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Research Article

Assessing the potential of small wind turbine electricity generation for small-sized hotels towards sustainable tourism in developing countries

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Abstract. The persistent reliance on fossil fuels for energy will yield enduring adverse effects on the tourism sector, particularly the hotel industry. Wind energy represents a renewable electricity source that can facilitate the transition of small-scale hotels to clean energy. The main objective of this research is to propose a methodology for evaluating the potential of wind energy to support sustainable tourism in developing nations, specifically in fulfilling the electricity requirements of small hotels. This study aims to assess and compare the potential contribution of small wind turbines to hotel energy demand by modelling a historical hourly wind dataset spanning ten years (2011-2020) and forecasting a portion of the dataset. This research selected three sites in Indonesia exhibiting varying wind energy potentials: Tepus District in Gunung Kidul Regency, Losari Beach in Makassar City, and Nusa Penida Island in Bali. This study utilises multiple linear regression to examine the impact of external variables on wind speed, and it applies Seasonal Autoregressive Integrated Moving Average (SARIMA) and Holt-Winters Exponential Smoothing (HWES) for wind speed forecasting in these three locations. The hourly and daily interval datasets analysis reveals a weak correlation between external factors and wind speed, with the HWES method identified as the most appropriate approach for modelling and forecasting wind speed, surpassing the SARIMA model by 0.309 RMSE. Forecasting results indicate that a 30-kW wind turbine could supply 8.8 - 35.3% of a small hotel's electricity consumption, depending upon the occupancy rate.

Keywords: Wind energy, sustainable tourism, multiple linear regression, SARIMA, Holt-Winters Exponential Smoothing

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1. Introduction

The hotel industry, one of the significant energy end-users, is among the most promising sectors in tourism for utilizing clean electricity to advance sustainable tourism (UNEP, 2024). The term "sustainable tourism" denotes tourism that comprehensively addresses its current and future socio-economic and environmental impacts while fulfilling visitors' needs, the industry, the environment, and local communities (GSTC 2024; UNT 2024). The beneficial effects of sustainable tourism may encompass a wide array of economic, environmental, sociocultural, wildlife conservation, and additional advantages (Li *et al.* 2024; Rahman *et al.* 2024). Sustainable tourism development, focusing on environmental sustainability, is increasingly recognized by countries, including those in the developing world, as it can significantly boost local and national economies.

In recent years, developing countries have been working to promote sustainable tourism in their accommodation sectors. The Indonesian government is partnering with the US on a $6 billion investment to develop eco-friendly hotels (IBP 2023). This is crucial as only a few tourist destinations have adopted sustainable tourism practices. Misool Eco Resort in Raja Ampat, Papua, uses solar photovoltaic systems for energy (MTCE 2024), while Lake Toba in North Sumatra province is developing electric vehicle charging stations and clean energy infrastructures (LTAIA 2022). These efforts aim to increase the number of establishments adhering to green standards.

Renewable energy (RE) provides a viable alternative for electrifying the untapped tourism potential in remote regions and enhancing the tourism appeal of specific locations (Beer *et al.* 2017). For businesses, RE could provide an economic benefit by lowering energy expenses and increasing potential income from the power produced by renewable sources (Luo *et al.* 2024). Meanwhile, visitors have expressed favourable attitudes towards using RE in tourism facilities (Navratil *et al.* 2019). An empirical study using long-term panel data has shown that RE positively influences sustainable tourism goal achievement (Hailiang *et al.* 2023). In practice, RE may be the sole viable option for developing tourism destinations in remote regions lacking access to conventional utility grids. Kamanggih Village in East Nusa Tenggara, Indonesia, for instance, fulfils its daily energy demand through RE sources (Petromindo 2024).

Several studies have examined the capacity of RE, particularly wind and solar, to improve the energy sustainability of hotels, while evaluating more economical and environmentally friendly

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energy sources for hotel operations. A grid-connected solar photovoltaic system was designed for a proposed hotel in Jordan utilising PVGIS and PVSyst simulation software (Al-Zoubi *et al.* 2021). The study analyzed various techno-economic metrics based on the projected energy consumption of the proposed hotel and the regional average occupancy rate.

Research on hybrid RE systems has garnered significant interest. A study was conducted in Turkey on meeting electricity demand in a medium-sized hotel utilising a hybrid system (Güler *et al.* 2013). The authors employed four scenarios to evaluate the techno-economic viability of the proposed systems, including a scenario permitting the purchase and export of electricity, and three others presuming that all demand is met by RE, with any surplus electricity sold to the grid. The research indicated that grid-wind turbines, exhibiting a renewable fraction of 74%, represented the optimal solution, surpassing other scenarios.

To achieve the net-zero energy consumption objective in Konya, Turkey, optimal off-grid and on-grid hybrid RE systems were designed and evaluated, encompassing a four-story hotel (Güğül 2023). The author determined that, for identical annual loads, on-grid photovoltaic and wind systems were more economically viable for the hotel building compared to other structures. Another study indicated that an on-grid small wind turbine, despite lacking sell-back payments, was the most economical solution for a small hotel in Jordan (Aagreh 2013).

A separate study identified the ideal hybrid grid-connected photovoltaic, wind, and biogas generators for a hotel in Egypt (Abdelhady 2023). Additional research utilised hybrid systems for a medium-sized hotel in Iran (Fazelpour *et al.* 2014). A study employed Monte Carlo simulation to determine the optimal proportions of solar and wind energy while addressing the variability of weather and occupancy in the Canary Islands (Meschede *et al.* 2017).

Another study integrated RE with energy storage and building automation systems (Beccali *et al.* 2018). Further studies compared hybrid renewable systems with grid-only and renewable-only configurations for a large-scale (over 100 beds) grid-connected hotel in Queensland, Australia (Dalton *et al.* 2009a), and for stand-alone settings (Dalton *et al.* 2008). The authors also examined the techno-economic of stand-alone RE systems utilizing hydrogen fuel cell storage across different small to medium-sized accommodations (Dalton *et al.* 2009b). Lastly, a study explored various RE fraction scenarios, including on-site wind and solar photovoltaic systems, to mitigate CO_2 emissions from a modelled hotel building in Qatar (Ayoub *et al.* 2014).

Existing studies, as shown above, have focused mainly on several aspects of the hotel energy supply, including the on-grid/hybrid feasibility analysis and design and techno-economic prospects of RE systems, but have left out the insights offered from exploring the performance of long-term RE data. Furthermore, although several RE adoption techniques have been proposed, little is known about wind energy adoption potential and effectiveness in small-scale hotels due to differences in hotel occupancy rates and long-term temporal data. Hence, despite some research on hotels' wind and solar potential and utilization strategies, there is still a lack of understanding about how small-scale hotels in developing countries deal with long-term renewable energy data, particularly wind energy resources, and the available strategies for utilization decisions.

Evaluating the potential influence of meteorological factors on wind speed and the power output capacity of wind turbines through long-term historical data may enhance comprehension of these factors and facilitate improved investment decisions in hotels. Nonetheless, studies examining the effects of wind energy on small hotels are scarce. In this context, minimal exploration has been done into the effects of long-term hourly temporal datasets of wind speed and other meteorological variables on the feasibility of small wind turbines for sustainable energy provision in hotels.

Thus, this study seeks to address the research problem of understanding the long-term hourly temporal wind speed dataset and how small-scale hotels can better deal with and utilize the historical and projected wind data for their sustainable energy supply. This research aims to provide valuable insights for system planners, hotel investors, and other stakeholders in planning and developing renewable energy systems, particularly wind to enhance energy resilience and reliability in the small-scale hotel sector in developing countries.

2. Methodology

Figure 1 illustrates the comprehensive workflow of this research. The process commences with identifying sites for investigation, succeeded by data collection and analysis to assess the potential energy generation of wind turbines. Multiple linear regression (MLR), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Holt-Winters Exponential Smoothing (HWES) are employed for model development, forecasting, and result assessment. The capacity to fulfil power requirements at designated locations is subsequently evaluated, followed by an outcomes analysis.

2.1 Sites Selection and Hotel's Electricity Efficiency Ratings

This research considers three sites in Indonesia with varying wind energy potentials for the case study. The evaluation of the three sites examined in this study commences with analysing location appropriateness. The indicators encompass tourism potential, the necessity for alternative energy sources, and geographical characteristics.

It should be noted that the case study's selected locations do not correspond to established hotels, given that this is a planning study focusing on temporal dataset analysis and modelling. This study not only identified sites for analysis but also collected relevant information to evaluate wind energy potential by determining the average number of guest rooms in small-sized hotels and their corresponding electricity energy efficiency ratings and total energy consumption threshold. Figure 2 illustrates the site selection and data collection and the hotel's electricity efficiency rating, followed by wind dataset collection and pre-processing.

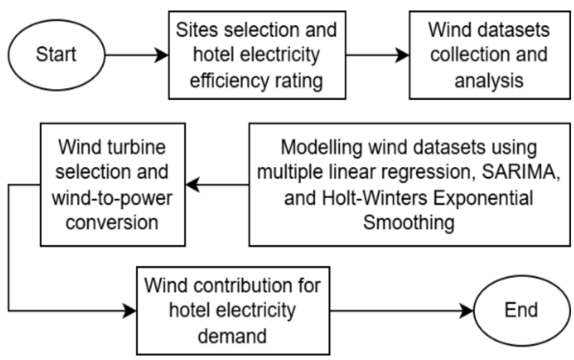

Fig 1 Research methodology flowchart

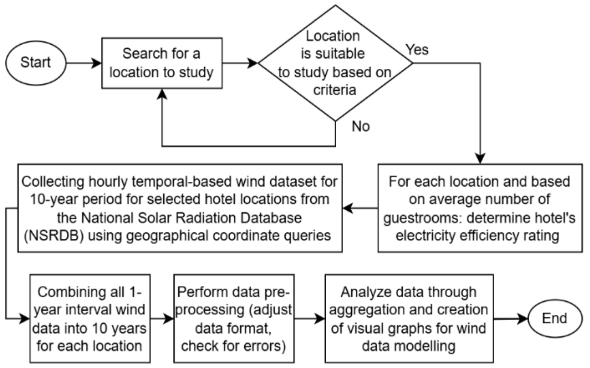

Fig 2. A detailed methodology for site selection and hotel's electricity efficiency rating followed by wind dataset collection and pre-processing

2.2 Wind Dataset Collection and Pre-processing

This study examines several critical variables for modelling and analytical purposes, including wind speed, relative humidity, temperature, wind direction, and pressure. As shown in Figure 2, the data collection procedure for these variables on selected locations involves downloading hourly data at one-year intervals over a decade (2011-2020) by querying coordinates on the National Solar Radiation Database (NSRDB) website, accessible at https://nsrdb.nrel.gov/ (NREL 2024). The collected information is subsequently combined into a singular data set.

Data preprocessing entails verifying and transforming data into the appropriate format, addressing errors, and implementing other essential modifications. Subsequently, the data is analyzed through aggregation and graphical representation to discern patterns or valuable insights, facilitating further wind dataset modelling and the selection of the optimal wind turbine model. The dataset and data preprocessing results are accessible through https://drive.google.com/drive/folders/1IwuR_bsiTt5Hx7ORHGRT7EfSdK3C9Fw7?usp=sharing.

2.3 Modelling of Wind Dataset

2.3.1 Multiple Linear Regression (MLR)

MLR is a statistical technique that broadens the scope of simple linear regression. Simple linear regression involves a single independent variable, while MLR encompasses two or more independent variables. Notwithstanding this distinction, the objective of MLR is identical to that of simple linear regression: to determine the relationship between variables and facilitate predictions. The equation model for MLR can be expressed as follows (Katić *et al.* 2024).

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_n X_n + \mathrm{e} \quad (1)$$

where: Y is the dependent variable, $X_1 \dots X_n$ is the 1st to the nth independent variable, α is a constant or the starting point (where all independent variables are equal to 0), $\beta_1 \dots \beta_n$ is the 1st to the nth regression coefficient and e is the prediction error.

Figure 3 shows the flowchart in which MLR is utilized in this research. The method is employed to analyze the correlation between selected independent variables (wind direction, temperature, pressure, and relative humidity) and the dependent variable (wind speed). If a strong correlation is found, additional independent variables may be added to improve the model's fit when using different methods. The model evaluation utilizes Root Mean Squared Error (RMSE).

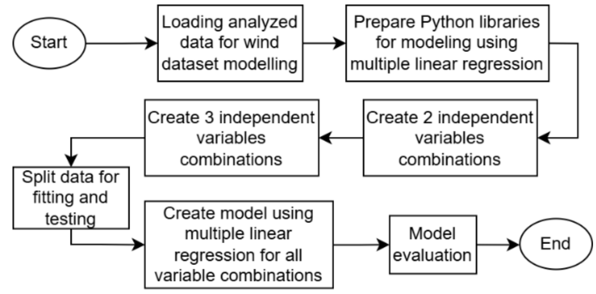

Fig 3 Modelling procedure using MLR

2.3.2 Seasonal Autoregressive Moving Average (SARIMA)

The SARIMA model is an extension of the Autoregressive Integrated Moving Average (ARIMA) model. The ARIMA method is effective in analyzing and forecasting time series data; however, it cannot accommodate seasonal characteristics or patterns within the wind dataset. This study formulates the SARIMA model and integrates seasonal elements into it. The SARIMA model consists of up to 7 components, namely p (the trend autoregression order), d (the trend difference order), q (the trend's moving average order), P (the seasonal autoregressive order), D (the seasonal difference order), Q (the seasonal moving average order), and m (the number of periods per season to be calculated) (Machine Learning Mastery 2019). The equation for SARIMA is as follows (Christie *et al.* 2022).

$$\phi_p(B^s)\phi_p(B)(1-B)^d(1-B^s)^D Y_t = \theta_q(B)\Theta_Q(B^s)\mathcal{E}_t \quad (2)$$

where: p is trend autoregression order, P is the seasonal autoregressive order, d is trend difference order, D is the seasonal difference order, q is the trend-moving average order, Q is seasonal moving average order, $\phi_p(B)$ is the non-seasonal autoregressive level, $\phi_p(B^s)$ is the seasonal autoregressive level, $(1-B)^d$ is the non-seasonal differencing level, $(1-B^s)^D$ is the seasonal differencing level, $\Theta_q(B)$ is the non-seasonal moving average level, $\Theta_Q(B^s)$ is the seasonal moving average level, Y_t is the actual data for the period t, and $\mathcal{E}_t$ represents the error in the period t.

Figure 4 illustrates the particular SARIMA process employed in this study. The Augmented Dickey-Fuller (ADF) test verifies the stationarity of data. Should the data exhibit non-stationarity, the differencing procedure is implemented repeatedly until stationarity is achieved. The data is subsequently partitioned for fitting and testing purposes. The optimal SARIMA model (the values for p, d, q, P, D, and Q) is determined using two approaches: the auto_arima function from a Python library and the grid search method. The grid search technique evaluates the spectrum of parameter values by analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs. Upon identifying the optimal parameters, a SARIMA prediction model will be developed, and the outcomes will be compared (auto_arima and grid search). The model's efficacy is assessed through Root Mean Squared Error (RMSE).

2.3.3 Holt-Winters Exponential Smoothing (HWES)

HWES is a modification of Holt's exponential smoothing, commonly called double exponential smoothing. The Holt-Winters method assumes that time-series data comprises level,

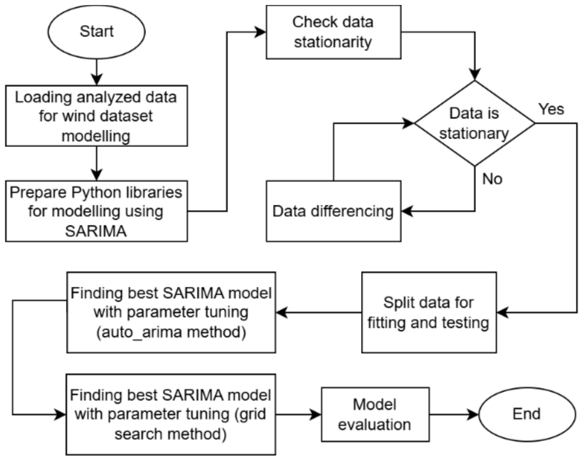

Fig 4 Flowchart for modelling using SARIMA

trend, and seasonal components. The Holt-Winters method for addressing seasonality comprises two variations: additive and multiplicative. Time series can be modelled through the additive trend with additive seasonality, the additive trend with multiplicative seasonality, the multiplicative trend with additive seasonality, and the multiplicative trend with multiplicative seasonality.

The formulas employed in HWES are presented below, beginning with level smoothing (L_t) for additive variation in Eq. 3 and multiplicative variation in Eq. 4 (Irandi *et al.* 2021). The formulas used to calculate trend pattern smoothing, seasonal pattern smoothing, and the prediction for the next period, are shown in Eq. 5, Eq. 6 (additive) and Eq. 7 (multiplicative), and Eq. 8 (additive) and Eq. 9 (multiplicative), respectively.

$$L_t = \alpha(y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + T_{t-1}) \quad (3)$$

$$L_t = \alpha\left(\frac{y_t}{S_{t-s}}\right) + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (4)$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (5)$$

$$S_t = \gamma\left(\frac{y_t}{L_{t-1}}\right) + (1-\gamma)S_{t-s} \quad (6)$$

$$S_t = \gamma\left(\frac{y_t}{L_t}\right) + (1-\gamma)S_{t-s} \quad (7)$$

$$F_{t+m} = L_t + b_t m + S_{t-s+m} \quad (8)$$

$$F_{t+m} = (L_t + b_t m)S_{t-s+m} \quad (9)$$

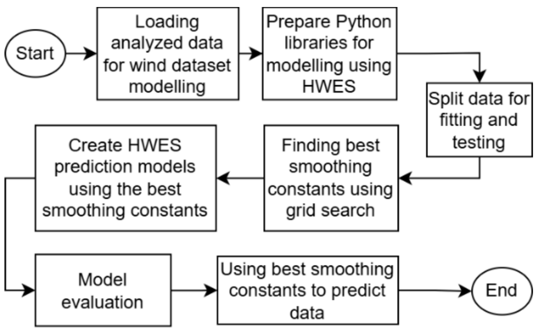

Fig 5 Flowchart for modelling using HWES

where: α, β, and γ are smoothing constants, y_t is the observed value at the time t, L_t is the smoothing level value at the time t, b_t is trend pattern smoothing value at the time t, S_t is the seasonal pattern smoothing value at the time t, F_{t+m} is forecast for a time $t+m$, and s represents the seasonal length.

Figure 5 shows the application of Holt-Winters exponential smoothing in this study. The dataset is partitioned into training and testing groups, and the grid search technique is employed to identify the optimal smoothing constants, considering variations in trend and seasonality types. The modelling results are assessed utilizing the RMSE method, and the optimal smoothing constants are selected for data prediction.

2.4 Wind Turbine Selection and Wind-to-Power Conversion

Small wind turbine candidates are identified after analyzing and modelling the wind dataset using the three techniques outlined in the previous section. The main criterion for selecting a wind turbine is its power curve, which should be aligned with the potential wind speed. In this context, the power curve of each wind turbine candidate is modelled using either polynomial, linear or piecewise regression techniques. Polynomial regression can be used due to the non-linear relationship between the independent variable (wind speed) and the dependent variable (power output). The equation for the polynomial regression is as follows (Morala *et al.* 2021).

$$Y' = b_0 + b_1X + b_2X^2 + \cdots + b_nX^n \quad (10)$$

where: Y' is the dependent variable, X is the independent variable, $X^2 \ldots X^n$ are the independent variables with n degree of the polynomial, b_0 is a constant or the starting point (where all independent variables are equal to 0), and $b_1 \ldots b_n$ are the regression coefficients.

Upon fitting, the polynomial regression model of the power curve converts wind speed into potential electrical power output at designated sites. The conversion outcomes will be assessed to ascertain the electrical power contribution provided by the wind to the hotel energy demand, given the selected historical and forecasted wind speed model, which is obtained from one of the three methods explained in Section 2.3. Figure 6 illustrates a flowchart detailing the wind turbine selection and wind-to-power conversion process.

3. Results and Discussion

This section presents the analysis results of all aspects described in the methodology section. These include the selected sites and the hotel's electricity efficiency ratings, the wind data characteristics over a decade (2011-2020) for all locations, and the modelling outcomes derived from MLR, SARIMA, and HWES techniques. This section also presents the analysis results of wind turbine selection and wind-to-power conversion, and the potential of wind energy in supplying hotel electricity, considering varying occupancy rates.

3.1 Selected Sites and Hotels' Electricity Efficiency Ratings

All three chosen locations are situated on different islands. The first location is the Tepus District, in Gunung Kidul Regency. The geographical coordinates for this study are 7°58'11.79" South latitude and 110°29'17.25" East longitude. Gunung Kidul, near the southern Java coastline, has significant tourism potential due to its elevation and wind speed. The low population density ensures minimal disruption to local communities. The predominantly level terrain allows for increased electricity generation from wind turbines due to enhanced wind velocity (Elgendi *et al.* 2023).

The second location is Losari Beach in Makassar (5°08'34" South and 119°24'25" East). It is a recognized coastal region potentially appropriate for small turbine applications (Prabowo *et al.* 2022). The third location is Nusa Penida Island in Bali Province. The selected geographical coordinates are 8°48'00.0" South latitude and 115°34'00.0" East longitude. Nusa Penida experiences elevated wind speeds. However, this resource remains underexploited, signifying considerable unutilized wind energy potential (Darmana, Koerniawan 2019).

The hotel's electricity efficiency rating is determined based on the hotel's capacity, i.e., the available rooms (Bohdanowicz 2001). The average number of guest rooms in small hotels within Gunung Kidul Regency is 23 (GKTA 2019), while the majority of small lodgings in Nusa Penida possess between 5 and 14 guest rooms (Berita Satu 2019).

The suggested electricity efficiency ratings are less than 60 kWh/m^2/year for Gunung Kidul and Nusa Penida and less than 70 kWh/m^2/year for Makassar, based on the average number of guest rooms. Following a similar study, the advised total energy consumption thresholds for Gunung Kidul and Nusa Penida are below 240 kWh/m^2/year, while for Makassar, it is below 260 kWh/m^2/year (Bohdanowicz 2001).

3.2 Wind Dataset Collection and Pre-processing Results

The analysis of wind data is initiated by data aggregation. The dataset comprises a decade of hourly data intervals for pressure (P), relative humidity (RH), temperature (T), wind direction (WD), and wind speed (WS). The hourly values collected over a decade (87,600 hours) are averaged in wind speed data for each 24-hour interval. Consequently, all daily averaged wind speeds are derived by consolidating the 24-hour wind speed data ranges. Upon acquiring the complete set of daily average wind speed data (3,650 entries), the weekly average wind speed values are determined by consolidating the daily averages every 7 days.

A monthly averaged wind speed is derived by consolidating all daily averaged data for that month. This study comprises 120 months of average wind speed data spanning 10 years. The minimum, maximum, and mean values for hourly to monthly

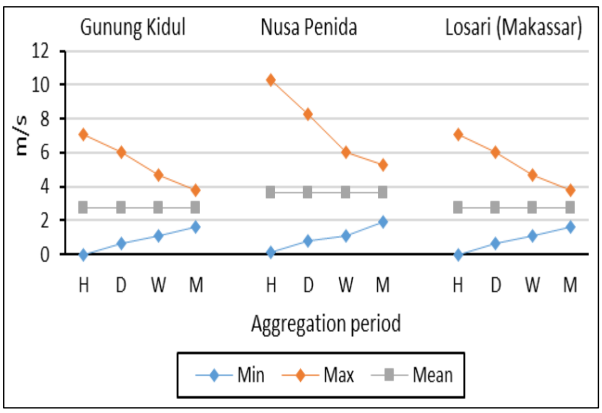

Fig 6. Comparison of hourly (H), daily (D), weekly (W), and monthly (M) aggregated wind speed during 2011-2020 in Gunung Kidul, Nusa Penida, and Losari Beach (Makassar)

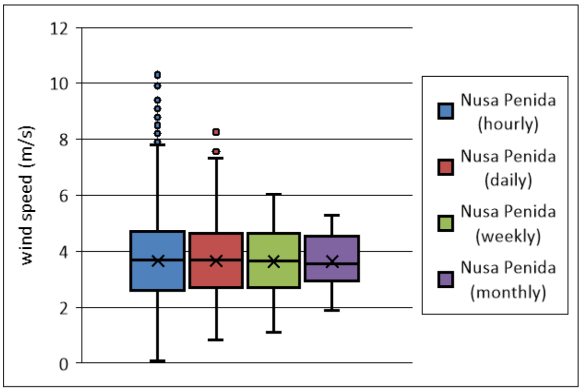

Fig 7. The range of hourly- to monthly average wind speed data in a selected location at Nusa Penida Island over a total of 10 years dataset (2011-2020)

aggregated wind speed at three locations are calculated accordingly.

Figure 6 presents the minimum, maximum, and mean values of hourly and monthly aggregated temporal wind speeds at three locations. The data indicates that Nusa Penida in Bali exhibits the highest maximum wind speed values across all aggregation periods compared to the other two locations. The peak wind speed at Nusa Penida is 10.3 m/s, with daily, weekly, and monthly averages of 8.3 m/s, 6 m/s, and 5.3 m/s, respectively. The average wind speed for data aggregated from hourly to monthly intervals is 3.64 m/s. A seasonal pattern is discernible, recurring roughly every 8760 data rows (equivalent to 12 months of data).

Figure 7 shows box-whisker plots of hourly to monthly average wind speed data collected over a decade at a selected location on Nusa Penida Island. The 87,600-hourly dataset exhibits a maximum wind speed of 7.8 m/s when excluding outliers, and 10.3 m/s when including them. The maximum daily average wind speed is 7.8 m/s excluding outliers and 8.3 m/s including outliers. The maximum average wind speeds for weekly and monthly intervals are 6 m/s and 5.3 m/s, respectively, while the minimum averages are 1.1 m/s and 1.9 m/s. All time intervals exhibit mean wind speeds of 3.6 m/s.

Figure 8 depicts a box and whisker plot representing the monthly average wind speed from 2011 to 2020 at a designated location on Nusa Penida. The graph illustrates various ranges of monthly average wind speeds, derived from daily average values, spanning from 2011 to 2020. In the 10-year dataset (up

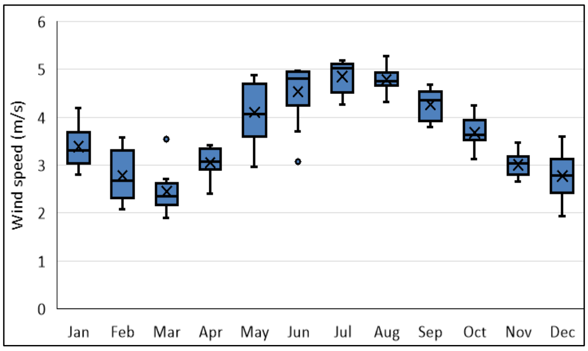

Fig 8. The ranges of monthly average wind speed from 2011-2020 in Nusa Penida as grouped monthly up to 120 months (aggregated from daily average values)

Table 1
Wind data characteristics – Nusa Penida

Interval	Variable	Mean	Max	Min
Hourly	Pressure (mbar)	1015	1034	993
	Relative humidity (%)	80,6	95,58	57,32
	Temperature (°C)	27,8	32,3	23
	Wind direction (°)	164	360	0
	Wind speed (m/s)	3,6	10,3	0,1
Daily	Pressure (mbar)	1015	1032,3	995,1
	Relative humidity (%)	80,6	91,9	65,4
	Temperature (°C)	27,8	31,1	24
	Wind direction (°)	164	334,3	31,1
	Wind speed (m/s)	3,6	8,3	0,8
Weekly	Pressure (mbar)	1015	1031,2	997,5
	Relative humidity (%)	80,7	89	73,1
	Temperature (°C)	27,8	30,7	24,4
	Wind direction (°)	164	332,4	80,7
	Wind speed (m/s)	3,6	6	1,1
Monthly	Pressure (mbar)	1015	1030,3	999,4
	Relative humidity (%)	80,7	87,3	74,4
	Temperature (°C)	27,8	30,3	24,8
	Wind direction (°)	164	256,3	109
	Wind speed (m/s)	3,6	5,3	1,9

to 120 months), the months from June to September exhibited higher monthly average wind speeds compared to the remaining months. Table 1 summarizes all principal variables examined in this study that are believed to influence wind-derived electrical energy in Nusa Penida from 2011 to 2020. The variables include pressure, relative humidity, temperature, wind direction, and wind speed. This study additionally examines the data for Gunung Kidul and Losari.

3.3 Wind Datasets Modelling Results

3.3.1 MLR results

The MLR method applies to all temporal data intervals, including hourly, daily, weekly, and monthly. The evaluation performance metrics employed are RMSE, R-squared, and adjusted R-squared. In Gunung Kidul, hourly, daily, and monthly models are predicated on relative humidity (RH), pressure (P), and temperature (T). The weekly period is determined by relative humidity (RH) and temperature (T). The optimal result, characterised by the minimal RMSE, is achieved at Losari Beach through the integration of relative humidity (RH), pressure (P), and temperature (T). The interplay of relative humidity (RH), pressure (P), temperature (T), and wind direction (WD) in Nusa Penida yields the minimal RMSE.

Table 2 presents the variable combinations employed in the MLR models, yielding the optimal RMSE and R-squared across all intervals. The coefficient of determination (R-squared) quantifies the extent to which the independent variable elucidates the dependent variable. The R-squared values in Table 2, especially for hourly and daily intervals, demonstrate a weak correlation between the independent variables (RH, P, T, and WD) and wind speed at all locations. This indicates that the independent variables are insufficient to completely elucidate the dependent variable. Simultaneously, the R-squared values for variable combinations at weekly and monthly intervals sufficiently elucidate aggregated wind speed, especially for Nusa Penida.

As the data aggregation interval increases, the performance metrics improve, indicated by a lower RMSE and a higher R-

Table 2
The best RMSE and R-squared, and combination of variables involved in the MLR models

Interval	Location	Involved Variables	RMSE	R-squared
Hourly	Gunung Kidul	RH, P, T	0.981	0.261
	Losari	RH, P, T	0.924	0.086
	Nusa Penida	RH, P, T, WD	1.264	0.241
Daily	Gunung Kidul	RH, P, T	0.757	0.279
	Losari	RH, P, T	0.668	0.241
	Nusa Penida	RH, P, T, WD	1.074	0.367
Weekly	Gunung Kidul	RH, T	0.540	0.464
	Losari	RH, P, T	0.502	0.327
	Nusa Penida	RH, P, T, WD	0.821	0.516
Monthly	Gunung Kidul	RH, P, T	0.384	0.641
	Losari	RH, P, T	0.357	0.433
	Nusa Penida	RH, P, T, WD	0.482	0.769

squared value. The performance metrics indicate that the ideal variable combinations for each location yield consistent results across all data intervals. The optimal variable combination for Gunung Kidul and Losari is relative humidity (RH), precipitation (P), and temperature (T), whereas for Nusa Penida, it includes RH, P, T, and wind direction (WD).

Nevertheless, incorporating additional independent variables into the MLR model does not enhance the fit of the Gunung Kidul and Losari data. The data from Nusa Penida presents divergent results. Despite the RMSE being greater than that of the other two locations, the R-squared value remains comparatively high.

3.3.2 SARIMA results

In SARIMA, the Augmented Dickey-Fuller (ADF) test is utilized to verify data stationarity. The test results are displayed in Table 3 and Table 4 for hourly, weekly, and monthly intervals, respectively. The ADF test results indicate that the data is stationary at the weekly interval but non-stationary at the monthly interval. This is evidenced by a p-value exceeding 0.05 and an ADF statistic surpassing the critical threshold. Seasonal differencing is applied once (D=1) to rectify the absence of stationarity in the monthly dataset.

Table 4 presents the results of the differencing analysis, while Table 5 shows possible SARIMA model parameters for all locations. The SARIMA model is subsequently fitted utilizing

Table 3
ADF Test results

Interval	Location	ADF	p-value	Critical values
Hourly	Gunung Kidul	-6.37	2.36×10^{-8}	1%: -3.44; 5%: -2.87; 10%: -2.57
	Losari	-8.68	4.27×10^{-14}	1%: -3.44; 5%: -2.87; 10%: -2.57
	Nusa Penida	-6.09	1.04×10^{-7}	1%: -3.44; 5%: -2.87; 10%: -2.57
Daily	Gunung Kidul	-2.05	0.26	1%: -3.49; 5%: -2.89; 10%: -2.58
	Losari	-2.46	0.13	1%: -3.49; 5%: -2.89; 10%: -2.58
	Nusa Penida	-1.70	0.43	1%: -3.49; 5%: -2.89; 10%: -2.58

Table 4
ADF Test results on seasonal differencing monthly data

Location	ADF statistic	p-value	Critical values
Gunung Kidul	-6.578	7.66×10^{-9}	1%: -3.493 5%: -2.890 10%: -2.581
Losari	-7.156	3.06×10^{-10}	1%: -3.493 5% : -2.890 10% : -2.581
Nusa Penida	-4.361	3.48×10^{-10}	1%: -3,501 5%: -2,892 10%: -2,583

Table 5
Possible SARIMA model parameters for all locations

Interval	parameter	Gunung Kidul	Losari	Nusa Penida
Weekly	p	0-3	0-1	0-3
	d	0	0	0
	q	0-9	0-5	0-8
	P	0-1	0	0
	D	0	0	0
	Q	0-2	0-2	0-2
Monthly	p	0-1	0-1	0-1
	d	0	0	0
	q	0-1	0-2	0-1
	P	0-2	0-1	0-2
	D	1	1	1
	Q	0-1	0-1	0-1

auto_arima and grid search techniques. The RMSE value identifies the optimal model and fitting technique. The number of periods per season (m) will be established as 52 weekly intervals and 12 monthly intervals. The results for weekly and monthly intervals are presented in Table 6.

Table 6
SARIMA fitting results comparison

Interval	Location	Method	Best model	RMSE
Weekly	Gunung Kidul	auto_arima	SARIMA (1,0,2);(2,0,0);52	0.802
		grid search	SARIMA (0,0,1);(1,0,2);52	0.490
	Losari	auto_arima	SARIMA (1,0,0);(2,0,0);52	1.655
		grid search	SARIMA (1,0,4);(0,0,2);52	0.575
	Nusa Penida	auto_arima	SARIMA (1,0,2);(0,0,0);52	1.468
		grid search	SARIMA (3,0,8);(0,0,2);52	1.067
Monthly	Gunung Kidul	auto_arima	SARIMA (1,0,0);(1,0,1);12	0.443
		grid search	SARIMA (0,0,0);(1,0,1);12	0.315
	Losari	auto_arima	SARIMA (1,0,0);(2,0,0);12	0.688
		grid search	SARIMA (0,0,2);(1,0,0);12	0.304
	Nusa Penida	auto_arima	SARIMA (0,0,2);(1,0,1);12	0.419
		grid search	SARIMA (0,0,0);(0,0,1);12	0.379

The findings in Table 6 indicate that the SARIMA method is appropriate for datasets of moderate size, as it can process data at weekly intervals within a reasonable timeframe. As the dataset size expands, the number of possible models fit also increases, augmenting the model's complexity and requiring additional computation time. In comparing RMSE results, the grid search method exhibits lower RMSE values across all data intervals at the three locations than the auto_arima method. Moreover, it was found that extending the data aggregation interval diminishes the RMSE.

3.3.3 HWES results

The HWES model is formulated to exclude trends and incorporate additive seasonality. This study utilizes RMSE to identify the optimal model and fitting method for each interval and location. Table 7 presents the optimal model outcomes for the HWES model.

The modelling outcomes presented in Table 7 utilize the 2011–2018 dataset for training and the 2019–2020 dataset for testing. The RMSE of 0.374 for Nusa Penida (monthly) indicates the prediction error for 2019-2020 concerning the actual data from that period. This study establishes the number of periods per season (s) as 365 for daily intervals, 52 for weekly, and 12 for monthly intervals. A grid search method is employed to identify the optimal alpha (α) and gamma (γ) values.

Upon establishing the optimal smoothing constants, the historical data is plotted, and model fitting is conducted for all potential intervals across all locations. This paper shows HWES results for Nusa Penida, as illustrated in Figures 9a to 9c. The figures show the model fitting for daily interval data, weekly intervals, and monthly intervals, respectively.

The analysis indicates that the HWES method can efficiently accommodate large datasets while maintaining high processing speed. Consequently, the method is effective with data characterized by lower aggregation levels or larger volumes. The HWES method surpasses both SARIMA and MLR methods in overall computational efficacy. While certain locations employing the SARIMA method exhibited marginally reduced RMSE values, the disparity was minimal (approximately 0.02).

Nevertheless, as the degree of data aggregation diminishes, the resultant RMSE value escalates. Datasets with monthly aggregation intervals exhibited the lowest RMSE for each location. The model-fitting graph can reflect the rising and falling trends of wind speed indicated by actual historical data.

Although the HWES model fittings for both daily and weekly intervals are insufficient for predicting short-term operational needs for wind turbines or supply systems, it provides

Table 7
HWES fitting results

Interval	Location	Alpha (α)	Gamma (γ)	RMSE
Daily	Gunung Kidul	0.05	0.05	0.819
	Losari	0.05	0.05	0.702
	Nusa Penida	0.8	0.05	1.014
Weekly	Gunung Kidul	0.2	0.25	0.511
	Losari	0.1	0.15	0.489
	Nusa Penida	0.05	0.25	0.769
Monthly	Gunung Kidul	0.05	0.15	0.309
	Losari	0.05	0.25	0.322
	Nusa Penida	0.05	0.15	0.374

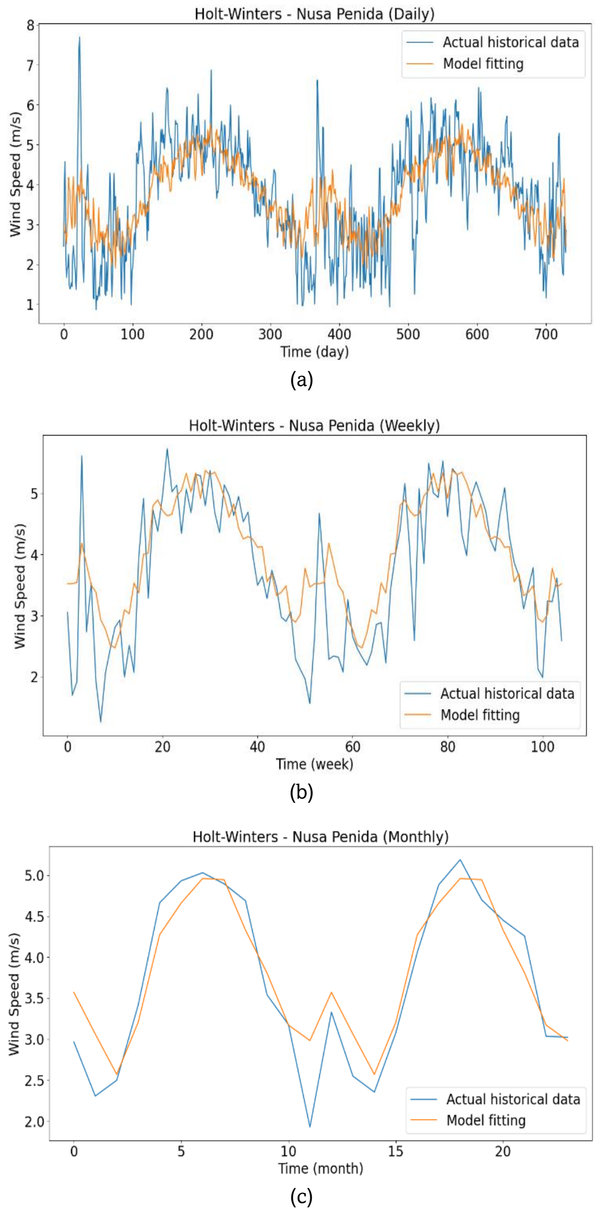

Fig 9. HWES plot for Nusa Penida – (a) daily interval, (b) weekly interval, (c) monthly interval

stakeholders with insights into the fluctuating wind speed patterns to forecast energy supply security rather than providing precise numerical wind speed values for a specific period. By providing more precise forecasts for monthly aggregated wind resources, the monthly model fitting can assist stakeholders in making investment decisions.

3.4 Wind Turbine Selection and Wind-to-Power Conversion

The analysis of wind data has resulted in the identification of three small wind turbines as candidates: Pitchwind Systems AB 30 kW, Eoltec WindRunner 25 kW (European Commission 2020), and Fuhrländer FL-100 100 kW (The Wind Power 2024). These turbines are selected primarily for their power curves, which align with the potential wind speed.

Figure 10a illustrates the power curves of the Pitchwind Systems AB 30 kW and Eoltec WindRunner 25 kW wind turbines, while Figure 10b illustrates the power curve of a Fuhrländer FL-100 100 kW wind turbine.

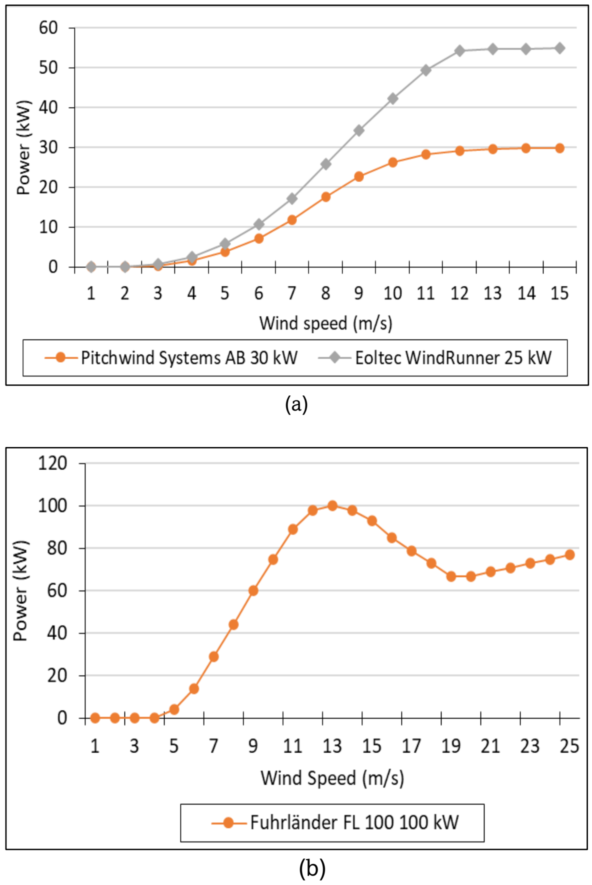

Fig 10. The power curves of (a) Pitchwind Systems AB 30 kW and Eoltec WindRunner 25 kW wind turbines, (b) Fuhrländer FL-100 100 kW wind turbine

The relevant regression equations can be derived from the wind turbine's supplied power curves. The Pitchwind Systems AB 30 kW and Eoltec WindRunner 25 kW models utilize a modified piecewise regression method, applying distinct regression types to specific intervals of data points along the power curve. Conversely, the Fuhrländer FL-100 100 kW model solely utilizes polynomial regression.

Eq. 11 presents the linear regression equation for Pitchwind Systems AB 30 kW, whereas Eq. 12 presents the polynomial regression equation. Meanwhile, the linear regression equations for Eoltec WindRunner 25 kW can be seen in Eq. 13, while the polynomial regression equation for the Fuhrländer FL-100 100 kW is presented in Eq. 14.

$$y = (0{,}1999999x) + (-0{,}2999977) \quad (11)$$

$$y = (0{,}0006013x^{11}) - (0{,}001071x^{10}) + (0{,}006777x^{9}) - (0{,}002255x^{8}) + (0{,}04551x^{7}) - (0{,}5942x^{6}) + (5{,}148x^5) - (29{,}66x^4) + (111{,}4x^3) - (259{,}1x^2) + (335{,}4x) - 182{,}8 \quad (12)$$

$$y = (0{,}49999999x) + (-0{,}99999996 \quad (13)$$

$$y = (-0{,}0005086x^{11}) + (0{,}004726x^{10}) - (0{,}001955x^{9}) + (0{,}04744x^{8}) - (0{,}7507x^{7}) + (8{,}123x^{6}) - (61{,}3x^{5}) + (322{,}4x^{4}) - (1157x^{3}) + (2696x^{2}) - (3671x) + 2209 \quad (14)$$

Table 8
Electricity Use Index - CHENACT Benchmarks

	Hotel Size (# of Guestrooms)			
	<=50	51-100	101-200	>200
High (kWh/Guest Night)	118	87	43	50
Average (kWh/Guest Night)	43	44	32	34
Low (kWh/Guest Night)	12	18	25	22

where: y is the power output, and x denotes wind speed.

3.5 Wind Contribution in Supplying Hotel Electricity Demand

This study examines a hotel's electricity consumption, considering usage levels and the number of rooms, with an emphasis on small hotels. It employs the Energy Use Index (EUI) metric from the Caribbean Hotel Energy Efficiency Action Programme (CHENACT) to evaluate the feasibility of satisfying a hotel's electricity requirements, as illustrated in Table 8 (CHTA 2012).

The EUI of the Caribbean Hotel was utilised in this study due to the resemblance between Indonesia's tropical climate and that of the Caribbean. This indicates that hotel energy consumption remains consistent regardless of variations in guests' cultural backgrounds, which may affect energy usage behaviour. The EUI evaluates three levels of energy consumption, measured in kWh per Guest Night, across four categories of hotel size based on the number of guestrooms. "Guest Night" denotes the aggregate count of hotel occupants.

This study suggests, according to the data in Table 8, that the small hotel comprises a maximum of 50 guestrooms, each occupied by a single guest, with a minimal electricity consumption of 12 kWh per guest night. This study computes total electricity consumption per night and hour by multiplying electricity usage by the number of rooms and dividing by 24. Consequently, a hotel with 50 rooms occupied by a single guest each, consuming 12 kWh per guest night, results in a total energy consumption of 600 kWh per night, equating to 25 kWh per hour.

Meanwhile, Table 9 presents the computation outcomes for various levels of energy consumption and occupancy. The energy consumption values in Table 9 may also reflect the hotel's total electricity usage, encompassing facilities such as the kitchen, office, lobby, and others, expressed as the average energy consumption per guest per night across different occupancy levels.

The contribution of wind energy to hotel electricity demand is quantified as a percentage, determined by dividing the average power output of the wind turbine by the energy consumption linked to hotel occupancy. This study employs low-to-high kWh/Guest Night values, specifically ranging from 25% to 100% hotel occupancy, to calculate the contribution of wind energy.

Table 9
The calculated electricity energy consumption

Energy consumption	Time	Occupancy			
		100%	75%	50%	25%
High	Per night	5,900	4,423	2,950	1,475
	Per hour	246	184	123	62
Average	Per night	2,150	1,613	1,075	538
	Per hour	90	67	45	22
Low	Per night	600	450	300	150
	Per hour	25	19	13	7

Table 10
Wind energy contribution (in percentage) for different hotel occupancies while considering daily, weekly, and monthly averaged wind speed data interval

Location	Data	Mean kWh	Occupancy (%)			
			100	75	50	25
Daily averaged wind speed-based data interval						
Gunung Kidul	Historical	0.45	1.8	2.4	3.6	7.2
	Predicted	0.32	1.3	1.7	2.6	5.1
Losari	Historical	0.35	1.4	1.9	2.8	5.6
	Predicted	0.24	1	1.3	1.9	3.8
Nusa Penida	Historical	1.83	7.3	9.8	14.7	29.3
	Predicted	2.21	8.8	11.8	17.6	35.3
Weekly averaged wind speed-based data interval						
Gunung Kidul	Historical	0.37	1.5	2	3	5.9
	Predicted	0.35	1.4	1.9	2.8	5.6
Losari	Historical	0.27	1.1	1.5	2.2	4.4
	Predicted	0.21	0.8	1.1	1.6	3.3
Nusa Penida	Historical	1.61	6.6	8.7	13.1	26.2
	Predicted	1.79	7	9.5	14.3	28.6
Monthly averaged wind speed-based data interval						
Gunung Kidul	Historical	0.32	1.3	1.7	2.5	5.1
	Predicted	0.35	1.4	1.9	2.8	5.6
Losari	Historical	0.22	0.9	1.2	1.8	3.5
	Predicted	0.22	0.9	1.2	1.7	3.5
Nusa Penida	Historical	1.46	5.8	7.8	11.7	23.3
	Predicted	1.57	6.3	8.4	12.5	25.1

Utilizing HWES to predict wind speed and wind turbine power output demonstrated that the Pitchwind Systems AB 30 kW turbine outperformed the Fuhrländer FL 100 100 kW and the Eoltec WindRunner 25 kW turbines. Therefore, the Pitchwind Systems AB 30 kW is chosen to evaluate the potential contribution of wind energy. Table 10 shows the potential percentages of electricity consumption that can be satisfied by a single installed wind turbine for small hotels across various locations, categorised by daily, weekly, and monthly data intervals, respectively.

The wind energy contribution shown in Table 10 evaluates both historical and projected average kWh produced by the Pitchwind Systems AB 30 kW turbine by its power curve characteristics. The predicted mean kWh is derived from the HWES models presented in Table 7. The data in Table 10 indicate that the anticipated energy contribution of a Pitchwind Systems AB 30 kW turbine to the hotel's energy requirements across all locations varies from 0.8% to 35.3%, based on hotel occupancy levels ranging from 100% to 25%, specifically at Losari (100% occupancy, weekly averaged interval) and Nusa Penida (25% occupancy, daily averaged interval).

According to daily average wind speed data, Nusa Penida exhibits the greatest contribution of wind turbine energy generation in fulfilling hotel electricity demand across various occupancy levels. The predicted mean energy output of the wind turbine, quantified at 2.21 kWh, could fulfil 8.8% of the hotel's energy requirements at full occupancy and escalate to 35.3% at 25% occupancy. Concurrently, Losari Beach has demonstrated the least potential across all data intervals.

Results in Table 10 also illustrate a trade-off between hotel occupancy rates and the contribution of wind turbine energy generation to the energy demands of hotels. The daily interval results for Nusa Penida indicate that reducing hotel occupancy to 25% has led to a fourfold increase in the energy generation contribution from wind turbines. Table 10 indicates that small wind turbines possess significant potential to fulfil partial electricity requirements of hotels at low-to-medium occupancy levels, specifically between 25% and 50%. Wind turbines are projected to fulfil 10% to 35% of energy requirements.

This contribution rate is particularly advantageous for the hotel as it alleviates the burden of grid energy expenses during the off-peak season. This also enables the integration of small wind turbines with other RE technologies, such as solar power and batteries, to enhance the clean energy supply for hotel energy requirements. This study, although focused on Indonesian locations, offers valuable methodology and analysis applicable to other developing countries and jurisdictions.

4. Conclusion

This study examined renewable energy (RE) use to promote sustainable tourism in developing countries. Using a 10-year historical wind dataset, it looked specifically at the role of small wind turbines in meeting some of the electricity demands of small-sized hotels. This study developed the wind speed model by incorporating the impact of pressure, relative humidity, temperature, and wind direction on wind speed over selected locations using MLR, SARIMA, and HWES.

The key findings of the case study, which considered three selected locations across different islands of Indonesia, are as follows:

- The hourly and daily interval datasets analysis reveals a weak correlation between weather factors (pressure, relative humidity, temperature, and wind direction) and wind speed. Wind direction has shown a stronger correlation for monthly interval data in locations exhibiting higher wind energy potential.
- The HWES method is the most appropriate approach for modelling and forecasting wind speed considering long-term datasets and different data intervals. The RMSE values indicate that monthly interval data has the lowest RMSE, followed by weekly and daily interval data.
- The Pitchwind Systems AB 30 kW wind turbine has been identified as the most appropriate type of turbine due to its power curve alignment with wind speed data and power output potential based on the HWES model's wind speed prediction.
- The installation of a single wind turbine could supply between 8.8% and 35.3% of the hotel's electricity demand, depending upon the occupancy rate levels ranging from 100% (8.8% contribution) to 25% (35.3% contribution).

This study is limited in that it analysed planned locations. It does not consider the economic feasibility of installing small wind turbines on-site. These economic implications can help determine the overall wind energy potential and feasibility of the chosen location. Furthermore, this study does not take into account or analyze the impact of hotel electricity demand patterns, such as hourly or daily, on the temporal contribution period of wind energy supply.

Nomenclature

Y	: dependent variable of multiple linear regression
α	: constant or the starting point (where all independent variables are equal to 0)
$\beta_1 \dots \beta_n$	: the 1st to the nth regression coefficient
$X_1 \dots X_n$	: the 1st to the nth independent variable
e	: prediction error
p	: trend on autoregression order
P	: seasonal autoregressive order
d	: trend on difference order
D	: seasonal difference order
q	: trend-moving average order
Q	: seasonal moving average order
$\phi_p(B)$	: non-seasonal autoregressive level
$\phi_p(B^s)$	: seasonal autoregressive level
$(1-B)^d$	: non-seasonal differencing level,
$(1-B^s)^D$	: seasonal differencing level
$\theta_q(B)$	: non-seasonal moving average level
$\Theta_q(B^s)$	: seasonal moving average level
Y_t	: actual data for the period t
$\mathcal{E}_t$	: error in the period t
α, β, γ	: smoothing constants
y_t	: observed value at the time t
L_t	: smoothing level value at the time t
b_t	: trend pattern smoothing value at the time t
S_t	: seasonal pattern smoothing value at the time t
F_{t+m}	: forecast for a time $t+m$
s	: seasonal length
y	: power output
x	: wind speed
Y'	: dependent variable of polynomial regression
X	: independent variable of polynomial regression
$X^2 \dots X^n$	: the independent variable with n degree of the polynomial
b_0	: constant or the starting point (where all independent variables are equal to 0)
$b_1 \dots b_n$	: polynomial regression coefficients

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