameters in January to April 2024, while the CDD method is useful for knowing the correlation of meteorological parameters to electricity consumption in winter. In line with this, this research produces predictions of electricity consumption based on meteorological parameters in January 2024 to April 2024 with an average range of 20.9 Watts per day. In addition, trends and predictions during model evaluation obtained a precision value of 0.796, recall of 0.793, F1 score of 0.793, MAPE of 17.2%, RMSE of 0.41, MAE of 0.167 and accurate of 0.98. These values indicate that the performance of the accuracy model is very high.

Keywords: Electricity, CDD, SVM CRISP-DM, Meteorological parameters

1. INTRODUCTION

Today, technology is developing so rapidly that it is not surprising that companies are competing in applying technology to help smooth the company's daily activities. This is because technology is a form of real contribution in helping

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human activities [1]. Along with the mass application of technology, electricity demand has increased from time to time. The increase in electricity demand is influenced by several factors such as human activity and meteorological parameters.

Meteorological parameters are among the measurement media that focus on weather symptoms that occur in the atmospheric layer [2]. The meteorological parameters used for the research are three elements, consisting of temperature, humidity, and wind speed. These three elements were chosen because they are closely related to human life. Meteorological parameters also serve to determine electricity consumption based on meteorological aspects in a region, so that people can find out the factors that cause an increase in electricity consumption caused by natural factors.

In line with that, there are previous studies that discuss the prediction of electricity consumption based on temperature and humidity in an area. Research conducted by Moon Keun Kim in 2020 aims to determine electricity consumption based on temperature and humidity in a campus building. This research uses two methods consisting of artificial neural network and linear regression. The use of these two methods aims to determine electricity consumption based on temperature and humidity in a campus building. This research produces electricity predictions in real time in the long term. However, this research has a weakness in the electricity consumption based on temperature and humidity, considering that temperature and humidity do not have a big effect on electricity consumption, so for future research it is expected to consider input data that has a greater influence on electricity consumption. [3]

The second research conducted by Ahmad Almuhtady in 2019 used the Heating Degree Day (HDD) and Cooling Degree Day (CDD) methods with piecewise linear functions. CDD and HDD are useful for measuring the number of degrees that the daily average temperature rises above or below a threshold value within a certain period. This study resulted in a sensitivity in electricity consumption in hot weather of 11% and was at 32.9°C, while in cold temperatures it experienced a sensitivity of 16.4% at 4.7°C. However, this study encountered difficulties in determining the base temperature and selecting the procedure for calculating degree days, which varied depending on the resolution of the weather data used. [4]

Research conducted by Musaed Al Hussein in 2020 is useful for predicting short-term electricity consumption of household customers in the residential sector using the LSTM (Long Short-Term Memory) and CNN (Convolutional Neural Network) algorithms [5]. This research results in the prediction of household electricity consumption that has regular and irregular usage. However, the method

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used for this research increases the overall Mean Absolut Percentage Error (MAPE) average, this can be seen in relatively large outliers. Correspondingly, the MAPE value obtained is 40.38% in the prediction of household electricity load [6].

This research was conducted by Nur Ezzati Mohd Izudin in 2021, this research is useful for developing Autoregressive Integrated Moving Average - Artificial Neural Network (ARIMA-ANN) hybrid models by considering the strengths of ARIMA and ANN in linear and nonlinear modeling, this modeling is useful for predicting accurate electricity consumption thereby increasing the reliability of the electric power system. This research resulted in the ARIMA-ANN model having a MAPE value of 0.0188. This value means that electricity consumption forecasting can be done well and has high accuracy [7].

Research conducted by Farshad Kheiri in 2023 used the split-degree day method, this method has better results in the accuracy of estimating energy use in buildings in the US compared to the conventional degree day method. By using the split degree day method, this research can improve more than 5% in the accuracy of total annual energy use prediction, 8% in predicting heating energy use, 0.3% in predicting cooling energy use, and 33% in predicting fan energy use. In addition, the analysis shows better results for models with higher thermal mass and models with a 24-hour operating schedule. This improvement is due to the divided degree-day method including more information related to the weather characteristics of a location, which does not rely on aggregated data at daily intervals like the conventional degree-day method [8].

Based on previous research, this research focuses on knowing the correlation of meteorological parameters with electricity consumption. In knowing the correlation between meteorological parameters and electricity consumption, this research uses the SVM [9] and CDD algorithms. The SVM algorithm was chosen because this algorithm does not have overfitting problems. In addition, the CDD algorithm is a measurement that utilizes low temperatures in an environment.

2. METHODS

As well as, other activities that require methods to get optimal results. This research also applies various methods that have been visualized in the form of figure 1. Based on Figure 1, information is obtained stating that this research uses a series of methods in determining optimal results. The first step in this research is data acquisition, then proceed to the preprocessing process to remove outliers, after the data is cleaned, the data is processed into modeling using SVM. After getting the curve from the modeling process, the next step is evaluation where the data will be calculated using confusion matrix, MSE, and RMSE. After the stage is well completed, the last step is deployment using Power BI.

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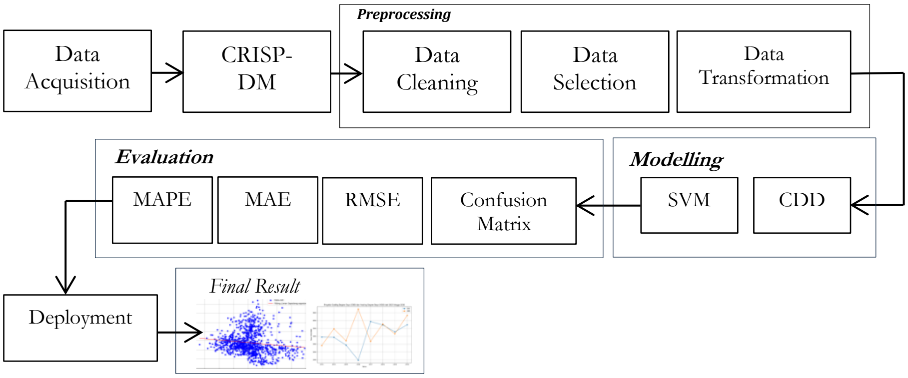

Figure 1. SVM and CDD trends related to electricity consumption

2.1 Data Acquisition

Data acquisition is the initial stage of a research, considering that this stage is used to find a dataset related to the research [10]. This research uses secondary data that is open data obtained from government agencies such as BMKG and PLN. This dataset obtained from the BKMG agency contains data dates and meteorological parameters in the form of temperature, humidity, and wind speed. In Table 1 is a dataset that comes from BMKG.

Table 1. BMKG Dataset

Data_Date	Humidity	Wind velocity	Temperature
2023-04-01 07:00:00	75.56	1575	25.28
2023-04-01 14:00:00	92.9	0.545	22.4
2023-04-01 15:00:00	93.2	0.364	22.03
2023-04-01 16:00:00	94	0.641	22.05
2023-04-01 17:00:00	94.2	0.012	21.89

Based on Table 1, information can be obtained that states each meteorological parameter has a different value even though the dates are the same. In line with that, the BMKG dataset totals 25,872 data, considering that each date has a diverse dataset depending on the time. In Table 2 is a dataset that comes from PLN.

Based on Table 2, information can be obtained stating that every hour the electricity consumption generated is different. Given, the use of electronic devices for each time is different. In line with that, the PLN dataset totals 3,762 data, considering that each date has a diverse dataset depending on the time.

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Table 2. PLN Dataset

Data_Date	Electricity
2023-04-01 07:00:00	28.298
2023-04-01 14:00:00	33.227
2023-04-01 15:00:00	25.846
2023-04-01 16:00:00	38.458
2023-04-01 17:00:00	39.574

2.2 CRISP-DM

2.2.1 Preprocessing

Preprocessing is a stage to perform an initial process in data processing, which aims to avoid disturbing data. (noise) or inconsistent data [11][12]. In this research, the preprocessing stage is used for data selection, data deformation, data cleaning and data disposal that does not have its own function. Correspondingly, this stage has three stages consisting of:

1) Data Cleaning
At this stage, it is done by removing data that contains missing values. This removal is carried out with the aim of making the prediction more accurate. Correspondingly, in this study, all columns in df1 and df2 were cleaned using the dropna function.

2) Data Selection
At this stage, the data used for training and testing in svm is selected. The data used as training and testing utilizes the train test split feature. Data selection is carried out which is used for training and testing in the form of training by 80% and testing by 20%.

3) Data Transformation
At this stage, data such as date_data is converted from integer data type to datetime data type. Correspondingly, at this stage the data is merged using merge data. This data merging is done to accelerate prediction using SVM and accelerate HDD and CDD calculations.

2.2.2 Modelling

Modeling is one of the CRISP DM stages that aims to create predictive or descriptive models [13]. At this stage, the data will be processed using CDD and SVM algorithms. The use of these two algorithms aims to find out the predictions

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along with the optimal model. The following is modeling using the CDD and SVM algorithms.

1) CDD

CDD is one of the temperature measurement media that uses low temperatures in environment. CDD is a measure of how hot the temperature is a certain period [14]. Meanwhile, CDD is a measurement index used to predict the amount of energy used for cooling in the summer [15]. In this study, CDD is used to determine the correlation of electricity consumption based on meteorological parameters in the cooling season, such as shown in Figure 2.

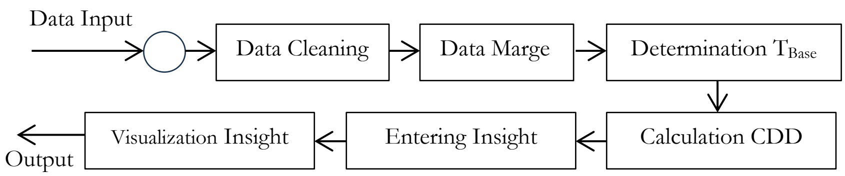

Figure 2. CDD algorithm

Based on Figure 2, information can be obtained stating that determining the base temperature (Tbase) aims to analyze the heating needs already needed in an area. In this study, Tbase was set at 18 degrees Celsius, this is because the temperature of 18 degrees Celsius shows that electricity consumption increases, considering that the tools used to warm the body are starting to be applied. In line with that, the determination of Tbase also has an impact on the resulting insight, this is because if the Tbase is too low or too high, it can result in an inaccurate estimate of electricity consumption needs. Correspondingly, CDD is applied to find insights in the dry season with a short period of time, such as a week.

2) SVM

Support Vector Machine (SVM) is one of the algorithms in python that is used to make predictions, predictions can be either classification or regression [16]. SVM is derived from a combination of computational theories that already existed in the previous year, such as margin hyperplane [17]. As well as, other algorithms that have usage techniques, SVM also has a technique that serves to get optimal hyperplane. This separation is done in order to make observations on target variables that have different values [18].

As such, it can solve problems related to data classification. Therefore, it is not surprising that it has more complex mathematical formulas than other algorithms. In fact, it has no overfitting problem even though the amount of data processed is small, as shown in Figure 3.

Based on Figure 3, information can be obtained stating that data that has been processed using the HDD and CDD algorithms, will be processed using the SVM

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algorithm to produce predictions. In line with that, the first step in using SVM is to determine the X and Y values used for testing and training data, for the X value filled in the meteorological parameter column, the Y value is filled in the electricity column, then the training data division is 80% and testing is 20%.

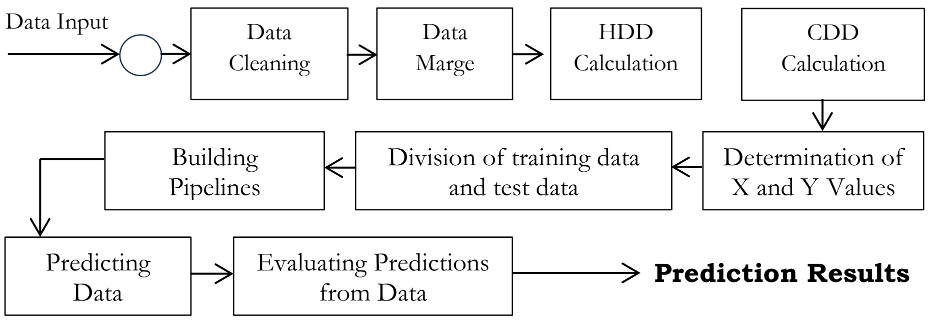

Figure 3. SVM algorithm

After that, initialize the numeric_feature column with meteorological parameters, then this column will initialize the pipeline using the SimpleImputer() and StandardScaler() functions. After that, build the pipeline using the RBF kernel, after that training the pipeline model with the training data in the numeric_features column, the trained model will make predictions by utilizing the testing data in the numeric_features column. After the prediction is generated, the last step is model evaluation. This evaluation aims, so that the model can be known for its accuracy value.

In this research, SVM is used to predict electricity consumption based on meteorological parameters. For the x value in SVM is denoted as a meteorological parameter, while the y value is denoted as electricity consumption. As is the case, the x1 value comes from humidity data, the x2 value comes from wind speed data, temperature data is denoted by x3, while the y value is obtained from electricity data. The x and y values will be used to obtain the hyperplane. Hyperplane comes from the calculation of weight and bias functions.

2.3 Evaluation

At this stage is the interpretation stage of a data mining result shown in the modeling process that has been carried out previously [19]. This modeling is done with Confusion Matrix, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), dan Mean Absolute Percentage Error (MAPE).

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1) Confusion Matrix

Confusion matrix Confusion matrix is one of the evaluation methods that shows the number of correctly classified test data and incorrectly classified test data [20]. This method is a table containing formulas to calculate accuracy, recall, precision, and error. In Table 3 explains the confusion matrix

Tabel 3. Confusion Matrix

		ACTUAL	
		Positive	**Negative**
PREDECTION	**Positive**	*True Positive (TP)*	*False Positive (FP)*
	Negative	*False Negative (FP)*	*True Negative (FP)*

Based on table 3, information is obtained stating that accuracy is calculated based on the formula ((TP+TN)/(TP+TN+FN+FP)), recall is obtained from the formula (TP)/(TP+FN), while precision is obtained from the formula ((TP)/(TP+FP)) [21][22].

2) RMSE

Root Mean Square Error (RMSE) is one of the evaluation methods of a model based on the error value of the estimation results. Correspondingly, the lower the value produced by RMSE, the closer the prediction model is to the actual value [23]. In this research, RMSE serves to evaluate the prediction results and correlation of meteorological parameters to electricity consumption.

3) MAE

Mean Absolute Error (MAE) is one of the types of model evaluation methods based on the average error value between the actual value and the predicted value [24]. As well as, RMSE is used to evaluate, MAE is also used to evaluate the prediction results and correlation of meteorological parameters to electricity expenditure.

4) MAPE

Mean Absolute Percent Error (MAPE) is one of the types of accuracy evaluation methods in value prediction. MAPE can give an indication of the prediction error compared to the actual value. Correspondingly, a low MAPE value means that the resulting prediction is accurate, but if the MAPE value is high, the resulting prediction value is inaccurate [25].

2.4 Deployment

This Deployment stage will explain the process after applying the machine learning model or algorithm to the production environment. In addition, Deployment is the last stage of the research, considering that this stage is the stage of

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implementing the entire model that has been built, and adjustments are made to the resulting model with the aim that the model can meet the standards that have been carried out previously [26].

In the context of this research, I used Power BI after going through the steps of data acquisition, preprocessing, and modeling with the CDD and SVM algorithm. The use of Power BI as a deployment media, because Power BI can visualize the data that has been processed before, which then the visualization will be published directly through the website [27]. The deployment step aims to generate probability estimates of meteorological parameters with electricity. These estimates obtained from meteorological parameters on weekdays and weekends are used to predict electricity expenditure.

3. RESULTS AND DISCUSSION

3.1 Electricity Consumption Based on Temperature Every Month

Electricity consumption has increased over time, due to various factors. One of the factors that increase electricity consumption every month is temperature. Temperature is a factor that is directly proportional to electricity consumption, considering that the increase in temperature is due to humans using electricity in the dry season more often than in the rainy season. Correspondingly, in Figure 4 there is a visualization related to electricity consumption based on temperature every month.

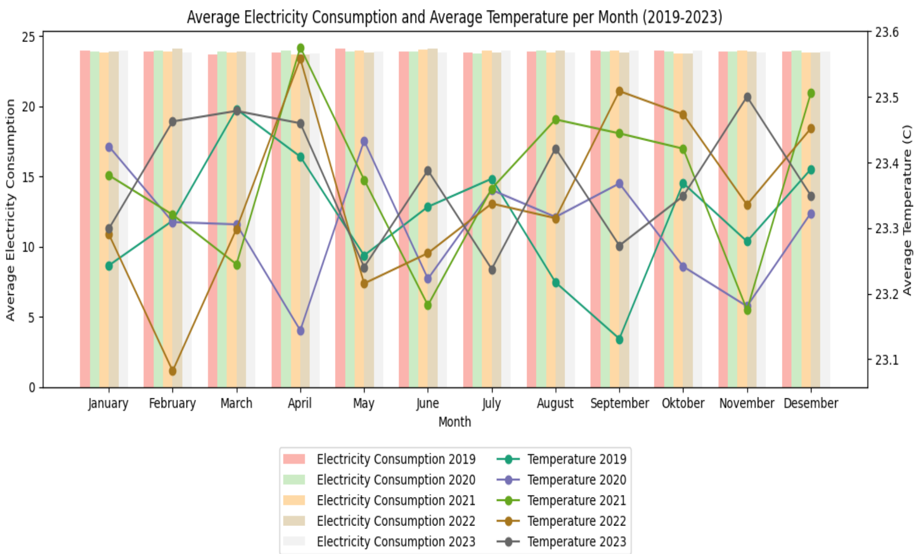

Figure 4. Electricity consumption based on temperature

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Based on Figure 4, information can be obtained stating that electricity expenditure caused by temperature fluctuates. Given that in 2023, the smaller the temperature in an area, the greater the electricity consumption, this can be seen in January, July, September, and October, besides that high temperatures cause relatively less electricity consumption, such as February to April where the temperature is higher than January but the electricity expenditure is less. Likewise, from 2019 to 2022, the increase in electricity consumption is influenced by low temperature.

3.2 Electricity Consumption Based on Humidity Every Month

Electricity has increased over time, the increase in electricity consumption can be caused by various factors. One of those factors is meteorological parameters. Meteorological parameters have various types, one of which is humidity. In line with that, this research states that humidity has a relatively considerable influence on increasing electricity consumption. Figure 5 shows that humidity is one of the factors that increase electricity consumption.

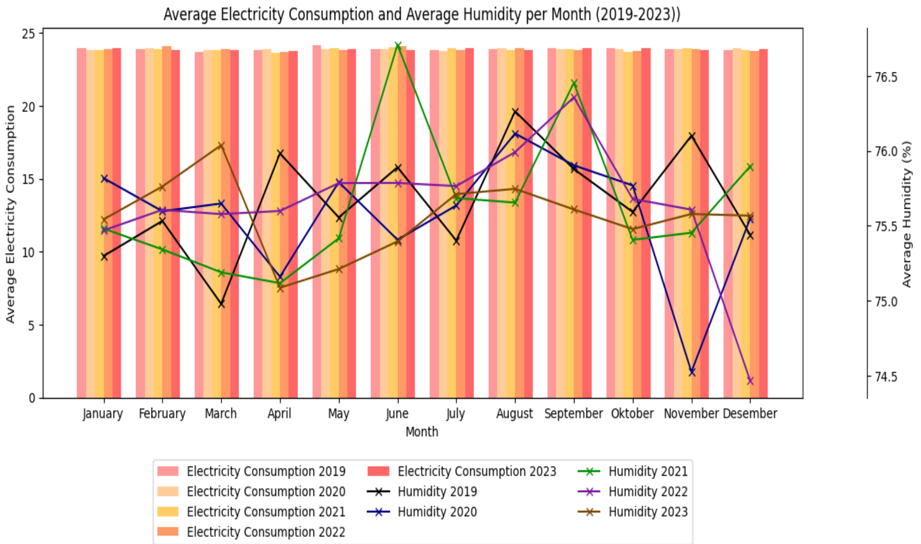

Figure 5. Electricity consumption based on humidity

Based on Figure 5, information can be obtained stating that electricity consumption due to humidity tends to fluctuate. In 2019, electricity consumption will tend to increase if the humidity of an area is low, this can be seen in January has lower humidity than February, but January electricity consumption is higher than February. As in 2019, electricity consumption increases when the humidity of an area is low, so too in 2020 to 2023 which explains that electricity consumption is higher when the humidity of an area is lower.

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3.3 Electricity Consumption Based on Wind Speed Every Month

Electricity is one of the crucial elements, considering that without electricity, human activities are disrupted. In the current era of globalization, the demand for electricity continues to increase, so that the electricity bills paid are increasingly soaring. In line with that, the increase in electricity demand is also influenced by natural factors. One of these natural factors is wind speed. However, in this study, wind speed does not have a significant influence on the electricity consumption generated each month. This can be seen in Figure 6.

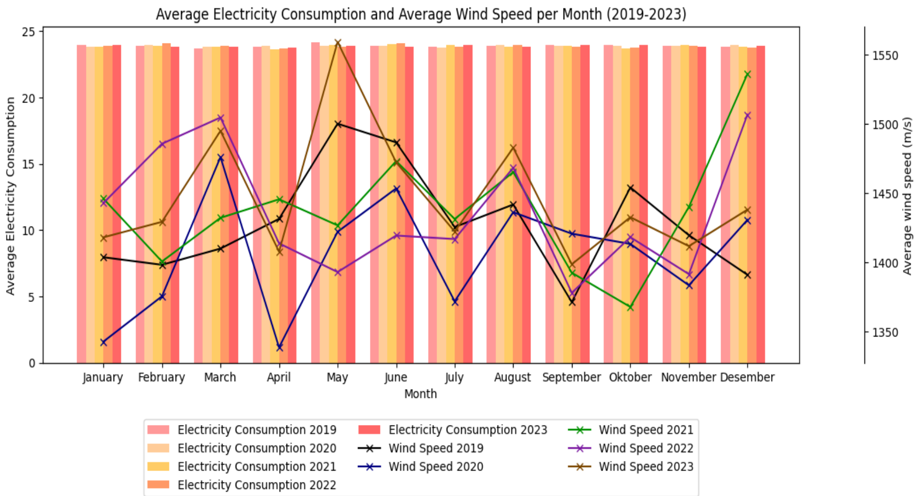

Figure 6. Electricity consumption based on wind speed

Based on Figure 6, information can be obtained stating that the average electricity consumption caused by humidity fluctuates. This can be seen in 2019, electricity consumption has increased when the wind speed in an area is higher than an area that has a lower wind speed. This can be seen in the month of May which has a greater wind speed than April so that electricity consumption in May is higher than April.

In 2020, electricity consumption increases when the wind speed is greater, such as only July and August, where August electricity consumption is greater than July, considering that August wind speed is greater than July. In 2021, electricity consumption is also affected by high wind speeds, such as the month of October which consumes less electricity than November, this is because the wind speed in October is smaller than in November.

In 2022, greater wind speed causes greater electricity consumption as well, this can be seen in January and February, where January has a lower electrical speed than

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February, so that February electricity consumption is greater than January. In 2023, electricity consumption tends to increase if the wind speed is greater, this can be seen in October where the wind speed is greater than November, so that electricity consumption in October is greater than November.

However, wind speed does not affect the amount of electricity consumption generated, this can be seen in March 2020 which has less wind speed than April 2023, but the electricity consumption is greater in March 2020 than April 2023.

3.4 Electricity Consumption by Temperature on Weekdays and Weekends

Increased electricity bills are caused by various factors, one of which is temperature. Therefore, this research presents insights related to electricity consumption on weekdays and weekends based on temperature. This insight aims to compare electricity consumption caused by temperature on weekends and weekdays so that it can be known that electricity usage is more dominant on weekdays or weekends, such as shown in Figure 7.

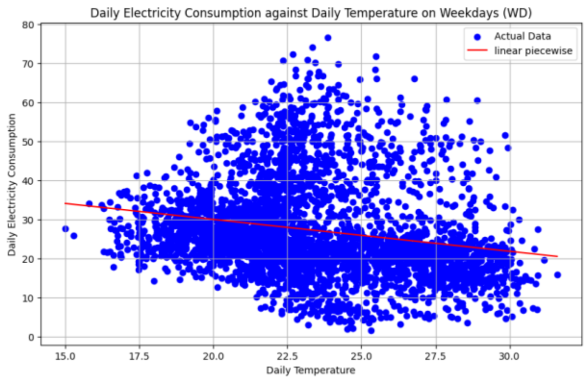

Figure 7. Electricity consumption on weekdays by temperature

Based on Figure 7, information is obtained stating that electricity consumption on weekdays increases significantly when the temperature is above 23°C. However, electricity consumption starts to decrease at 28°C, In line with this, Figure 8, shows the electricity consumption on weekend days based on temperature.

Based on Figure 8, information can be obtained stating that, the use of electricity has increased at a temperature of 18 °C. However, electricity decreased at 30 °C. Correspondingly, the temperature at which the increase in electricity consumption begins is used as the cooling sensitive temperature. The determination of this temperature is based on the temperature at which the need for cooling does not have a high urgency. Therefore, this study set a temperature of 22°C as Tbase in the CDD calculation.

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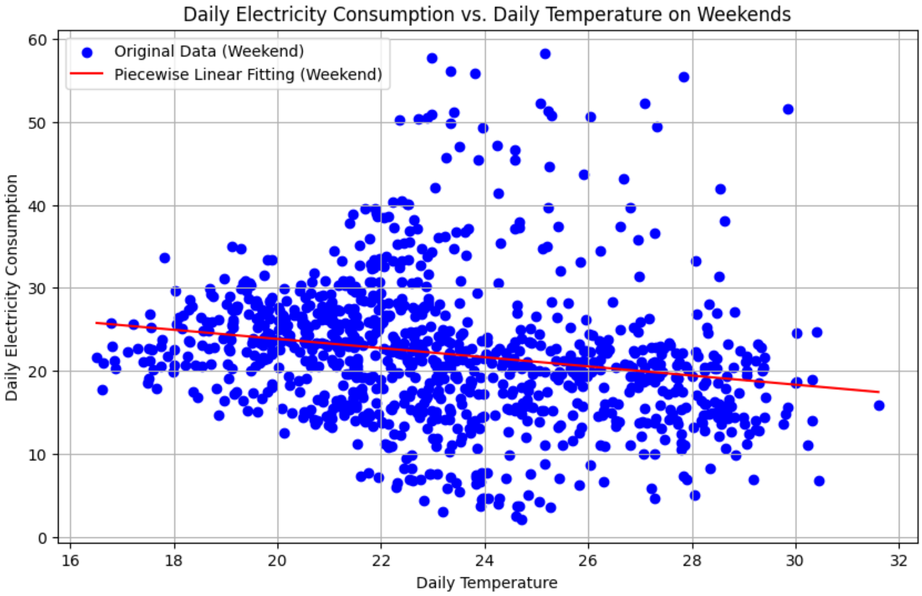

Figure 8. Electricity consumption on weekend days by temperature

Meanwhile, in HDD, the temperature set for Tbase as well as the sensitive temperature is 18°C. This temperature is set based on the low urgency of heating. In addition, electricity demand on weekdays and weekend days is more dominant on weekdays because electricity consumption on weekdays is more and denser than on weekend days. This can be seen in Figures 3 and 4 circles that represent electricity demand is denser on weekdays than on weekend days.

3.5 Electricity Consumption by Humidity on Weekdays and Weekend Days

In this era of globalization, the use of electricity is increasing from time to time, but not all people know that the increase in electricity is also caused by natural factors. One of those natural factors is humidity. This study presents some insights related to electricity consumption on weekdays and weekends based on humidity. This insight aims to compare electricity consumption caused on weekend days and weekdays caused by humidity so that people can find out which electricity consumption is more dominant on weekdays or weekend days. In line with this, Figure 9 shows the electricity consumption on weekdays based on Humidity.

Based on Figure 9, information can be obtained stating that consumption on weekdays begins to increase in areas containing humidity levels of 70. In line with this, Figure 7 shows the electricity consumption on weekend days based on temperature.

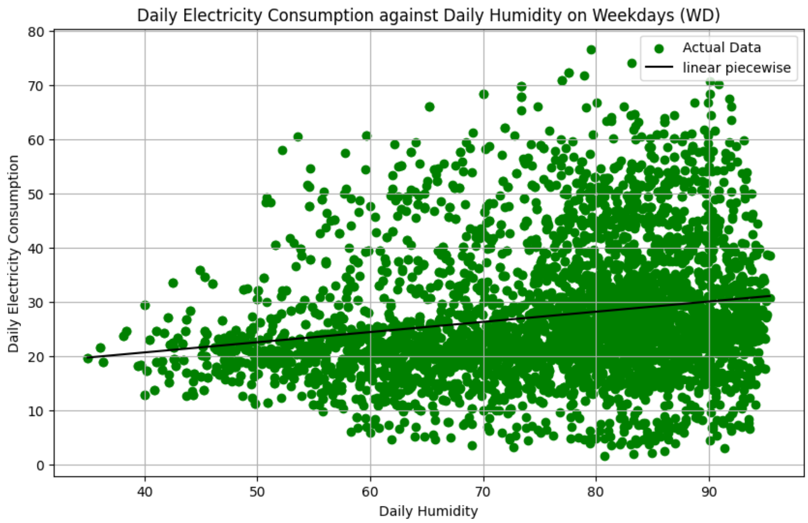

Figure 9. Electricity Consumption on Weekdays Based on Humidity

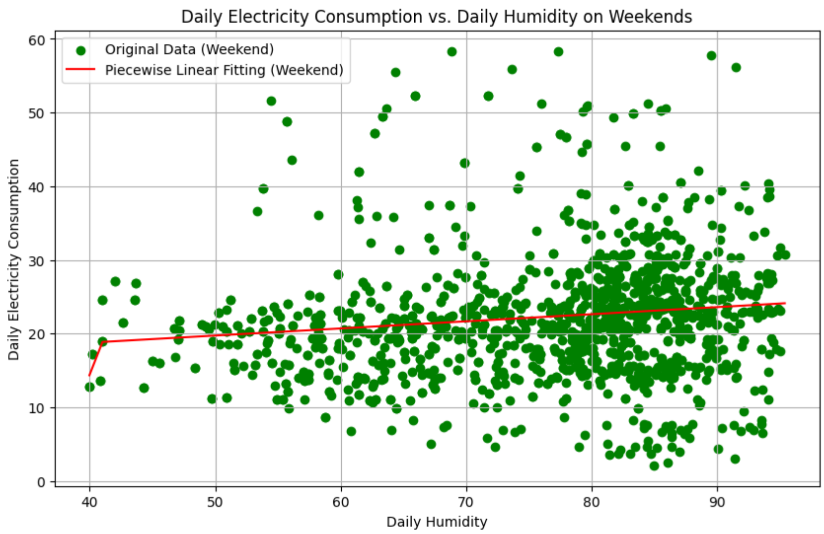

Figure 10. Electricity Consumption on Weekend Based on Humidity

Based on Figure 10, information can be obtained stating that electricity consumption on weekends has increased in areas that have humidity levels of 60. Correspondingly, electricity demand on weekdays and weekend days is more dominant on weekdays due to more electricity consumption on weekdays than on weekend days. This can be seen in Figure 6 and 7 circles that represent denser and more electricity demand on weekdays compared to weekend days.

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3.3 Electricity Consumption based on Wind Speed on Weekdays and Weekend Days

The increase in electricity consumption in the current era of digitalization will continue, considering that the fulfillment of the needs of living beings mostly uses electricity. However, electricity use can also be caused by natural factors. One of those natural factors is wind speed. Therefore, this research will present some insights related to electricity consumption on weekdays and weekends based on wind speed. This insight aims to compare electricity consumption caused on weekend days and weekdays caused by wind speed so that people can find out which electricity consumption is more dominant on weekdays or weekend days. In line with this, Figure 11 shows the electricity consumption on weekend days based on wind speed.

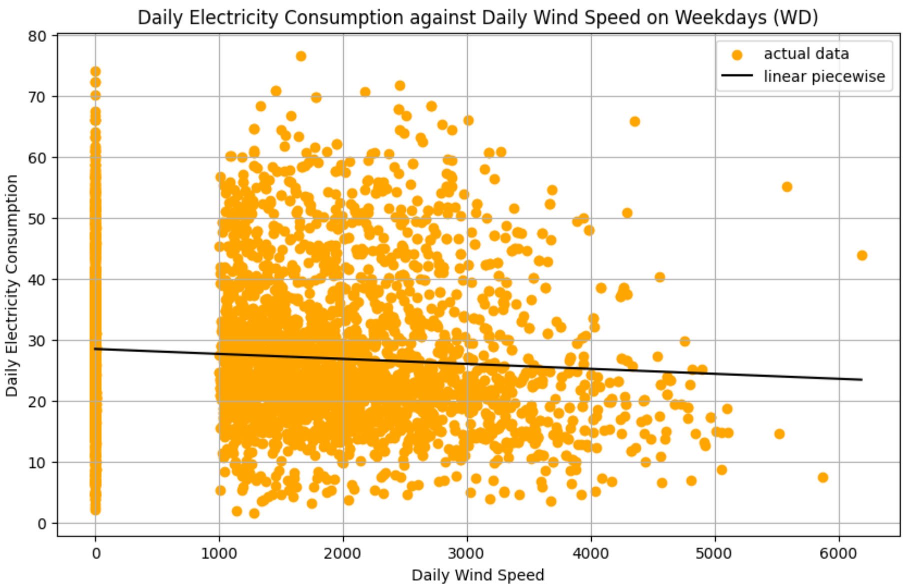

Figure 11. Electricity consumption on weekdays based on wind speed

Based on Figure 11, information can be obtained stating that electricity consumption will increase if the wind speed value is small such as the wind speed is in the 0-1 value range. This is because, the smaller the wind speed in an area, the greater the electricity consumption, and vice versa. In line with this, Figure 12 shows the electricity consumption on weekend days based on wind speed.

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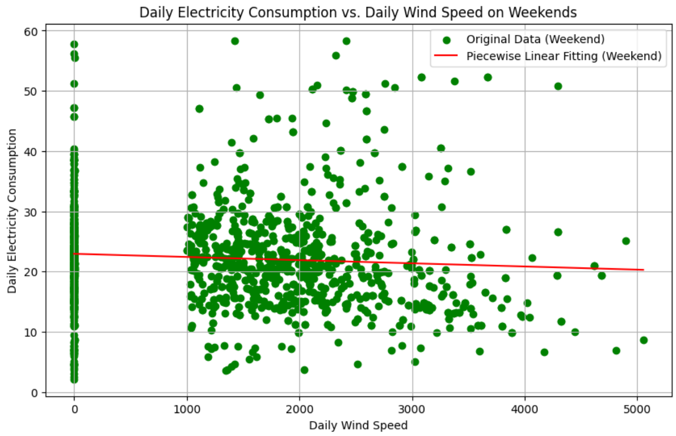

Figure 12. Electricity consumption on weekend days based on wind speed

Based on Figure 12, information is obtained stating that electricity on weekend days is used more when the wind speed is in the 0-1 range, while in the range above 1, electricity is rarely used by humans. This is because the higher the wind speed value, the smaller the electricity consumption generated, and vice versa.

3.4 HDD and CDD Projections from 2023 to 2030

HDD and CDD are among the parameters used to determine electricity consumption in an area based on temperature. In general, the HDD parameter is applied to high temperatures or dry season, while CDD is applied to low temperatures or in the rainy season. This application is based on a predetermined Tbase. In line with that, this research will predict HDD and CDD starting from 2023 to 2030 with visualization in the form of time series. In line with this, Figure 13 shows the electricity consumption on weekend days based on temperature.

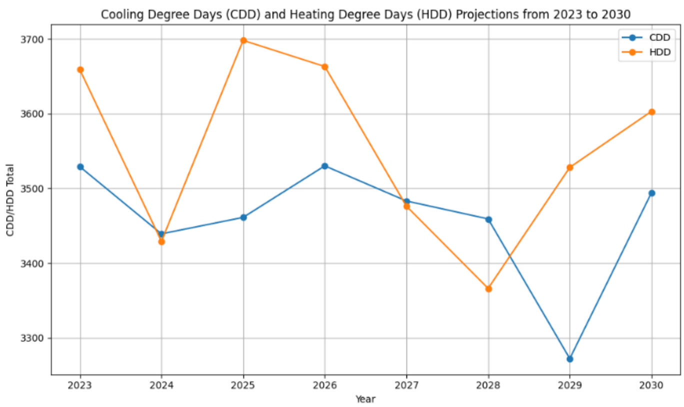

Figure 13. Time Series of HDD and CDD

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Based on Figure 13, information can be obtained stating that the projection of CDD and HDD from 2023 to 2030 results in an increasing trend. For CDD, the increasing trend is around 6.27°C per year, while for HDD, the increasing trend is around 14.4°C per year.

3.5 Prediction of Electricity Consumption in December 2023

Electricity consumption has increased over time, this increase is caused by several factors. One of those factors is meteorological parameters. In this research using electricity consumption dataset based on meteorological parameters from April to November, so that in December, electricity consumption prediction is carried out based on meteorological parameters. In Table 4 explains the prediction of electricity in December 2023.

Table 4. Predictions for December 2023

Date_data	humidity	temperature	wind	electrity
2023-12-01 00:00:00	84.35	17.38	56.62	26.76
2023-12-02 00:00:00	79.76	19.67	1784.31	27.99
2023-12-03 00:00:00	80.28	21.9	694.74	26.45
2023-12-04 00:00:00	77.73	14.44	1249.54	25.75
2023-12-05 00:00:00	70.69	20.44	854.63	26.34
2023-12-06 00:00:00	68.03	25.62	153.07	21.1
2023-12-07 00:00:00	83.57	31.03	2023.07	16.58
2023-12-08 00:00:00	65.02	17.89	18.36	25.18
2023-12-09 00:00:00	57.17	23.97	355.26	22.45
2023-12-10 00:00:00	72.88	18.23	2930.28	26.21
2023-12-11 00:00:00	65.26	25.75	0	21.7
2023-12-12 00:00:00	71.12	21.36	2692.68	26.75
2023-12-13 00:00:00	82.88	18.73	372.4	27.73
2023-12-14 00:00:00	73.29	21.01	378.94	26.12
2023-12-15 00:00:00	81.51	24.43	1902.35	24.82
2023-12-16 00:00:00	90	20.64	1679.01	27.85
2023-12-17 00:00:00	86.99	24.18	2031.03	26.66
2023-12-18 00:00:00	82.99	23.63	1628.69	25.74
2023-12-19 00:00:00	90	18.4	521.99	25.78
2023-12-20 00:00:00	74.41	20.93	729.69	26.62
2023-12-21 00:00:00	68.99	25.14	48.13	21.47
2023-12-22 00:00:00	76.21	20.79	160.94	26.61

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Date_data	humidity	temperature	wind	electrity
2023-12-23 00:00:00	87.65	17.11	1791.69	25.57
2023-12-24 00:00:00	90	18.95	1155.41	25.9
2023-12-25 00:00:00	90	24.3	1493.94	25.23
2023-12-26 00:00:00	56.62	20.51	2581.27	25.8
2023-12-27 00:00:00	67.98	24.53	3928.58	23.6
2023-12-28 00:00:00	78.34	22.64	2750.28	27.59
2023-12-29 00:00:00	85.64	20.73	0	26.9
2023-12-30 00:00:00	81.58	25.01	1147.19	21.9
2023-12-31 00:00:00	89.8	13.9	337.15	23.79

Based on table 4, information can be obtained which states that predictions of electricity consumption based on meteorological parameters in December are obtained from calculating the average and standard deviation from the previous month, the results of which will be processed using SVM. The results of electricity consumption predictions using meteorological parameters produce a MAPE value of 1.3. This value shows high accuracy, considering that the average relative error between prediction and actual value is only 1.3%. Correspondingly, electricity consumption in December per day averages 25 Watts. This consumption depends on the value of the meteorological parameter, so the greater the value of the meteorological parameter, the greater the electricity consumption.

3.6 Dashboards

Dashboard is an interface that contains the most important information, and the information is combined and organized in a single screen so that it can be monitored quickly [28]. Dashboards have a variety of benefits, one of which can facilitate stakeholders in making decisions and can see the impact of decisions that have been made [29]. In this research, dashboards are used to presenting information related to electricity consumption and meteorological parameters over a certain period of time.

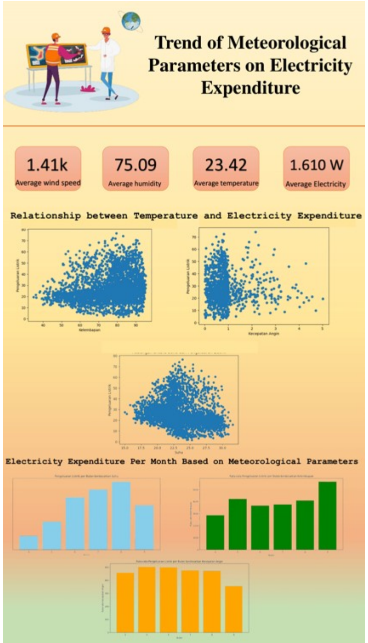

Figure 14. Visualization with Power BI

Based on Figure 14, several key insights can be derived, which are valuable for both the public and government agencies. Firstly, areas with high humidity, typically found in highland regions, tend to have increased electricity expenditure. In contrast, lowland areas with lower humidity do not experience significant changes in electricity output due to meteorological parameters.

Secondly, regions with slightly higher wind speeds generally use more electricity, leading to increased electricity expenditure. However, this study found that wind speed did not significantly affect the increase in electricity expenditure, indicating that other factors may play a more critical role.

Thirdly, areas with high temperatures tend to use more electricity, resulting in higher electricity expenditure. Conversely, regions with lower temperatures tend to use less electricity, leading to reduced electricity costs. This highlights the impact of temperature on energy consumption and expenditure.

From April to November 2023, electricity expenditure due to meteorological parameters showed fluctuations. This suggests that other seasonal or environmental factors may influence electricity usage patterns, and further investigation is needed to understand these dynamics fully.

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4. CONCLUSIONS

Based on the results of the analysis, the study on the trend analysis of meteorological parameters on the use of electrical energy using SVM, HDD, and CDD concludes the following: Increased humidity correlates with decreased electricity consumption, while higher electricity consumption correlates with lower humidity. Temperature fluctuations have minimal impact on electricity consumption, as evidenced by the inconsistent consumption patterns in April, October, and November. Wind speed does not significantly influence electricity consumption. Projections for CDD and HDD from 2023 to 2030 indicate an upward trend, with CDD increasing by approximately 6.27℃ annually and HDD by about 14.4℃ per year. Electricity consumption is higher on weekdays compared to weekends. Lastly, the prediction of December's electricity consumption using meteorological parameters yielded a highly accurate MAPE value of 0.98, indicating the model's precision.

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