Comparative Assessment of Physical and Machine Learning Models for Wind Power Estimation: A Case Study for Hungary

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Abstract: In the context of the planned mid-term development of wind power plants in Hungary, the authors evaluated the applicability of a physical-based model and several machine-learning models for wind power production estimation and wind resource availability assessments based on wind speed time series retrieved from climate reanalysis. While the physical-based model relies on a national wind power plant database and follows a bottom-up approach transforming wind speed time series into aggregate power output by using type-specific power curves, the machine learning models estimate the aggregate wind power production directly from climate data. Three types of machine learning models are trained and tested: a conventional Recurrent Neural Network (RNN) model, a Long Short-Term Memory (LSTM) model, a Support Vector Regression (SVR) model. The modelling performance is evaluated against historical aggregate wind power generation data. Machine learning models achieved similar performance metrics when compared to the physical-based model. However, different use cases can be attributed to the different types of models, considering the availability of training data sets for machine learning models. A specific use case is demonstrated for the physical-based model, where the existing set of wind turbines was extended by additional, hypothetical wind turbines. This allows for analyzing the impact of geographic distribution on expected wind resource availability for different development scenarios.

Keywords: Renewable Energy; Wind Power; Machine Learning; Physical-based Model; Wind Speed Time Series; Climate Data

1 Introduction

A vast majority of new European power generation capacity additions is made up of wind and solar power plants. The availability and actual power generation of these variable resources is heavily influenced by weather conditions, challenging the security of electricity supply. In power systems exposed to increased volatility [1], model-based assessments, being a well-established approach to solve engineering problems [2-3], are of key importance. Both the recent advances in the availability of climate data and the novel modelling approaches such as the emergence of machine learning-based methods opened new ways for power system analysis and prospective studies on renewable energy integration.

Focusing on the assessment of wind power availability in the context of the mid-term development of the wind energy sector in Hungary, a two-fold objective was set: (1) setting-up and assessing the modelling accuracy of a physical-based model and different types of machine learning models for the existing Hungarian wind generation fleet to estimate the aggregate wind power output from wind speed data, (2) demonstrating the applicability of the physical-based model for scenario analysis use cases where the existing generation fleet can be extended by additional, hypothetical wind turbines and wind power production can be estimated directly from wind speed time series.

The twofold modelling approach is reflected by the terminology, as well. The term 'physical-based model' emphasizes that the underlying physical process and the physical characteristics of the modelled system are integral parts of the model, while machine learning models rely on statistics to identify patterns in the input data sets. (While considering physical-based modelling and machine learning as two distinct methodological approaches in the paper, we refer here to the novel paradigm of physics-informed machine learning that integrates physical and data models [4].) All models were developed for estimating wind power production from synchronous wind speed data rather than forecasting wind power generation.

Wind power generation in Hungary dates to the early 2000s. After commissioning the first wind turbine of 0.6 MW in Kulcs, several other wind energy installations followed in the next years. The opening of a wind capacity quota of 330 MW in the feed-in tariff system in 2006 resulted in a larger increase in installed capacity. Due to the restrictive legal framework, wind generation capacity has been nearly constant for over a decade. At the end of 2022, the total installed capacity of wind power plants in Hungary amounted to 323.2 MW [5]. As consequence of the absence of new capacity additions, long historical time series for a virtually unchanged wind power are available for the country, well-suited for training and testing machine learning models.

As for exploring the potential for wind energy utilization in Hungary, several studies have been conducted beginning from the 1990s. In a national research project started in 1995, wind climatological data from multiple sources were collected to study and map the wind climate of Hungary [6-7]. In the framework of this project, mean hourly wind speed data of 29 climate stations were evaluated, including multilevel wind profile measurements, as well. For selected regions, a WAsP (Wind Atlas Analysis and Application Program [8]) model was developed to map spatially continuous wind fields. The first set of higher resolution (5 × 5 km) wind maps for Hungary for height levels between 25 and 150 m was compiled by using the regional Numerical Weather Prediction (NWP) model ALADIN and the ERA-40 climate reanalysis archive produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) [9]. A complex national study on the wind climate of Hungary evaluated the mean and extreme wind characteristics by applying statistical methods and provided a comparative analysis of observed wind data at climate stations and hindcasts retrieved from ERA-Interim reanalysis archive, developed by ECMWF as the successor of ERA-40 [10]. The study concluded that a strong relationship exists between Hungarian station data and ERA-Interim time series. As another contribution to the research on the wind climate of Hungary, the hourly measured with speed data of seven Hungarian meteorological station were evaluated from the period between 1991 and 2000 [11]. The statistical analysis focused on the probability of wind speeds exceeding 3 m/s at different height levels, a chosen reference value for cut-in wind speed where wind turbines start producing power.

In addition to the climatological assessments, also advanced simulation methods have been developed to meet the modelling requirements of renewable energy integration studies [12]. As it is essential to use consecutive time intervals instead of single points in time to consider all aspects related to variability and flexibility requirements, simulated power generation time series for wind and solar energy derived from historical meteorological datasets are gaining increasing attention recently. The spatially and temporally homogenous gridded weather data of reanalysis archives compiled from historical observations combined by the simulations of NWP models are well-suited to energy modelling applications. Subjects to continuous improvement, the latest global reanalysis archives offer more highly resolved data in both time and space [13]. The Modern-Era Retrospective Analysis for Research and Applications (MERRA/MERRA-2) global reanalysis datasets produced by the National Aeronautics and Space Administration (NASA) Goddard Earth Sciences (GES) Data and Information Services Center provide gridded hourly wind speed data at a reference height of 50 m [14]. The time series served as an input for several renewable energy integration studies ranging from national wind and power resource assessments [15-18] to a European analysis on variability and flexibility requirements [19] and production of open-source datasets for wind power output simulations [20-22]. For this paper, the wind speed time series downloaded from the ERA5 reanalysis archive were chosen. As the latest reanalysis archive of ECMWF, ERA5 is based on improved modelling and data assimilation systems making available hourly time series of gridded weather data of a spatial resolution of approximately 31 km [13, 23]. As an advanced feature relevant for energy modelling applications, the ERA5 reanalysis archive contains wind speed data at a reference height of 100 m, close or equal to the hub height of most wind turbines currently operating in Hungary.

In addition to the use of well-established physical models transforming wind speed data into power output, machine learning-based models are gaining increasing attention when simulating the electricity generation by variable renewable energy sources. A comparative assessment for solar power plants demonstrated that machine learning models can outperform the physical models [24]. [25] combined the use of the ERA5 land data set and several machine learning models for short-term wind power forecasting.

The remainder of the paper is organized into three parts. Input data sets and time series are described in Section 2. The methodology is summarized in Section 3, covering the main steps of the model set-up for both the physical-based model and machine learning models. Section 4 evaluates the performance metrics obtained for the different types of models and presents the main results of applying the physical-based model for scenario analysis, pointing out the impact of geographical diversification of wind power availability.

2 Input Data

2.1 Input Data from Climate Reanalysis Archive

Hourly wind speed data, used as input for both the physical-based and machine learnig models, were retrieved from the ERA5 archive dataset "ERA5 hourly data on single levels from 1979 to present", a publicly available global reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) [13]. ERA5 is the latest, fifth generation global atmospheric reanalysis data set published by ECMWF. While its predecessor, ERA-Interim was less suitable for wind power modelling due to a limited temporal resolution (3-hours) and low reference height (10 m) of wind speed data, ERA5 implemented some important advances that made it well-suited to wind resource assessment. Being ahead of other open-access global reanalyses, hourly time series at a native resolution of 0.28125 degrees (31km) can be retrieved. In addition to the reference height of 10 m in ERA-Interim, wind speed data are available at 100 m height, as well, closer to the hub height of state-of-the-art wind turbines.

The retrieved wind speed time series are re-gridded to a regular latitude/longitude grid at a resolution of 0.25 degree of latitude/longitude. Wind speed parameters are provided as two components for both reference heights: 10 metre and 100 metre U wind component (10u and 100u), 10 metre and 100 metre V wind component (10v and 100v), corresponding to eastward wind (west-to-east flow) and northward wind (south-to-north flow), respectively. The time series consist of instantaneous data and point values at the grid points rather than temporal or area means.

Using the Copernicus Climate Data Store operated by ECMWF [26], the data set ‘ERA5 hourly data on single levels from 1940 to present’ was accessed to download wind speed data. For model-building and performance evaluation, the data of 2021-2022 were considered. (Using an extended period allows for evaluating annual wind power yield for different, historical climate years.)

2.2 Wind Turbine Database and Power Curves

As a basis for a detailed bottom-up modelling, a country-level data collection was conducted covering all wind turbines above 0.5 MW in Hungary. Information on technical data and location were collected from the power plant register and the annexes of the small power plant licenses issued and published by the Hungarian Energy and Public Utility Regulatory Authority and its predecessor, Hungarian Energy Office. An overview of the present generation capacity consisting of 170 wind turbines is provided in Table 1. (As currently not operating, the wind energy installation located in Felsőzsolca, consisting of one Vestas V90-1.8 MW wind turbine, was not considered in the existing set of wind turbines used for modelling.)

Table 1
Wind turbines above 0.5 MW operating in Hungary

Type	Hub height [m]	Number of wind turbines	Generation capacity [MW]
ENERCON E-40	65	5	3
ENERCON E-40	78	2	1.2
ENERCON E-48	76	5	4.1
ENERCON E-70	113	5	11.6
Fuhrländer FL MD77	100	2	3.1
Gamesa G90	78	12	24.0
Gamesa G90	100	79	158.0
Repower MM82	100	12	12.0
Vestas V52	86	1	0.9
Vestas V90-1.8 MW	105	8	14.4
Vestas V90-2.0 MW	80	5	4.0
Vestas V90-2.0 MW	105	29	58.0
Vestas V90-3.0 MW	105	8	24.0

Technical data contained in the annexes of the licenses included manufacturer, type of equipment, installed generation capacity, cut parameters (cut-in and cut-out wind speed), rated output speed, hub height and rotor diameter. The location data included in the licences were verified by checking the latitude and longitude coordinates of the individual wind farms based on the aerial photographs and high precision satellite images of the Hungarian Land-Parcel Identification System (LPIS), MePAR [27]. For all types listed in Table 1, also the power curves were collected from various data sources, including but not limited to The Wind Power [28].

2.3 Aggregate Output from Wind Power Plants

In addition to the data of the wind power plant database, power curves and the wind speed time series, also aggregate wind power output time series for Hungary were collected to be used for calibrating the physical-based model, training or testing the machine learning models and performance evaluation.

As the data of highest resolution available for 2021-2022, the 15-minute net settlement data published by the Hungarian electricity transmission system operator, MAVIR under the electricity market transparency arrangements were used [29]. We refer here to the inconsistency that synchronous wind speed data are instantaneous values (points-in-time) while aggregate wind power output data are temporal means of 15-minute resolution. (Recently, MAVIR started publishing 1-minute data, as well, less affected by temporal smoothing.)

2.4 Reference for the Siting Assumptions on Future Wind Turbines

To demonstrate the applicability of the physical-based model for scenario analysis, the set of the existing wind turbines needs to be extended by additional wind turbines. To make realistic assumptions on site selection, the project plans of a former wind power tender for 410 MW of additional wind power capacity, announced in August 2009 and recalled in July 2010, were used as a reference. The locations of the proposed projects along with existing wind turbines and neighboring ERA5 grid points are shown in Figure 1.

As part of the tender procedure for new-build wind farms, the Hungarian Energy Regulatory Authority published the cover sheet, including latitude and longitude coordinates for each of the 68 project proposals, amounting to a total additional wind power capacity of 1117.5 MW.

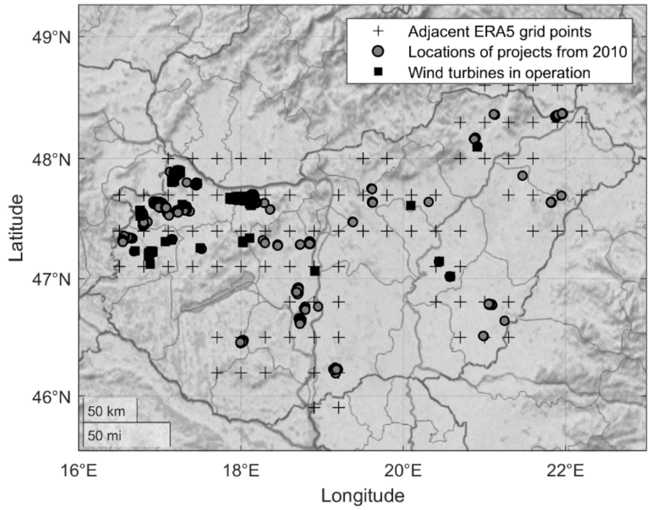

Figure 1
Geographical location of the ERA5 grid points and wind turbines over Hungary

2.5 Scenario Assumptions for Wind Turbine Types

As for wind turbine types in the scenario assessment, two types were considered: Nordex N131/3900 of 3.9 MW per wind turbine and Vestas V150-4.2 MW of 4.2 MW per wind turbine, optimized for IEC 61400 Wind Class III, low wind conditions, in line with the moderate wind climate of Hungary. For Nordex N131/3900, a hub height of 134 m was chosen, while for Vestas V150-4.2 MW, the selected hub height is 145 m.

3 Models and Methodology

3.1 Physical-based Model

To the physical-based model constructed for assessing wind power availability, existing Hungarian wind farms were added as a first step. That allowed for the calibration against historical wind power production data. The model includes the wind generating units with a registered capacity of at least 0.5 MW currently in operation in Hungary.

The model development consisted of four major steps: (1) compilation of a national wind turbine database for the existing generation fleet, (2) retrieving and processing wind speed data from the reanalysis archive, (3) conversion of wind speed data to aggregate output and (4) calibration and parameter adjustment.

3.1.1 Conversion of Wind Speed Data to Aggregate Output

The model that was developed relies on the detailed dataset of existing generation equipment covering all installations above 0.5 MW, as seen in Section 2.2. For each type of wind turbine presently operating in Hungary, a conversion function was defined based on the type-specific power curve; divided into four segments defined by the cut-in wind speed, rated output wind speed and cut-out wind speed. For the segment between the cut-in and rated wind speed a polynomial approximation was used, by fitting a polynomial $\mathrm{p}_i(\mathrm{w})$ to the points of the power curve for each type of wind turbine. In general, power curve functions of the wind turbines consist of the following segments:

$$P_{WT,i} = 0 \qquad \text{for w} \leq w_{cut-in,i} \tag{1}$$
$$P_{WT,i} = \mathrm{p}_i(\mathrm{w}) \qquad \text{for w} > w_{cut-in,i} \text{ and w} < w_{rated,i} \tag{2}$$
$$P_{WT,i} = \mathrm{P}_{rated} \qquad \text{for w} \geq w_{rated,i} \text{ and w} \leq w_{cut-out,i} \tag{3}$$
$$P_{WT,i} = 0 \qquad \text{for w} > w_{cut-out,i}, \tag{4}$$

in which:

$P_{WT,i}$ power output of wind turbine type *i*
w wind speed
$w_{cut-in,i}$ cut-in wind speed of wind turbine type *i*
$\mathrm{p}_i(\mathrm{w})$ polynomial approximation for the power curve of wind turbine type *i* between the cut-in and the rated wind speed
$w_{rated,i}$ rated wind speed of wind turbine type *i*
$w_{cut-out,i}$ cut-out wind speed of wind turbine type *i*

In the next step, the wind speed time series obtained from the ERA5 reanalysis were interpolated to the actual location of wind turbines by using bilinear interpolation. While bilinear interpolation, a type of statistical downscaling is a simplified approach, in cases of more complex terrains, where the capture of local wind patterns is of high importance, statistical downscaling should be replaced by dynamical downscaling involving more precise orographic description and the use of additional numerical weather prediction models of higher resolution.

For the wind turbines having a hub height other than 100 m, an extrapolation (or interpolation) to the hub height was necessary, as well. When estimating wind speed at hub heights from the data available at a limited number of vertical levels, the role of several factors need to be considered: wind speed, atmospheric stability, surface roughness and height interval. Among the two most common analytical approaches, power law and logarithmic law, the power law was found to give a better representation of the vertical wind profile. The extrapolation (interpolation) to hub height was done by estimating the wind share coefficient α from the wind speed data at the reference heights of 10 m and 100 m:

$$\alpha = \frac{\ln\left(\frac{\mathrm{w}_{100\,m}}{\mathrm{w}_{10\,m}}\right)}{\ln\left(\frac{\mathrm{h}_{100\,m}}{\mathrm{h}_{10\,m}}\right)} \tag{5}$$

$$w_{hub} = \mathrm{w}_{100\,m}\left(\frac{h_{hub}}{h_{100\,m}}\right)^{\alpha}, \tag{6}$$

in which:

α	wind share coefficient,
$w_{100\,m}$	wind speed at 100 m reference height,
$w_{10\,m}$	wind speed at 10 m reference height,
$h_{100\,m}$	100 m reference height,
$h_{10\,m}$	10 m reference height,
w_{hub}	wind speed at hub height,
h_{hub}	hub height.

3.1.2 Calibration and Parameter Adjustment

As reanalyses contain systematic errors (biases) resulting from the underlying numerical weather prediction models, calibration is a key factor when using wind speed time series derived from reanalysis. For calibration, the country-level aggregate output time series of the years 2021-2022 were considered.

Additionally, a correction was introduced to the wind speed time series consisting of a multiplicative factor and a linear offset:

$$w' = \beta \cdot w + \gamma, \tag{7}$$

in which:

w'	corrected wind speed,
β	multiplicative factor for wind speed correction,
γ	linear offset for wind speed correction.

After optimizing the values of β and γ to achieve the highest possible correlation coefficient to the period 2021–2022, 0.99 was used as β, and 0.42 m/s as γ. (Furthermore, site-specific γ linear offset values can be specified by an iterative search to improve the performance of the model. As only publicly available data sets were used for the paper, we did not consider any site-specific time series for the model development.)

In addition to the correction for the underlying wind speed data, another multiplicative factor of 0.94 was considered for the aggregate output power representing losses and impacts of degradation. The multiplicative factor was estimated from the ratio of the model-based and metered simultaneous peak power output.

3.1.3 Extension of the Base Model for Scenario Assessment

The methodology that transforms wind speed data from reanalysis via power curves to power output and aggregates the production of the individual wind turbines is well suited to follow the changes in the generation fleet. Therefore, the set of operating wind farms can be complemented by additional, hypothetical wind farms located in diverse geographic regions. This approach formed the basis of the scenario assessment.

By adding additional, hypothetical wind turbines to the physical base model consisting of the existing wind turbines, different wind power development scenarios can be modelled for Hungary and evaluated in terms of wind power availability. This method allows for assessing the impact of geographic diversification, as well.

3.2 Machine Learning Models

The direct estimation of the aggregate wind power output from climate data can be interpreted as a multivariate regression problem, for which different supervised machine learning models can be applied, including a number of models handling the sequential nature of data. Three types of machine learning models were trained and tested: a traditional Recurrent Neural Network (RNN) model, a Long Short-Term Memory (LSTM) model, and a Support Vector Regression (SVR) model.

In the machine learning models, the wind speed time series at 10 m and 100 m reference heights of the ERA5 grid points neighbouring the existing wind turbine locations were used as features X. As the target (or label) variable, the historical aggregate wind power output time series, described in Section 2.3, were used.

3.2.1 Selected Types of Machine Learning Models

Recurrent Neural Network (RNN) Model

Deep Learning is increasingly popular due to its attractive characteristics, encompassing automatic feature engineering, excellent performance with unstructured data, robust generalization capabilities, and adept handling of large-scale and time-series datasets. The neural network architecture comprises three layers: the input layer, hidden layers, and output layer. The structure involves a single input and output layer, with one or more hidden layers positioned between them.

RNN models, which are integral branches of Deep Learning, employ a sequential approach to process input data, effectively capturing temporal dependencies between successive data points. The Recurrent Neural Network (RNN) stands out for its capacity to consistently manage extensive datasets by incorporating past information through a looping mechanism in each unit. In each time step, the RNN employs multiple activation function units, each containing a hidden state as an internal representation. This hidden state encapsulates prior information processed by the unit and persists at the specific time step. Regular updates to the state information at each time step ensure the representation of extension of knowledge.

In the RNN, the hidden state undergoes updates via a recurrence relation. At time *t*, input is provided for a single time step, and the current state is computed using both the input and the previous state value. Subsequently, the calculated current state h_t serves as the previous state value for the subsequent time step at *t-1*. This iterative process continues until all time steps are completed. The final current state is then derived, and the ultimate output of the recurrent network is computed based on this final state. After the completion of this for all time steps, the error is evaluated by comparing the calculated output against the actual output.

Moreover, RNN's advantage is underscored by its effectiveness in modeling temporal dependencies, making it particularly suitable for tasks involving sequential data, e.g. time-series forecasting. The recurrent nature of RNN enables it to maintain context and memory over extended sequences, distinguishing it as a valuable tool in Deep Learning. The recurrent structure of RNN facilitates the modeling of dynamic patterns and dependencies, enhancing its versatility across various applications.

In general, the recurrence relation in RNN can be expressed by Eq. (8):

$$h_t = f(W_{hh}h_{t-1} + W_{hx}x_t + b_h), \tag{8}$$

in which h_t represents the current hidden state, x_t stands for the input at time *t*, W_{hh} and W_{hx} are weight matrices, and b_h denotes the bias term. The output calculation in RNN is given by Eq. (9):

$$y_t = f\left(W_{hy}h_t + b_y\right), \tag{9}$$

in which y_t is the output at time *t*, W_{hy} is the weight matrix connecting the hidden state to the output, and b_y is the output bias term.

Long Short-Term Memory (LSTM) Model

The LSTM is an extension of the Recurrent Neural Network, which addresses the challenge of limited short-term memory by incorporating a vector of internal cell state, enabling the reservation of hidden state information for an extended duration. The limitation of the basic RNNs lies in their sensitivity to the vanishing or exploding gradient problem, hindering the effective propagation of information over long sequences during training. In contrast, to the basic RNN's short-term memory constraints, the LSTM introduces long-term memory, selectively preserving relevant information from past learning while discarding irrelevant data. Our research explores the performance of LSTM also, using its filtering capabilities achieved through the incorporation of gates.

LSTM employs three distinct types of gates—input, forget, and output gates—each serving a specific purpose. The input gate identifies information essential for the subsequent processes, preserving it in the internal cell state. Conversely, the forget gate identifies information to discard, preventing its retention in the internal cell state from past learning. The output gate determines the information to be generated as output from the internal cell state, subsequently serving as the next hidden state. To initiate this process, the sigmoid layer plays a crucial role in discerning information to be discarded from the internal cell state. It makes decisions regarding the retention of internal state information for the next cell state, considering inputs from the previous state h_{t-1} and the current state x_t. The output of the sigmoid layer, either 0 or 1, signifies whether specific information should be preserved in the cell state (output 1) or removed (output 0). Detailed description of the operation can be read, for instance in [30].

Furthermore, several other network architectures, including Depth Gated LSTM [30], Multiplicative LSTMs (mLSTMs) [31], and Bidirectional LSTMs [32], have been developed to overcome the limitations associated with the basic RNN. These networks represent diverse approaches to enhancing memory and information processing capabilities within neural networks, showcasing the continual evolution and refinement of Deep Learning models, whiches investigation is part of our future work.

Support Vector Regression (SVR) Model

The Support Vector Machine (SVM), specifically Support Vector Regression (SVR), is a supervised Machine Learning algorithm that is also expected to prove a valuable tool for direct estimation of aggregate wind power output from climate data, treating it as a multivariate regression problem. SVR operates by transforming input data into a higher-dimensional space using kernel functions, and its effectiveness is strongly influenced by the choice of the kernel. Mathematically, SVM seeks to find a hyperplane in the transformed space that maximizes the margin between data points and minimizes prediction errors. The selection of the kernel function is pivotal, as it determines the algorithm's capacity to capture complex patterns within the data. Commonly used kernels include linear, polynomial, and radial basis function (RBF) kernels. The linear kernel assumes a linear relationship between features, while polynomial and RBF kernels enable the model to capture non-linear patterns.

In the specific context of predicting wind power output from climate data, the choice of kernel becomes crucial. For instance, the RBF kernel is adept at capturing intricate relationships in non-linear data, which may be prevalent in climate time series. Conversely, the linear kernel might be suitable if the relationships are predominantly linear.

The utility of SVM in the present study lies in its versatility, offering a robust approach to modeling the complex relationship between wind speed time series features *(X)* and historical aggregate wind power output *(y)*. By experimenting with different kernel options and tuning their parameters, SVM can be optimized to effectively model the complex interdependencies within the data, ensuring accurate predictions in the multivariate regression problem, thus this method is a candidate for investigation in our present research.

3.2.2 Implementation and Hyperparameter Optimization

All machine learning models were implemented in a Python environment. After setting up the machine learning models, the optimization of the hyperparameters was performed by grid search, as summarized by *Table 2*, in order to find the optimal combination of hyperparameters for each type of model.

Table 2
Summary of Hyperparameter Optimization for the Machine Learning models

Model	Hyperparameter	Settings	Search Options
RNN	Optimization solver	Adam	Adam, RMSProp, SGD
	Learning rate	0.002	0.001, 0.002, 0.01, 0.02, 0.05
	Dropout	0.1	0.1, 0.2, 0.3, 0.4
	Number of layers	3	1, 3, 5, 7
	Hidden nodes	24	12, 24, 48, 96
	Batch size	12	12, 24, 48
	Epochs	100	10, 100, 200
LSTM	Optimization solver	Adam	Adam, RMSProp, SGD
	Learning rate	0.002	0.001, 0.002, 0.01, 0.02, 0.05
	Dropout	0.1	0.1, 0.2, 0.3, 0.4
	Number of layers	5	1, 3, 5, 7
	Hidden nodes	24	12, 24, 48, 96
	Batch size	12	12, 24, 48
	Epochs	100	10, 100, 200
SVR	C	950	1, 50, 100, 500, 950, 100
	ε	5	0.1, 1, 5, 10 20
	Kernel	rbf	linear, rbf

The performance metrics (scores) used for the comparative assessment are summarized in Table 3.

Table 3
Metrics for Evaluating the Modelling Performance

Coefficient of Determination	$R^2 = 1 - \frac{\sum(P_i^{actual} - P_i^{est})^2}{\sum(P_i^{actual} - P_{average})^2}$
Root Mean Square Error or Root Mean Square Deviation	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i^{actual} - P_i^{estimate})^2}$
Mean Absolute Error	$MAE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert P_i^{estimate} - P_i^{actual}\right\rvert$
Mean Bias Difference	$MBD = \frac{1}{n}\sum_{i=1}^{n}\left(P_i^{actual} - P_{average}^{estimate}\right)$

4 Results

4.1 Comparison of Modelling Performance

For the physical-based model, performance evaluation is based on the whole set of 2021–2022 data; at the same time, only the test data sets were considered for machine learning models.

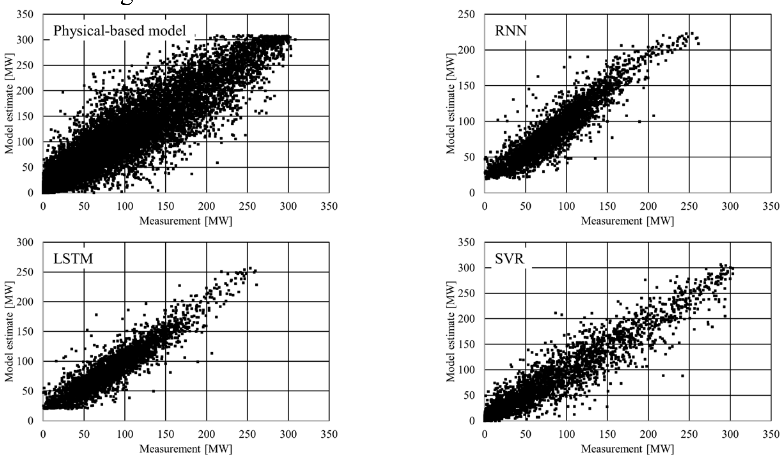

Figure 2
Comparison of the aggregate wind power output [MW] estimated by the different types of models to historical measurement data

The scatterplots in Figure 2 show the estimated and measured aggregate wind power output data. The figures highlights some limitations of the modelling approaches:. zero or close-to-zero production tends to be overestimated by the RNN-type of models while a higher difference between the model output and actual data can be seen in the case of the physical-based model.

The modelling performance was evaluated based on the performance metrics summarized in Table 3, as well. The indicators are given in Table 4, indicating the ability of machine learning models to outperform the physical-based model in terms of all indicators.

Table 4

Performance Metrics for the Models

Model	R^2 [-]	RMSE [MW]	MAE [MW]	MBD [MW]
Physical-based model	0.86657	29.14	19.41	-4.92
RNN	0.84848	**16.53**	**12.24**	-1.76
LSTM	0.85216	16.65	12.33	-3.62
SVR	**0.90454**	21.96	15.07	**1.03**

4.2 Scenario Assessment

The extended physical base model allowed for simulating the aggregate power output of an extended wind generation fleet based on ERA5 2021–2022 wind speed data. Figure 3 shows the computed annual duration curves for the various scenarios: Base case, Scenario A and Scenario B.

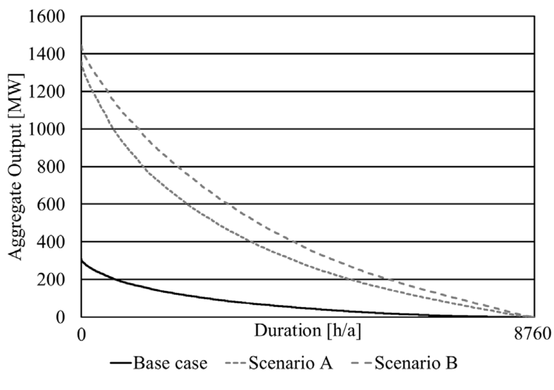

Figure 3

Duration curves of the aggregate power output from existing and potential additional wind farms

As Base case, only generation existing wind farms are considered. Scenario A includes the existing wind generation fleet and 290 additional wind turbines of type Nordex N131/3900, located at the sites considered for the 2010 tender procedure, as shown in Figure 1. In scenario B, the Nordex N131/3900 installations are replaced by 290 Vestas V150-4.2 MW installations at the same locations. For both scenarios A and B, the production of the whole set of wind turbines was simulated. However, it is possible to consider a subset of additional wind turbines when assessing the potential for geographic diversification to reduce the volatility of aggregate wind power output. However, the results shown in Figure 3 suggest a moderate potential for geographic smoothing.

Conclusions

The development and use of novel methodological approaches, especially the accurate representation of generation by variable renewable energy sources are essential to address the different aspects of renewable energy integration. With the aim of evaluating the applicability of different modelling approaches for wind power output estimation, we set up a detailed physical-based model backed by a national wind power plant database and in parallel, trained and tested several machine learning models.

When comparing and evaluating the results, the main conclusion is twofold. (1) First, the performance metrics confirmed the applicability of machine learning models to estimate aggregate wind power output directly from wind speed data. However, while a similar or higher level of accuracy can be achieved when compared to the physical-based model, the areas of applications are limited to use cases where a sufficient set of training data for existing wind energy installations is available, e.g. data validation of wind power generation time series. (2) Second, the physical model allowed for an assessment considering additional, hypothetical wind turbines in addition to the existing Hungarian wind power plant portfolio and evaluating the wind resource availability for different wind power extension scenarios for Hungary. In the context of the new wind power capacity additions expected in Hungary on the mid-term, the results suggest that geographic diversification has only a very limited impact on reducing the volatility of aggregate wind power generation due to the overall similar weather conditions related to the relatively small country area and geographically less diversified landscape.

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