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Review and Assessment of Wind Power Forecasting Studies for Very Short-Term and Short-Term Horizons

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Rüzgâr Gücü
Tahmin Ufku
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Değerlendirme

Graphical/Tabular Abstract (Grafik Özet)

This study evaluates the current status of very short-term and short-term wind power forecasting by comparing existing studies in the literature from different aspects. / Bu çalışma, literatürdeki mevcut çalışmaları farklı yönlerden karşılaştırarak çok kısa dönem ve kısa dönem rüzgâr gücü tahmininin mevcut durumunu değerlendirmektedir.

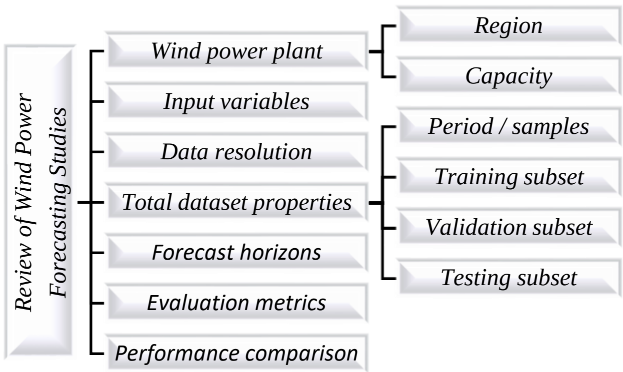

***Figure A**: The different aspects used in reviewing very short-term and short-term wind power forecasting studies / **Şekil A:** Çok kısa dönem ve kısa dönem rüzgâr gücü tahmin çalışmalarını incelerken kullanılan farklı yönler*

Highlights (Önemli noktalar)

- *Initially, the reviewed studies have been compared in terms of properties of wind power plants, input variables of forecasting methods, data resolution and total dataset properties. / İlk olarak, incelenen çalışmalar rüzgâr güç santrallerinin özellikleri, tahmin metotlarının girdi değişkenleri, veri çözünürlüğü ve toplam veri seti özellikleri açısından karşılaştırılmıştır.*
- *Then, they have been compared in terms of forecast horizons, evaluation metrics and performance of forecasting methods. / Daha sonra, tahmin ufukları, değerlendirme metrikleri ve tahmin metotlarının performansı açısından karşılaştırılmıştır.*
- *Many beneficial evaluations and guiding recommendations have been presented to researchers for more consistent wind power forecasting studies. / Araştırmacılara, daha tutarlı rüzgâr gücü tahmin çalışmaları için pek çok yararlı değerlendirme ve yol gösterici öneri sunulmuştur.*

Aim (Amaç): *This study aims to identify the current limitations in the literature to improve the consistency of wind power forecasting research. / Bu çalışma, rüzgâr gücü tahmin araştırmalarının tutarlılığını artırmak için literatürdeki mevcut sınırlılıkları belirlemeyi amaçlamaktadır.*

Originality (Özgünlük): *This study constitutes the highly-informative tabulated contents of all the reviewed studies. / Bu çalışma, incelenen tüm çalışmaların son derece bilgilendirici tablolaştırılmış içeriklerini oluşturmaktadır.*

Results (Bulgular): *Overall evaluations regarding wind power forecasting studies have been made by utilizing the created literature tables. / Oluşturulan literatür tablolarından yararlanılarak rüzgâr gücü tahmin çalışmalarına ilişkin genel değerlendirmeler yapılmıştır.*

Conclusion (Sonuç): *The important points to be taken into consideration by researchers have been indicated for future works. / Gelecekteki çalışmalar için araştırmacıların dikkat etmesi gereken önemli noktalar belirtilmiştir.*

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Review and Assessment of Wind Power Forecasting Studies for Very Short-Term and Short-Term Horizons

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Abstract

Wind energy penetration is continuously increasing in electricity grids and the intermittent nature of wind speed causes the problems in system operations. Therefore, utilities, system operators and researchers focus on alleviating the negative impacts of volatile generation and harvesting wind energy efficiently. At this point, accurate wind power forecasts serve as the promising research studies in the literature. To this end, this paper presents a comprehensive literature review of wind power forecasting studies for very short-term and short-term horizons. The reviewed studies have been compared in terms of installation properties of wind power plants, inputs of forecast models, data recording intervals and periods, training, validation and test subsets, forecast horizons, accuracy measures and forecast performance. As a result of the knowledge-intensive literature tables created, the up-to-date assessments of very short-term and short-term forecasting studies have been made from different perspectives, and noteworthy recommendations have been highlighted for fairer comparisons of the reviewed studies.

Çok Kısa Dönem ve Kısa Dönem Ufukları için Rüzgâr Gücü Tahmin Çalışmalarının İncelenmesi ve Değerlendirilmesi

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Öz

Elektrik şebekelerinde rüzgâr enerjisinin penetrasyonu sürekli olarak artmakta ve rüzgâr hızının kesintili doğası sistem operasyonlarında sorunlara neden olmaktadır. Bu nedenle, kamu hizmet kuruluşları, sistem operatörleri ve araştırmacılar değişken üretimin olumsuz etkilerini hafifletmeye ve rüzgâr enerjisini verimli bir şekilde toplamaya odaklanmaktadır. Bu noktada, doğru rüzgâr gücü tahminleri literatürde umut vadeden araştırma çalışmaları olarak hizmet vermektedir. Bu amaçla, bu makale çok kısa dönem ve kısa dönem ufukları için rüzgâr gücü tahmin çalışmalarının kapsamlı bir literatür incelemesini sunmaktadır. İncelenen çalışmalar rüzgâr güç santrallerinin kurulum özellikleri, tahmin modellerinin girdileri, veri kayıt aralıkları ve periyotları, eğitim, doğrulama ve test alt kümeleri, tahmin ufukları, doğruluk ölçümleri ve tahmin performansı açısından karşılaştırılmıştır. Oluşturulan bilgi yoğun literatür tabloları sonucunda, çok kısa dönem ve kısa dönem tahmin çalışmalarının güncel değerlendirmeleri farklı perspektiflerden yapılmış ve incelenen çalışmaların daha adil karşılaştırmaları için dikkate değer öneriler vurgulanmıştır.

1. INTRODUCTION (GİRİŞ)

The demand for energy is rapidly increasing due to high levels of economic and technological development, population growth and urbanization [1, 2]. At the same time, global warming and climate change have led to an exponential increase in greenhouse gas emissions into the atmosphere over the past few decades [3-5]. With increasing environmental issues, renewable energy sources have gained significant interest as a potential solution to fossil fuels [6-8]. Many countries around the world are increasingly investing in renewable energy installations and the reduction in system costs have accelerated this global transition in a more sustainable and resilient way [9, 10].

Wind energy is one of the leading renewable energies with its high usable potential [11]. Wind energy also stands out with its clean, environmentally friendly and pollution-free structure, as well as its easy accessibility,

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competitive costs and large storage capacity [12-14]. The IRENA's World Energy Transitions Outlook forecasts that global wind installations will reach approximately 3.5 TW by 2030, comprising 3,040 GW of onshore capacity and 494 GW of offshore capacity [15]. Similarly, the IEA's Net Zero by 2050 Scenario targets a total global wind capacity of 2.75 TW by 2030, with an additional 320 GW of new wind installations [15].

Although wind energy offers numerous advantages, it is influenced by external environmental factors such as weather conditions, geographic location and seasonality, causing to uncertainty and instability [16, 17]. The randomness and fluctuation of wind energy can complicate the planning and distribution processes for power system management [18-20]. In case of integrating wind energy into electricity grids, its forecasting accuracy is crucial for both security and economic assessments [21-23]. Wind power forecasting not only provides the guidance for the operation and maintenance units of wind farms but also ensures the stable operation of power system and the reduction of operational costs [13, 14]. In the literature, various methods have been proposed to enhance the accuracy in wind power forecasting, which are fundamentally categorized into physical, statistical and hybrid approaches [24, 25].

This study has been conducted to identify the existing limitations in the literature, such as the rare availability of capacity information of wind power plants, the lack of a common approach in creating test, validation and training subsets, the uncertainties in the selection of input variables and data recording intervals, the variety of forecast horizons and evaluation metrics in performance comparisons, etc. To overcome such shortcomings, in this study, very short-term and short-term wind power forecasting studies in the literature have been reviewed from different criteria. Initially, the existing studies have been characterized by the region and capacity of the operated wind power plant, input variables of the employed forecasting methods, data resolution, total dataset period/ samples, and dataset partitioning ratios/amounts. Then, the corresponding studies have been featured with forecast horizons, evaluation metrics, and performance rankings of forecasting methods. According to the up-to-date and information-rich tables constructed, many useful assessments have been made about the current status of very short-term and short-term wind power forecasting, and many guiding suggestions have been presented to the researchers for more consistent forecasting studies.

The remainder of this review is organized as follows: Sections 2.1 and 2.2 present and describe the literature tables created for very short-term and short-term wind power forecasts. Section 2.3 provides the overall assessments made on very short-term and short-term wind power forecasts. Conclusions and recommendations are given in Section 3.

2. WIND POWER FORECASTING (RÜZGÂR GÜCÜ TAHMİNİ)

In the following subsections, we first introduce the highly-summarized content of the relevant literature. We then evaluate the current status of very short-term and short-term wind power forecasting in the literature.

2.1. Very Short-Term Wind Power Forecasting (Çok Kısa Dönem Rüzgâr Gücü Tahmini)

Very short-term wind power forecasting plays a critical role in developing power generation plans, adjusting operation strategies, and providing the fundamental information for electricity market trading [26]. Very short-term wind power forecasts cover the time horizons ranging from a few seconds to 30 minutes [27]. Table 1 summarizes wind power plant information, input variables of forecasting methods, total dataset properties and data resolution of the reviewed studies for very short-term wind power forecasting. In addition, Table 2 presents the corresponding forecast horizons, evaluation metrics and performance comparison of forecasting methods.

For instance, in [36], a 10 MW wind power plant located in USA was utilized. Wind power production, air density, atmospheric pressure, wind direction, temperature and wind speed were used as the input variables of forecasting methods. The total dataset included the measurements collected at 5 min. intervals over a 2-year period. It was partitioned into one-year subsets for training and testing of the forecasting methods. RMSE was utilized as the evaluation metric, while 5 min. was used as the forecast horizon. According to the performance comparison, DDA-LightGBM method surpassed LightGBM, Adaboost, RF, Bagging, Extra-Trees, GBRT, XGBoost and SVR methods, respectively.

2.2. Short-Term Wind Power Forecasting (Kısa Dönem Rüzgâr Gücü Tahmini)

Short-term wind power forecasting has a crucial task in the optimization of the grid connection of wind power, and in the reduction of the backup capacity of power grid [26]. Short-term wind power forecasts include the time horizons between 30 minutes to 6 hours [27]. Wind power plant information, input variables of forecasting methods, total dataset properties and data resolution of the reviewed studies for short-term wind power forecasting are summarized in Table 3. In addition, the corresponding forecast horizons, evaluation metrics and performance comparison of forecasting methods are presented in Table 4.

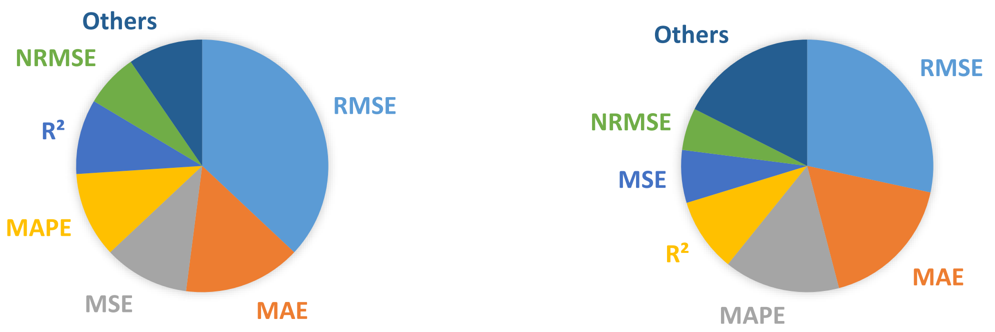
For instance, in [85], a wind power plant located in China was used. Wind speed, ambient temperature, wind direction and historical power prediction residuals were utilized as the input variables of forecasting methods. The total dataset contained 2264 measurements collected at 1 hour intervals. It was split into training and testing subsets with the ratios of 70% and 30%, respectively. MSE, RMSE and SSE were used as the evaluation metrics, while 1 hour was utilized as the forecast horizon. According to the performance comparison, CEEMDAN-SVR-TCN method outperformed CEEMDAN-SVR, CEEMDAN-TCN, CEEMDAN -BP, TCN, LSTM, BP and SVR methods, respectively.

2.3. Overall Assessments On Very Short-Term And Short-Term Wind Power Forecasting (Çok Kısa Dönem Ve Kısa Dönem Rüzgâr Gücü Tahmini Üzerine Genel Değerlendirmeler)

As a result of the overall evaluations of Tables 1 to 4, the following important findings are obtained for very short-term and short-term wind power forecasting:

- In both forecast horizons, the regional information of the wind power plant has been provided in almost all studies, but the capacity information of it has been specified in a limited number of studies.
- In both forecast horizons, the first three most greatly-utilized input variables of forecasting methods are wind power, wind speed and wind direction, respectively. These are followed by the ones of air temperature, atmospheric pressure, relative humidity and air density, respectively.
  - In the very short-term forecast horizon, it is very rare to use the input variables of solar radiance, other climatic factors, generator current, generator frequency, generator torque, heat flux, etc.
  - In the short-term forecast horizon, it is very seldom to use the input variables of zonal and meridional wind components, NWP data, historical power prediction residuals, etc.
- The first two most widely-utilized data resolutions in the very short-term forecast horizon are 15 min. and 10 min., respectively, followed by 5 min. Those in the short-term forecast horizon are 1 hour and 15 min., respectively, followed by 10 min.
  - It is very rare to use the data resolutions of 30 min. and 3 min. in the very short-term forecast horizon. That is 12 hours in the short-term forecast horizon.
- In both forecast horizons, the total dataset is often partitioned into the training subset with the ratio of 80% to 90%, and the testing subset with the ratio of 10% to 20%. Validation subsets are of limited utilization.
- The first two most preferred horizons in the very short-term forecasting are 15 min. and 10 min, respectively. Those in the short-term forecasting are 1 hour and 4 hours, respectively.
  - It is very seldom to prefer the horizons of 30 min., 20 min. and 5 min. in the very short-term forecasting. Those are 6 hours, 3 hours, 2 hours, 45 min. and 40 min. in the short-term forecasting.
- The first three commonly-employed evaluation metrics in the very short-term forecast horizon are RMSE, MAE and MSE, respectively, followed by MAPE, R^2 and NRMSE, respectively. Those in the short-term forecast horizon are RMSE, MAE and MAPE, respectively, followed by R^2, MSE and NRMSE, respectively. The usage rates of evaluation metrics in very short-term and short-term wind power forecasting studies are presented in Figures 1(a) and 1(b), respectively.
  - It is very rare to employ the evaluation metrics of MASE, CRPS, NMAE, MRE, U^1, etc. in the very short-term forecast horizon. Those are SDE, SSE, NMAE, MAAPE, SMAPE, PAR, etc. in the short-term forecast horizon.
- In both forecast horizons, hybrid models, which inherit the strengths of individual models, have mostly been implemented. In the design of these hybrid models,
  - LSTM, VMD, EEMD, CNN, PSO, ELM, SVR and GRU individual models have frequently been used in the very short-term forecast horizon. Among them, LSTM, VMD and EEMD stand out as the main models that contribute to achieving successful forecasting performance.
  - WOA, VMD, LSTM, TCN, ELM, KELM, CEEMDAN and SVR individual models have often been utilized in the short-term forecast horizon. Among them, WOA, VMD and LSTM come out as the essential models that help to accomplishing high prediction performance.

- Both forecast horizons suffer from the lack of sharing of total datasets used for wind power forecasting, the lack of usage of reference forecast models for benchmark tests, and the lack of provision of information on the computational requirements of forecast methods.



a) *b)*

Figure 1. The usage rates of evaluation metrics for *a)* very short-term and *b)* short-term wind power forecasting studies (*a)* Çok kısa dönem ve *b)* kısa dönem rüzgâr gücü tahmin çalışmaları için değerlendirme metriklerinin kullanım oranları)

Table 1. Region and capacity of wind power plant, input variables of forecasting methods, data resolution and total dataset properties of the reviewed studies for very short-term wind power forecasting (Çok kısa dönem rüzgâr gücü tahmini için incelenen çalışmaların rüzgâr güç santralinin bölgesi ve kapasitesi, tahmin metotlarının girdi değişkenleri, veri çözünürlüğü ve toplam veri seti özellikleri)

Ref.	Wind Power Plant		Input Variables of Forecasting Methods	Data Resolution	Total Dataset Properties			
	Region	Capacity			Period / Samples	Training Subset	Validation Subset	Testing Subset
[28]	Germany	463 MW	Wind power	15 min.	38112	80%	10%	10%
	China	99.5 MW			8544			
[29]	China	200 MW	Historical wind speed (10m, 30m, 50m, 70m), historical power generation	15 min.	1 year	90%	10%	
[30]	South Africa	100 MW	Historical wind generation power	30 min.	3 years	70%	20%	10%
[31]	China	99 MW	Wind speed (10m, 30m, 50m, hub height), wind direction (10m, 30m, 50m, hub height), air pressure, ambient temperature, humidity	15 min.	2 years	80%	-	20%
		99 MW						
		96 MW						
[32]	China	200 MWh	Actual power, wind speed (10m, 30m, 50m, 70m, hub height), wind direction (10m, 30m, 50m, 70m, hub height)	15 min.	5760	97.6%	-	2.4%
[33]	China	1.5 MW	Wind power series	15 min.	8929	7142	-	1787
		49.5 MW			8929	7142		1787
[34]	China	1.5 MW	Raw wind power series	15 min.	~6 months	80%	-	20%
		49.5 MW						
[35]	Turkey	3600 kW	Wind power	10 min.	1 year	First 80%	-	Last 20%
	France	2050 kW						
[36]	USA	10 MW	Wind power production, air density, atmospheric pressure, wind direction, temperature, wind speed	5 min.	2 years	1 year	-	1 year
[37]	China	50 MW	Wind direction, wind speed, wind power	15 min.	11 months	60 days	-	30 days
[38]	China	2 MW	Historical wind power time series	5 min.	1 year	5760 per month	-	2304 per month
[39]	France	2050 kW	Relative wind direction, wind speed	10 min.	1000	70%	-	30%
[40]	China	400 MW	Wind speed, temperature, solar irradiance	15 min.	34560	-	-	-
[41]	Denmark	2 MW	Wind power time series	10 min.	5760	-	-	-
[42]	China	-	Wind speed, wind direction, temperature, wind power	15 min.	865	60%	20%	20%
[43]	China	-	Wind power	15 min.	2976	60%	20%	20%

					2976			
[44]	China	-	Wind power, wind speed, wind direction, air temperature, atmospheric pressure	10 min.	52069	80%	10%	10%
[45]	Turkey	-	Average wind speed, absolute wind direction	10 min.	1008	60%	20%	%20
[46]	Australia	-	Wind power	5 min.	119232	~7 months	~3 months	4 months
[47]	USA	-	Surface pressure, wind direction, temperature, air density, wind speed	5 min.	1 year 1 year	80%	10%	10%
[48]	USA	-	Wind speed, wind direction, air density, air pressure	10 min.	1 year	75%	33% of training set	25%
[49]	Turkey	-	Raw wind power data	15 min.	10000 10000 10000	90%	-	10%
[50]	Spain	-	Wind power series	10 min.	1500	1200	-	300
[51]	China	-	Wind speed, active power, generator frequency, generator torque, generator current, historical wind power data	10 min.	1 year	3964	-	500
[52]	China	-	Wind speed, wind direction, temperature, atmospheric pressure, other climatic factors	10 min.	894	750	-	144
[53]	China	-	Raw wind power data	10 min.	13248	11952	-	1152
[54]	China	-	Wind power, wind speed, wind direction	10 min.	390	360	-	30
[55]	China	-	Wind speed, sine and cosine of wind direction, air density	15 min.	2 years	1 year	-	1 year
[56]	Inner Mongolia	-	Historical wind power, historical wind power vector	3 min.	13440	10080	-	3360
[57]	China	-	Historical power dataset	15 min.	31 days	24 days	-	7 days
[58]	China	-	Scada dataset	15 min.	3 months	First 85 days	-	Last 7 days
[59]	China	-	Wind speed, wind direction, temperature, air pressure, humidity, measured power data	15 min.	1 year	80%	-	20%
[60]	China	-	Wind speed (10m, 60m, 80m), wind power of Wangzi, wind speed of Wangzi (10m, 50m, 70m), wind power of Ruifeng, wind power of Dagang, air pressure (10m), temperature (10m), wind speed of Dagang (10m, 20m, 40m)	15 min.	35136	-	-	-
			Wind direction (70m), humidity (10m), temperature (10m), atmospheric pressure (10m), wind speed (10m, 50m, 70m), wind power of Taobei	15 min.	1 year			
[61]	USA	-	Wind power generation	10 min.	~3 years	-	-	-
[62]	USA	-	-	5 min.	-	80%	-	20%
[63]	-	48 MW 96 MW 55.5 MW	Wind speed, wind direction, pressure, temperature, humidity, wind farm operation data	15 min.	1 year	First 20 days per month	-	Last 10 days per month
[64]	-	130 MW	Historical wind power data, air temperature, solar radiance, surface temperature, relative humidity, soil moisture, soil temperature, wetness, wind speed, pressure, air temperature at hub height, wind direction, wind speed at hub height, air density, heat flux, change in surface temperature	10 min.	1 year	80%	-	20%
[65]	-	200 MW	Relative humidity, barometric pressure, environment temperature, wind direction, wind speed, generating power	15 min.	1500	80%	-	20%
[66]	-	-	Raw wind power time series	10 min.	5999	4199	-	1800
[67]	-	-	Wind velocity, wind direction	15 min.	6912	5760	-	384
[68]	-	-	Wind power data, NWP data	15 min.	1 year	70%	-	30%
[69]	-	-	Atmospheric pressure, humidity, temperature, wind direction, wind speed	15 min.	6000	First 5100	Last 900	-
						First 5808	-	Last 192

Table 2. Forecast horizons, evaluation metrics and performance comparison of forecasting methods of the reviewed studies for very short-term wind power forecasting (Çok kısa dönem rüzgâr gücü tahmini için incelenen çalışmaların tahmin ufukları, değerlendirme metrikleri ve tahmin metotlarının performans karşılaştırması)

Ref.	Forecast Horizons	Evaluation Metrics	Performance Comparison of Forecasting Methods
[28]	15 min.	RMSE	OLE-SANN > SANN > AGRU > TCN = MLP > CNN > BiLSTM > LSTM > CNN-LSTM > Persistence
			OLE-SANN > TCN > SANN > BiLSTM = Persistence > AGRU > LSTM > CNN > CNN-LSTM > MLP
[29]	15 min.	R^2, RMSE	VMD-2D-CNN-Transformer > VMD-1DCNN-Trans > VMD-1DCNN-GRU > VMD-LSTM > LSTM > BP
[30]	30 min.	MAE (pu)	EMD-LSTM-Output Restriction > EMD-GRU > EMD-GRU-Output Restriction > EMD-LSTM > LSTM
[31]	15 min.	MSE, R^2	GNN-LSTM-RSA > CNN-LSTM-Attention > ARIMA > CNN-LSTM
[32]	15 min.	RMSE	WPCA-PSO-GRU > PCA-PSO-GRU > WPCA-GRU > PCA-GRU > PSO-GRU > GRU = LSTM > SVM > MLR
[33]	15 min.	MSE, RMSE	VMD-ConvLSTM-LSTM > VMD-ConvLSTM > VMD-LSTM > LSTM > VMD-BPNN > BPNN > VMD-ELMAN > ELMAN
			VMD-ConvLSTM-LSTM > VMD-ConvLSTM > VMD-LSTM = LSTM > VMD-BPNN > BPNN > ELMAN > VMD-ELMAN
[34]	15 min.	MRE, RMSE	VMD-kmeans-LSTM > VMD-LSTM > LSTM > BP > VMD-ELMAN > VMD-BPNN > ELMAN
			VMD-kmeans-LSTM > VMD-LSTM > LSTM > BP > VMD-BPNN > VMD-ELMAN > ELMAN
[35]	10 min.	RMSE	CEEMDAN-EWT-LSTM > CEEMDAN-LSTM > EEMD-LSTM > EEMD- BO-LSTM > EMD-ENN > EMD-LSTM > LSTM > ANN > RF > SVR
			CEEMDAN-EWT-LSTM > CEEMDAN-LSTM > EEMD-LSTM > EMD-LSTM > LSTM > ANN > RF > SVR
[36]	5 min.	RMSE	DDA-LightGBM > LightGBM > Adaboost > RF > Bagging > Extra-Trees > GBRT > XGBoost > SVR
[37]	15 min.	MAE, MAPE, NRMSE	DC+FR+CNN > FR+CNN > DC+CNN > CNN > GRU > LSTM > ARIMA-Kal
[38]	5 min.	CRPS	EDM > KDE > DWT-SBL > k-NN > SBL > Persistence
[39]	10 min.	MAE, MAPE, R^2, RMSE	HICS-SVR > IDA-SVR > CS-SVR > GA-SVR
[40]	15 min.	MAE, MAPE, RMSE	ELM-PSO > ELM > BPNN
[41]	10 min.	MAPE	ARIMA(1,1,2) > WMA > ARMA(1,1) > MA
[42]	15 min.	RMSE	PVMD-ESMA-DELM > EEMD-ESMA-DELM > CEEMD-WOA-KELM > WT-ESMA-DELM > EEMD-ISpSA-LSSVM > FC-FWA-LSSVM > WT-PCA-RBF > EEMD-CSO-LSTM > PVMD-DELM > VMD-DELM > EEMD-DELM > WT-DELM > ESMA-DELM > SMA-DELM > WOA-DELM > PSO-DELM > GA-DELM > DELM > ELM > BP > RF
[43]	15 min.	MSE, RMSE	GWO-VMD-SE-ELM-SVR-GRU > IVMD-ELM > IVMD-GRU > IVMD-ELM-GRU > IVMD-ELM-SVR > IVMD-SVR-GRU > IVMD-SVR > SVR > GRU > ELM
			GWO-VMD-SE-ELM-SVR-GRU > IVMD-SVR-GRU > IVMD-SVR > IVMD-ELM-GRU > IVMD-ELM-SVR > IVMD-GRU > IVMD-ELM > GRU > SVR > ELM
[44]	10 min.	RMSE	EMD-CCTransformer(C) > CCTransformer(I) > CCTransformer > EMD-LSTM > Transformer > LSTM > WT-LSTM > EMD-BP > RNN > ARIMA
[45]	10 min.	MSE, RMSE	Adaboost-PSO-ELM > PSO-SVM > RF > BaggedTrees > PSO-ELM > GPR > Adaboost-GA-ELM > GA-ELM > Adaboost-PSO-BP > PSO-BP > BoostingTrees
[46]	5 min.	MAE, MASE, RMSE	CST-WPP > DBN > ANN > VAR > AR > Persistence
[47]	10 min.	RMSE	SATCN-LSTM > TCN-LSTM > LSTM > TCN > CNN-LSTM
			SATCN-LSTM > TCN-LSTM > TCN > CNN-LSTM > LSTM
[48]	10 min.	R, R^2	DAED > Simple-LSTM > LSTM-Attention > Ensemble method > N-BEATS
[49]	15 min.	MAPE	EEMD-SVR > eEEMD-SVR > eEEMD-LSTM > eEEMD-BR > GRU > EEMD-BR > EEMD-GRU > eEEMD-GRU > EEMD-LSTM > LSTM > SVR > BR
			eEEMD-LSTM > EEMD-LSTM > eEEMD-BR > eEEMD-GRU > EEMD-GRU > EEMD-SVR > eEEMD-SVR > GRU > LSTM > EEMD-BR > SVR > BR
			eEEMD-BR > eEEMD-LSTM > EEMD-LSTM > EEMD-BR > eEEMD-SVR > EEMD-SVR > eEEMD-GRU > EEMD-GRU > BR > LSTM > GRU > SVR
[50]	10, 20, 30 min.	Average Forecasting Stability	ICEEMDAN-MOMVO-WNN > ICEEMDAN-MOMFO-WNN > CEEMD-MOMFO-WNN > ICEEMDAN-MOWOA-WNN > EMD-MOMFO-WNN > ICEEMDAN-MOWCA-WNN >

			LSSVM > WNN > EEMD-MOMFO-WNN > ARIMA > GRNN > VMD-MOMFO-WNN > CEEMD-MFO-WNN > CEEMD-WNN
[51]	10 min.	MSE, RMSE	CSSOA-LSTM > SBO-LSTM > SpSA-LSTM > PSO-LSTM > LSTM
[52]	10 min.	MAE, R^2, RMSE	SaSA-ELM > PSO-ELM > ELM > BP
[53]	10 min.	MSE, RMSE	VMD-LSSVM-ARMA-BPNN > EEMD > EMD > BPNN > ARMA > LSSVM
[54]	10 min.	MAE, RMSE	CNN-GA > BPNN > GA
[55]	15 min.	MAE, RMSE	TPA-MBLSTM > TPA-LSTM > BiLSTM > LSTM
[56]	15 min.	MAE, MSE, RMSE	WOA-VCGRU > PSO-VCGRU > GA-VCGRU > VCGRU > VCLSTM > VGRU > VLSTM > EGRU > ELSTM > ECGRU > ECLSTM
[57]	15 min.	MAE	SM1MKL > SM2MKL > SimpleMKL > SM1SVM > SM2SVM > KELM > ELM > SVM
[58]	15 min.	NRMSE	Wavelet-LSTM > GRU-LSTM > CNN-LSTM > GBR > DRNets
[59]	15 min.	RMSE	HFM > ATCN > TCN > TPA-LSTM > LSTM > CNN > DNN > CNN-LSTM > Persistence
[60]	15 min.	MSE, RMSE, U_1	SiSA-HM1-MOMVMD-HM2+AM > SiSA-HM1-MOMVMD-ELM > SiSA-HM1-MOMVMD-HM2 > SiSA-HM1-MVMD-HM2+AM > SiSA-HM1-VMD-HM2+AM > SiSA-MOMVMD-HM2+AM > HM2+AM > SiSA-HM1-HM2+AM > HM1-MOMVMD-HM2+AM
			SiSA-HM1-MOMVMD-HM2+AM > SiSA-HM1-MVMD-HM2+AM > SiSA-MOMVMD-HM2+AM > HM1-MOMVMD-HM2+AM > SiSA-HM1-MOMVMD-HM2 > HM2+AM > SiSA-HM1-HM2+AM > SiSA-HM1-VMD-HM2+AM > SiSA-HM1-MOMVMD-ELM
[61]	10 min.	RMSE	STAN > STANta > STANsa > GRUm > GRUs > ANN > ARIMA > HA
[62]	5 min.	NMAE, NRMSE	FedDRL > ARIMA > RDPG > BPNN > MLR
[63]	15 min.	RMSE	CatGAN-ITCN > CatGAN-GRU > CatGAN-MLP > CatGAN-TCN > Hierarchical-ITCN > kmeans-ITCN > Hierarchical-TCN > Hierarchical-GRU > Hierarchical-MLP > kmeans-TCN > kmeans-GRU > kmeans-MLP > CatGAN-RF > kmeans-RF > CatGAN-SVM > Hierarchical-RF > Hierarchical-SVM > kmeans-SVM
			CatGAN-ITCN > kmeans-ITCN > Hierarchical-ITCN > CatGAN-MLP > kmeans-MLP > CatGAN-TCN > CatGAN-GRU > Hierarchical-GRU > Hierarchical-TCN > kmeans-GRU = kmeans-TCN > CatGAN-RF > kmeans-RF > Hierarchical-MLP > Hierarchical-SVM > CatGAN-SVM > Hierarchical-RF > kmeans-SVM
			CatGAN-ITCN > Hierarchical-ITCN > kmeans-ITCN > CatGAN-TCN > CatGAN-GRU > kmeans-GRU > CatGAN-MLP > Hierarchical-TCN > kmeans-TCN > Hierarchical-GRU > kmeans-MLP > CatGAN-RF > Hierarchical-RF > kmeans-RF > Hierarchical-MLP > CatGAN-SVM > Hierarchical-SVM > kmeans-SVM
[64]	10, 20, 30 min.	Overall NRMSE	TCN > CNN-LSTM = MLR > LSTM
[65]	15 min.	MAE, MAPE, R^2, RMSE	PCA-SpSA-VMD-BiLSTM > PCA-VMD-BiLSTM > PCA-SpSA-BiLSTM > PCA-BiLSTM > PCA-LSTM > PCA-BP
[66]	10 min.	R^2, RMSE	EEMD-PSO-LSTM > EEMD-LSTM > EMD-LSTM > PSO-LSTM > LSTM
[67]	15 min.	MAPE, NRMSE	EEMD-Tent-SpSA-LSSVM > Tent-SpSA-LSSVM > SpSA-LSSVM > LSSVM
[68]	15 min.	ACC	SVR-LSTM > LSTM > SVR
[69]	15 min.	MAPE	TCN > LSTM > RNN > BP
			EEMD-TCN > EMD-TCN > EEMD-LSTM > EMD-LSTM

Abbreviations: ACC (Accuracy), AGRU (Attention-Based GRU), AM (Attention Mechanism), ANN (Artificial Neural Network), AR (Auto-Regression), ARIMA (Autoregressive Integrated Moving Average), ARMA (Autoregressive Moving Average), ATCN (Attention TCN), Bagging (Bagging Regressor), BiLSTM (Bidirectional LSTM), BO (Bayesian Optimization), BP (Back Propagation), BPNN (BP Neural Network), BR (Bayesian Ridge Regression), CatGAN (Categorical Generative Adversarial Network), CCTransformer (Causal Convolutional Transformer), CEEMD (Complementary Ensemble EMD), CEEMDAN (Complete Ensemble Empirical Mode Decomposition with Adaptive Noise), CNN (Convolutional Neural Network), ConvLSTM (Convolutional LSTM), CRPS (Continuous Rank Probability Score), CS (Standard Cuckoo Search Arithmetic), CSO (Cuckoo Search Optimization), CSSOA (Chaotic Sparrow Search Optimization Algorithm), CST (Convolution-Based Spatial-Temporal), DAED (Dual Attention-Based Encoder-Decoder), DBN (Deep Belief Network), DC (Data Cleaning), DDA (Drift Detection and Adaption), DELM (Deep ELM), DRNets (Deep Concatenated Residual Networks), DWT (Discrete Wavelet Transform), ECGRU (EMD-CNN-GRU), ECLSTM (EMD-CNN-LSTM), EDM (Empirical Dynamic Modeling), eEEMD (Entropy EEMD), EEMD (Ensemble EMD), EGRU (EMD-GRU), ELM (Extreme Learning Machine), ELSTM (EMD-LSTM), EMD (Empirical Mode Decomposition), ENN (Elman Neural Network), ESMA (Enhanced SMA), EWT (Empirical Wavelet Transform), Extra-Trees (Extremely Randomized Trees), FC (Fuzzy Cluster), FedDRL (Federated Deep Reinforcement Learning), FR (Feature Reconfiguration), FWA (Fire Works Algorithm), GA (Genetic Algorithm), GBM (Gradient Boosting Machine), GBR (Gradient Boosting Regression), GBRT (GBR Tree), GNN (Graph Network Model), GRU (Gated Recurrent Unit), GRNN (Generalized Regression Neural Network), GPR (Gaussian Process Regression), GWO (Grey Wolf Optimization), HA (Historical Average), HFM (Hybrid Wind Power Forecasting Model), HICS (Hybrid Improved Cuckoo Search Arithmetic), HM1 (Clustering-MOVMD-GRU), HM2 (CNN+BiLSTM), ICEEMDAN (Improved CEEMDAN), IDA (Improved Dragonfly Algorithm), ISpSA (Improved SpSA), IVMD (Improved VMD), Kal (Kalman Filter), KDE (Kernel Density Estimation), KELM (Kernel ELM), k-NN (k-Nearest Neighbors), LightGBM (Light GBM), LSTM (Long Short-Term Memory), LSSVM (Least Square Support Vector Machine), MASE (Mean Absolute Scaled Error), MAPE (Mean Absolute Percentage Error), MAE (Mean Absolute Error), MA (Moving Average), MBLSTM (Multi-Layer Stacked BiLSTM), MFO (Moth-Flame Optimization), MKL (Multiple Kernel Learning), MLP (Multilayer Perceptron), MLR (Mixed Logistic Regression), MOMFO (Multi-Objective MFO), MOMVO (Multi-Objective Multi-Verse Optimization), MOWCA (Multi-Objective Water Cycle Algorithm), MOWOA (Multi-Objection WOA), MSE (Mean Square Error), MRE (Mean Relative Error), MVMD (Multivariate VMD), N-BEATS (Neural Basis Expansion Analysis for Time Series), NMAE (Normalized MAE), NRMSE (Normalized RMSE), OLE-SANN (Online-Learning-Enabled SANN), PCA (Principal Component Analysis), PSO (Particle Swarm Optimization), PVMD (PSO-VMD), R^2 (Coefficient of Determination), RBF (Radial Basis Functions), RDPG (Recurrent Deterministic Policy Gradient), RF (Random Forest), RMSE (Root Mean Square Error), RNN (Recurrent Neural Network), RSA

(Random Sampling Algorithm), SANN (Self-Attention-Based Neural Network), SaSA (Salp Swarm Algorithm), SATCN (Self-Attention TCN), SBL (Sparse Bayesian Learning), SBO (Satin Blue Gardener Bird Optimisation Algorithm), SE (Sample Entropy), SiSA (Singular Spectrum Analysis), SMMKL (Soft Margin MKL), SMA (Slime Mould Algorithm), SpSA (Sparrow Search Algorithm), STAN (Spatiotemporal Attention Networks), SVM (Support Vector Machine), SVR (Support Vector Regression), TCN (Temporal Convolutional Network), TPA (Temporal Pattern Attention), U_1 (Theil U Statistic 1), VAR (Vector AR), VCGRU (VMD-CNN-GRU), VCLSTM (VMD-CNN-LSTM), VGRU (VMD-GRU), VLSTM (VMD-LSTM), VMD (Variational Mode Decomposition), WMA (Weighted MA), WNN (Wavelet Neural Network), WOA (Whale Optimization Algorithm), WPCA (Feature-Weighted Principal Component Analysis), WPP (Wind Power Predictor), WT (Wavelet Transform), XGBoost (eXtreme Gradient Boosting), 1D (1 Dimensional), 2D (2 Dimensional)

Table 3. Region and capacity of wind power plant, input variables of forecasting methods, data resolution and total dataset properties of the reviewed studies for short-term wind power forecasting (Kısa dönem rüzgâr gücü tahmini için incelenen çalışmaların rüzgâr güç santralinin bölgesi ve kapasitesi, tahmin metotlarının girdi değişkenleri, veri çözünürlüğü ve toplam veri seti özellikleri)

Ref.	Wind Power Plant		Input Variables of Forecasting Methods	Data Resolution	Total Dataset Properties			
	Region	Capacity			Period / Samples	Training Subset	Validation Subset	Testing Subset
[70]	Spain	17.6 MW	Historical wind power, wind speed, wind direction	10 min.	37 days	15 days	15 days	7 days
[71]	China	603 MW	Wind speed, pressure, temperature, humidity	15 min.	34818	8 months	4 months	
[72]	Ethiopia	153 MW	Outdoor temperature, wind speed	1 hour	6 years	5 years	1 year	
[73]	France	2050 kW	Original wind power series	10 min.	1484	1440	-	24
[74]	Belgium	806.71 MW	Wind power sequences	15 min.	4350	3500	-	850
	USA	80 MW						
[75]	China	135 MW	Actual power, humidity, air temperature, air pressure, wind direction, wind speed	15 min.	25384	12 months	-	8 months
[76]	China	265.5 MW	Historical wind power sequences	15 min.	2880	1632	-	1248
[77]	France	2050 kW	Temperature, wind direction, wind speed	10 min.	864	720	-	144
[78]	India	5480 MW	Historical generated wind power	15 min.	30 days	29 days	-	1 day
[79]	China	49.5 MW	Historical wind speed, NWP data, historical wind power	15 min.	2 years	-	-	10 days for each season
		48 MW						
		48 MW						
[41]	Denmark	2 MW	Wind power time series	1 hour	960	-	-	-
[80]	Guangxi	-	Wind speed (10m, 30m, 50m, 70m, hub height), wind direction (10m, 30m, 50m, 70m, hub height), pressure (10m), temperature (10m), air humidity (10m), actual power	15 min.	17840	70%	10%	20%
	China		Wind speed (10m, 30m, 50m), wind direction (10m, 30m, 50m), pressure, temperature, air humidity, actual power		17264			
[81]	USA	-	Wind direction (100m), wind speed (100m), air temperature (2m), surface air pressure, density (hub height), 6 historical wind power data	1 hour	5000	80%	10%	10%
[82]	Europe	-	Wind power, zonal and meridional components of surface winds (10m), wind speed, wind direction	1 hour	3 years	70%	20%	10%
[83]	Canada	-	Actual wind power series	1 hour	12312	9852		2460
[48]	USA	-	Air pressure, air density, wind direction, wind speed	1 hour	1 year	75%	33% of training set	25%
[84]	Belgian	-	Wind power times series	15 min.	12 months	1000 per month	-	1000 per month
[85]	China	-	Wind speed, ambient temperature, wind direction, historical power prediction residuals	1 hour	2264	70%	-	30%
[86]	Europe	-	Zonal and meridional wind components, wind direction, wind speed, wind power	1 hour	3 years	70%	-	30%
[87]	Europe	-	Zonal and meridional wind components, wind direction, wind speed, wind power	1 hour	~5 years	70%	-	30%

[88]	China	-	Wind speed, wind direction, relative humidity, air temperature, air pressure	1 hour	2 years	22 months	-	2 months
[58]	China	-	Scada dataset	15 min.	3 months	First 85 days	-	Last 7 days
[89]	Germany	-	Wind power data	15 min.	171 days	70%	-	30%
[57]	Canada	-	Historical power dataset	10 min.	29 days	22 days	-	7 days
[90]	China	-	Wind power time series	1 hour	2209	1767	-	442
[91]	China	-	Historical wind power segment	1 hour	1 year	4 weeks	-	1 week
[92]	China	-	Wind power time series	10 min.	7 days	6 days	-	1 day
[93]	China	-	Wind energy data	10 min.	8000	6000	-	2000
[94]	China	-	Temperature data, wind speed, wind power data	1 hour	720	696	-	24
[95]	China	-	Wind power, atmospheric pressure, humidity and wind speed time series data	15 min.	5400	70%	-	30%
[96]	USA Turkey	-	Pressure, temperature, wind direction, wind speed	1 hour	1 year	80%	-	20%
[97]	Australia	-	Wind power data, wind direction, wind speed	1 hour	16800	-	-	-
[98]	Canada	-	Raw wind power time series	10 min.	1 year	-	-	-
[99]	Turkey	-	Active power, wind speed, wind direction, theoretical power curve	10 min.	50530	-	-	-
[100]	-	20 MW	Wind speed, wind direction, the corresponding output of wind power	1 hour	1264	696	520	48
[101]	-	-	Wind speed, wind direction, air density	1 hour	1 year	80%	-	20%

Table 4. Forecast horizons, evaluation metrics and performance comparison of forecasting methods of the reviewed studies for short-term wind power forecasting (Kısa dönem rüzgâr gücü tahmini için incelenen çalışmaların tahmin ufukları, değerlendirme metrikleri ve tahmin metotlarının performans karşılaştırması)

Ref.	**Forecast Horizons**	**Evaluation Metrics**	**Performance Comparison of Forecasting Methods**
[70]	1 hour	MAE, RMSE, SMAPE	WGANGP-EEMD-ARENN > WGANGP-EEMD-NN(Huber) > WGANGP -EEMD-NN(Log-Cosh) > WGANGP-EEMD-NN(MAE) > WGANGP-EEMD-NN(MSE) > WGANGP-EEMD-CSO-NN > WGANGP-EEMD-GA-NN > WGANGP-EEMD-DE-NN > WGANGP-EEMD-PSO-NN
[71]	1 hour	MAE, MAPE	MLP > RF > k-NN > Persistence > SVM
[72]	1 hour	MAE, MAPE, R^2, RMSE	TRF-RHS > TRFE-RHS
[73]	4 hours	IA, MAPE, NMAE, NRMSE	WPD-VMD-SiSA-IGWO-KELM > WPD-VMD-SiSA-IGWO-GABPNN > WPD-VMD-IGWO-KELM > WPD-VMD-PSO-LSSVM > VMD-IGWO-KELM > VMD-ARIMA > WPD-IGWO-KELM > WPD-GMDH > LSTM > Original-IGWO-KELM
[74]	1, 4 hours	RMSE	CNN-MLSTMs-T > CNN-MLSTMs-D > MLSTMs > LSTM > Persistence
[75]	4 hours	RMSE	WOA-ELM > WNN > PSO-LSSVM > ELM > PSO-BP > LSTM > LSSVM
[76]	4 hours	DMAP, DMQP, NRMSE	IEMD-R > EMD-R > EMD > Persistence > ANN
[77]	1 hour	MAPE, R^2, RMSE	ENCSA-ELM > GWO-ELM > MFO-ELM > CSA-ELM > SVM
[78]	6 hours	MAE, MAPE, PAR, RMSE	R-LSTM > ARMA > RF > XGBoost
[79]	2 hours	RMSE	TSF > DWT-LSTM > MM-DFS > Persistence > SDL > ARIMA TSF > DWT-LSTM > MM-DFS > Persistence > ARIMA > SDL TSF > MM-DFS > Persistence > DWT-LSTM > ARIMA > SDL
[41]	2 hours	MAPE	ARMA(2,2) > WMA > MA > ARIMA(2,1,2)
[80]	4 hours	MSE, RMSE	Powerformer > LSTM > GRU > Transformer > BP Powerformer > GRU > LSTM > BP >Transformer
[81]	1 hour	MAE, RMSE	TCN > GRU > LSTM > MLP > SVM
[82]	1 hour	MAE, RMSE, SDE	GpeANN > Amjady model > Grassi model
[83]	6 hours	MAAPE	MRMLE-AMS > Liu's model > Li's model > Hao's model > Du's model > Persistence
[48]	1 hour	R, R^2	DAED > LSTM-Attention > N-BEATS > Simple-LSTM > Ensemble method
[84]	1, 2, 3, 4 hours	Average MAPE	ILSTM > LSTM > ELMAN > BP

[85]	1 hour	MSE, RMSE, SSE	CEEMDAN-SVR-TCN > CEEMDAN-SVR > CEEMDAN-TCN > CEEMDAN-BP > TCN > LSTM > BP > SVR
[86]	1 hour	MAE	MWN-LSTM > SWN-LSTM > RWN-LSTM > GWN-LSTM > GPeANN > DNN-MRT > SVR > ARIMA
[87]	1 hour	MSE, R^2, RMSE	GLSTM > LSTM > SVR-RBF > SVR-Linear > SVR-Polynomial
[88]	1 hour	RMSE	CLFNet > LSTNet > RNN-GRU > TPA-LSTM = XGBoost > WT-LSTM
[58]	45 min.	NRMSE	Wavelet-LSTM > GRU-LSTM > CNN-LSTM > GBR > DRNets
[89]	45 min.	MSE	EMD-ESN > GPI > Transformer > Informer > LSTNet = TCN > LSTM = GRU > Autoformer > DLinear
[57]	90 min.	MAE	SM1MKL > SM2MKL > SimpleMKL > SM1SVM > KELM > SM2SVM > ELM > SVM
[90]	1 hour	MAPE	CEEMDAN-WOA-GRU > CEEMDAN-GRU > EEMD-GRU > WOA-GRU > EMD-GRU > GA-GRU > PSO-GRU > GRU > LSTM > SVM > BP
[91]	1 hour	MAE, MAPE, RMSE	VMD-CAT > FVAD > RWA > WEE > EAW > LSSVM > BP > ARIMA
[92]	1 hour	MAE, MAPE, RMSE	CEEMD-WOA-KELM > EEMD-WOA-KELM > CEEMD-PSO-KELM > CEEMD-KELM > EMD-WOA-KELM > KELM
[93]	100 min.	RMSE, R^2	WOA-BiLSTM-Attention > BiLSTM > BiLSTM-Attention > LSTM > BP
[94]	1 hour	MAE, MSE, R^2	GSA-VMD-BiLSTM-MHSA > LSTM-MHSA > LSTM > BPNN
[95]	2 hours	MAE, MAPE, RMSE, R^2	WD-MIC-VMD-DNN > VMD integrated model > Pure weather model > Power-weather model
[96]	1 hour	RMSE	RF-CatBoost-XgBoost-LR > XgBoost > CatBoost > LSTM > GRU > RF
			RF-CatBoost-XgBoost-LR > XgBoost > LSTM > CatBoost > GRU > RF
[97]	1 hour	MAE	TCN-MTTS > LSTM > GRU > BP > GP > SVM
[98]	40 min. 120 min.	NMAE, NRMSE	MHF-LSH-SVR > MHF-SVR > SVR > Persistence
[99]	1 hour	RMSE	SFS-PSO-LSTM > LSTM > k-NN > DNN > Bagging > RF > Averaging = GB
[100]	1 hour	RMSE, SDE, SSE	LSSVM-GSA > SVM-GSA > BP > SVM > LSSVM
[101]	1 hour	RMSE	MMF > LMF + SDLM > IDBSCAN + SDLM > SDLM > TDLM > DLEA = IRCNN > BGRU > LESN > Se-net > Resnet-18

Abbreviations: AMS (Adaptive Model Selection), ARENN (Asexual-Reproduction Evolutionary Neural Network), BGRU (Bidirectional GRU), CAT (Component-Attention Mechanism-Based Transformer), CatBoost (Categorical Boosting), CLFNet (Image Fusion Network Based on Contrastive Learning), CSA (Crow Search Algorithm), DE (Differential Evolution), DFS (Deep Feature Selection), DLEA (Deep Learning-Based Ensemble Approach), DMAP (Daily Mean Accuracy Percent), DMQP (Daily Mean Qualified Percent), DNN (Deep Neural Network), EAW (EEMD-Adaptive Wavelet Neural Network), EMD-R (EMD-Run-Length), ENCSA (Enhanced CSA), FVAD (Fruit Fly Optimization Algorithm-VMD-ARIMA-DBN), GB (Gradient Boosting), GLSTM (Genetic LSTM), GMDH (Group Method Data Handling), GPeANN (Gaussian Process-Based Ensemble of ANN), GPI (Graph Patch Informer), GSA (Gravitational Search Algorithm), GWN (Gaussian Wavenets), IA (Index of Agreement), IDBSCAN (Improved Density-Based Spatial Clustering of Applications with Noise), IEMD-R (Improved EMD-R), IGWO (Improved GWO), ILSTM (Improved LSTM), IRCNN (Improved Residual-Based CNN), LESN (Leaky Echo State Network), LMF (Low-Rank Matrix Fusion), LSH (Local-Sensitive Hashing Algorithms), LSTNet (Long and Short-Term Time-Series Network), MAAPE (Mean Arctangent Absolute Percentage Error), MHF (Morphological High-Frequency Filter), MHSA (Multi-Head Self-Attention), MIC (Maximum Information Coefficient), MLSTMs (Establish LSTM for each category separately), MLSTMs-D (MLSTMs with CNN Features in Dimension Direction), MLSTMs-T (MLSTMs with CNN Features in Time Direction), MM-DFS (Multi-Model Forecasting with DFS), MMF (Multi-Modal Multi-Step Forecasting), MRMLE (Multi-Resolution Multi-Learner Ensemble), MRT (Meta Regression and Transfer Learning), MTTS (Multiple Train-Test Splits), MWN (Morelet Wavenets), NWP (Numerical Weather Prediction), PAR (Prediction Accuracy Rate), R-LSTM (Rolling LSTM), RWA (Repeated WT-ARIMA), RWN (Ricker Wavenets), SDE (Standard Deviation of Errors), SDL (Smart Deep Learning), SDLM (Stacking Deep Learning Model), Se-net (Squeeze-and-Excitation Network), SFS (Stochastic Fractal Search), SMAPE (Symmetric MAPE), SSE (Sum of Squared Errors), SWN (Shannon Wavenets), TDLM (Two-Phase Deep Learning Model), TSF (Two-Stage Forecasting), TRF-RHS (Tuned Random Forest with Reduced Hour Space), TRFE-RHS (TRF Errors with RHS), WD (Wavelet Denoise), WEE (WPD-EMD-ELM), WGANGP (Wasserstein Generative Adversarial Network with Gradient Penalty), WPD (Wavelet Packet Decomposition)

3. CONCLUSIONS (SONUÇLAR)

This paper presents an extensive review of the current status of very short-term and short-term wind power forecasting in the literature. The available studies on this issue have been summarized on the basis of wind power plant properties, input variables of forecasting methods, total dataset properties and data resolution, forecast horizons and evaluation metrics, and the accuracy results of forecasting methods. Many reasonable and beneficial outcomes have been achieved by comparing the highly-informative tabulated contents of all the reviewed studies. In light of the findings obtained from the reviewed studies, several key insights have been identified to enhance the consistency and reliability of wind power forecasting research. Moreover, by analyzing the forecasting performance of different approaches in detail, this study provides a structured framework that helps researchers to select appropriate methodologies and evaluation criteria in wind power forecasting. Researchers should also pay attention to the following points in their further studies:

- specifying the installed capacity information in order to evaluate how large a wind power plant the proposed forecast models have been applied to.

- creating a data description section in order to present the total dataset properties in a more compact manner, and to more easily evaluate what kind of data has been utilized.
- avoiding from the usage of ambiguous terms for input variables, such as other climatological factors, in order to make the input-output analysis of forecasting methods more reliable.
- making the correlation analysis between input and output variables in order to improve the forecasting accuracy, and to evaluate how much they affect the success of the forecasting methods,
- applying the data normalization process to the training, validation and testing subsets to contribute to the stability, precision and speed of forecasting methods,
- conducting a benchmark test against the persistence reference model and sharing the total dataset utilized in the forecasting process in order to realize a fairer comparison,
- providing information on the computational requirements in order to assess how dependent the methods used are on computer resources and software tools,
- considering the time frames predominantly used in the literature in order to categorize and evaluate the existing studies under the correct forecast horizon,

DECLARATION OF ETHICAL STANDARDS (ETİK STANDARTLARIN BEYANI)

The authors of this article declare that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

Bu makalenin yazarları çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan ederler.

AUTHORS' CONTRIBUTIONS (YAZARLARIN KATKILARI)

***Mehmet YEŞİLBUDAK*:** He conducted the literature review, research, editing and writing process.

Literatür taraması, araştırma, düzenleme ve yazma sürecini yürütmüştür.

***Mustafa BENLİ*:** He conducted the literature review, research, editing and writing process.

Literatür taraması, araştırma, düzenleme ve yazma sürecini yürütmüştür.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study.

Bu çalışmada herhangi bir çıkar çatışması yoktur.

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