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SYSTEMATİCEXAMİNATİON OF THE PERFORMANCE AND PREDİCTİON ACCURACY OF MACHİNE LEARNİNG ALGORİTHMS USED İN WİNDENERGYFORECASTİNG: A COMPARATİVE REVİEW

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ABSTRACT

Windenergy, despitebeingone of thefastest-growing technologies among renewable energy sources, contains significant uncertainties in production forecasting dueto itsvariable naturedependent on atmosphericconditions. Reducingtheseuncertainties has made it necessary to developaccurateforecastingmodels in terms of energyproductionplanning, gridoperation, management of energystoragesystems, and the efficient functioning of electricitymarkets. Inrecentyears, machinelearning algorithm shave started to be widelyused in wind energy fore casting studies due to their ability to model nonlinear relationshipsandlearnfromlargevolumes of data. However, comprehensiveevaluationsregardingwhichalgorithmsaremoresuccessful in terms of different data structures, forecastinghorizons, andperformancemetricsarelimited. Theaim of thisstudy is toevaluatethemachine learningalgorithmsused in windenergyforecastingthrough a systematicliteraturereviewapproachand to comparatively analysethepredictionaccuracyandperformancecharacteristics of thealgorithms. Inthiscontext, nationalandinternationalstudiesthathaveundergonepeerreviewwereexamined; SupportVectorRegression (SVR), DecisionTrees, RandomForest, XGBoost, LightGBM, CatBoost, ArtificialNeural Networks (ANN), LongShort-Term Memory (LSTM), ConvolutionalNeural Networks (CNN), andhybridmachinelearningmodelswerecompared in terms of performance, computationalcost, data requirements, interpretability, andgeneralisability. Additionally, theroles of performancemetricscommonlyused in theliterature, such as RMSE, MAE, MAPE, and R^2, in algorithm evaluations havebeen addressed. Thereviewresultsshowthat a singlemachinelearningalgorithmdoes not providethebest performance for all datasetsandallpredictionscenarios. It has been determinedthatthesuccess of thealgorithmdepends on manyfactorssuch as data quality, sample size, diversity of meteorologicalvariables, data preprocessingtechniques, featureselection, andhyperpara meteroptimisation. Especially, it has been observed thatensemblelearningmethodsanddeeplearning-basedhybridmodelsprovidehighprediction accuracy; however, they introduce new challenges in terms of computationalcostandinterpretability. Theliteraturealsoidentifiesrisingresearchtrends in thefield of windenergyforecasting, such as explainableartificialintelligence, automatedmachinelearning, digitaltwintechnologies, andphysics-informed artificial intelligence approaches. Inconclusion, thisstudy not onlyintroduces themachinelearning algorithms used in windenergyforecasting but alsoprovides a comprehensive evaluationfor researchers andpractitionersby critically comparingtheir performancesandapplicationareas. Additionally, it identifiesresearchgaps in theexistingliterature, proposing a scientificroadmapforfuturestudies.

KEYWORDS: Windenergy, machinelearning, windenergyforecasting, predictionaccuracy, performanceanalysis, systematicliteraturereview, artificialintelligence.

1. INTRODUCTİON

Therapidincrease in theshare of renewableenergysources in electricitygeneration has made it necessarytomanageenergysystems in a moreflexible, reliable, andsustainablemanner. Inthistransformationprocess, windenergy has becomeone of thekeycomponents of the global energytransitionduetoitslowcarbonemissions, decreasinginvestmentcoststhroughtechnologicaladvancements, andsignificantincreases in installedcapacity (International EnergyAgency [IEA], 2023; Global WindEnergyCouncil [GWEC], 2025). However, thevariableproductioncharacteristics of windenergy, whichdepend on meteorologicalconditions, createsignificantuncertainties in terms of energyproductionplanning, loadbalancing, reservecapacitymanagement, andtheoperation of electricitymarkets.

Windspeedandtheassociatedpowergenerationareinfluencedbynumerousenvironmentalvariable ssuch as temperature, atmosphericpressure, humidity, turbulence, terrainstructure, andseasonalchanges. Therefore, thedevelopment of accurateforecastingmodels is criticallyimportant not onlyforenergyproducers but alsofortransmissionsystemoperators, distributioncompanies, andenergy market participants. Thankstoreliableforecasts, production-planningprocessesareimproved, operationalcostsarereduced, renewableenergyintegration is facilitated, andgridreliability is enhanced (Foley et al., 2012; Santhosh et al., 2020). Theinitialstudies on windenergyforecastingwereprimarilybased on physics-basedmodelsandstatistical time seriesmethods. However, thenon-linear, non-stationary, andhighlyvariablenature of wind data has causedtraditionalmethodsto be inadequate in manyapplications. Inrecentyears, advancements in data collectiontechnologies, largedatasetsobtainedfrom SCADA systems, andhigh-performancecomputinginfrastructureshaveledtothewidespreaduse of machinelearningalgorithms in windenergyforecasting (Dou et al., 2023; Yang et al., 2024). Machine learningalgorithmsoffersignificantadvantages in thefield of windforecastingduetotheirabilitytolearncomplex data patternswithouttheneedforpredefinedphysicalequations. Especiallymethodssuch as SupportVectorRegression (SVR), RandomForest, XGBoost, LightGBM, CatBoost, andArtificialNeural Networks haveyieldedsuccessfulresults in differentdatasets; in lateryears, LSTM, GRU, andTransformer-basedmodelshavegainedsignificantimportance in theliteraturebymoreeffectivelymodellinglong-termdependencies in time series (Breiman, 2001; Chen&Guestrin, 2016; Liu et al., 2025). However, theperformance of algorithmsvariesdepending on manyfactorssuch as data quality, sample size, predictionhorizon, featureselection, andhyperparameteroptimisation. Thissituationshowsthat a singlealgorithm is not thebestsolutionforallapplications. Althoughtherearenumerousstudies in theliterature on machinelearning-basedwindforecasting, a significantportion of theresearch is limitedtoreportingthesuccess of a specificalgorithm on a specificdataset. Incontrast, systematicandcomparativereviewstudiesthatevaluatealgorithmstogether in terms of performancemetrics, data requirements, computationalcosts, interpretability, andapplicationareasarelimited. Additionally, thenumber of Turkishacademicstudiesthataddress data preprocessingstrategies, performanceevaluationcriteria, andnext-generationmachinelearningapproachesaffectingpredictionaccuracywithinthesameframework is quitelimited.

Theaim of thisstudy is toevaluatethemachinelearningalgorithmsused in windenergyforecastingthrough a systematicliteraturereview approachandtocomparatively analysethepredictionaccuracyandperformancecharacteristics of thealgorithms. Inthiscontext, supervisedmachinelearningalgorithms, ensemblelearningmethods, deeplearningmodels, andhybridapproacheshavebeenexaminedtogether; theperformancemetricsused, data preprocessingtechniques, andfactorsinfluencing model selectionhavebeencriticallyevaluated. Inaddition, prominentresearchtrends in thecurrentliteratureandresearchareasexpectedtogainimportance in thefuturehavebeendiscussed, providing a comprehensiveevaluation forresearchersand practitioners.

This studyaimstomakethree main contributions to the literature. Firstly, it comparesthe main machinelearningalgorithmsused in windenergyforecastingwithin a singlesystematicframework. Secondly, it evaluatesthealgorithms not only in terms of predictionaccuracy but also in terms of data requirements, computationalcost, interpretability, andapplicability. Thethirdonediscussesemergingresearchareassuch as explainableartificialintelligence, automatedmachinelearning, digitaltwintechnologies, andphysics-informedartificialintelligence in light of thecurrentliterature, proposing a researchagendaforfuturestudies.

2. LiteratureReview

2.1. The Development of Machine Learning in WindEnergyForecasting

Windenergyforecasting has become a criticalresearchareaforthesafeintegration of renewableenergysystemsintothegrid. Thevariability of windproductionduetometeorologicalconditionscreatessignificantuncertainties in powersystembalancing, reserveplanning, and market operations. Therefore, windspeedandwindpowerforecasting is not only a technicalmodelling problem but also a strategicissue in terms of energysupplysecurityandsustainableenergymanagement (Foley et al., 2012; Soman et al., 2010; Colak et al., 2012).

Intheearlystudies, physicalmodelsandstatistical time seriesapproacheswereprominent, while in recentyears, machinelearningalgorithmshavefoundwiderapplications. The main reasonforthis is thatmachinelearningmethods can learnnonlinearrelationships, workwithmultivariatemeteorologicaldatasets, andextract complex patterns fromhistorical production data (Santhosh et al., 2020; Dou et al., 2023; Yang et al., 2024). Especiallythelarge-scaleturbine data obtainedfrom SCADA systemshaveacceleratedthe development of machine learning-basedpredictionmodels.

Currentliteratureshowsthat a singlealgorithm is not superiorforalldatasetsandforecastinghorizons in windprediction. Model successdepends on a multitude of factorssuch as data resolution, prediction time, diversity of meteorologicalvariables, data preprocessing, featureselection, andhyperparameteroptimisation (Liu et al., 2025; Elmousalami et al., 2024; Rajaperumal et al., 2025). Therefore, recentstudieshavefocused not only on algorithmdevelopment but also on comparingalgorithms in terms of performance, interpretability, computationalcost, andgeneralisability.

2.2. Supervised Machine Learning Algorithms

Supervisedmachinelearningalgorithmsareone of themostcommonlyusedmethodgroups in windenergyforecasting. Thisgroupincludesmethodssuch as linearregression, decisiontrees, SupportVectorRegression (SVR), k-NearestNeighbours, RandomForest, andartificialneuralnetworks. Especially SVR has longbeenconsidered a strongalternativeforwindspeedpredictionduetoitshighgeneralisationcapacity in limitedandmedium-sizeddatasets (Cortes&Vapnik, 1995; Smola&Schölkopf, 2004; Zabihi et al., 2025).

Themostimportantadvantage of the SVR algorithm is itsabilityto model nonlinearpatternsthroughkernelfunctions. However, thealgorithm'sperformance is quitesensitivetohyperparameterssuch as thekernelfunction, penaltyparameter, and epsilon-insensitivezone. Thissituation can cause SVR toprovidehighaccuracy in somedatasets, whileshowingperformancevariability in datasetswithdifferentmeteorologicalconditions (Smola&Schölkopf, 2004; Zabihi et al., 2025). Therefore, while SVR is effective, especially in well-structuredandrelativelylimiteddatasets, it can be disadvantageous in terms of computation time in big data environments.

DecisiontreesandRandomForestalgorithmsprovideadvantages in terms of interpretabilityandvariableimportanceanalysis in windforecasting. RandomForestproducesmorestablepredictionsbycombining a largenumber of decisiontreesandreducesthe risk of overfitting (Breiman, 2001). Intheliterature, it is notedthattheRandomForestalgorithmprovidesrobustresults, especially in noisydatasets, but the model complexityandcomputationalcost can increase in verylargedatasets (Gu,et. al. 2024; Rajaperumal et al., 2025).

Supervisedlearningalgorithmsgenerallyoffer a moreflexiblemodellingcapacity compared to statistical
methods. However, thesuccess of thesealgorithms is stronglydependent on data quality, featureselection, and model optimisation. Therefore, currentstudiesevaluate not onlytheselection of thealgorithm but alsotheprocesses of data preprocessing, missing data imputation, outlierremoval, andvariableselection as fundamentaldeterminants of predictionperformance (Santhosh et al., 2020; Elmousalami et al., 2024; Liu et al., 2025).

2.3. Ensemble Learning Algorithms

Ensemblelearningalgorithmsaimtocreatestrongerpredictionmodelsbycombiningmultipleweakormoderatelystronglearners. Inwindenergyforecasting, ensemblemethodssuch as RandomForest, GradientBoosting, XGBoost, LightGBM, CatBoost, andAdaBoosthavebeenintensivelyused in recentyears. Thesealgorithmsoffersignificantadvantages in modellingnonlinearrelationships, capturinginteractionsbetweenvariables, andenhancinggeneralisationsuccess (Friedman, 2001; Chen&Guestrin, 2016; Ke et al., 2017).

XGBoost is one of themostcommonlyusedensemblealgorithms in windenergyforecasting. Duetoitsregularisationstructure, gradientboostingapproachthatoptimisesthelossfunction, andhighpredictionsuccess, it yieldsstrongresults on differentdatasets (Chen&Guestrin, 2016). However, thesuccess of XGBoostdepends on hyperparameteroptimisation. Whenthetreedepth, learning rate, sampling rate, andregularisationparametersare not appropriatelydetermined, the model can becomepronetooverfitting (Liu et al., 2025; Rajaperumal et al., 2025).

LightGBMandCatBoostalgorithmshavestartedtofeaturemoreprominently in recentstudiesduetotheirpotentialforfasttrainingandhighpredictionaccuracy, especially in largedatasets. LightGBM can provide a computationaladvantage in largedatasetsthankstoitshistogram-basedlearningstructure, whileCatBoostoffers a strongalternative in processingcategoricalvariablesandreducingoverfitting (Ke et al., 2017; Prokhorenkovaet al., 2018). However, thesuccess of thesealgorithms in windenergyforecastingvariesdepending on the size of thedataset, thediversity of variables, andthehyperparametersearchstrategy.

The main limitation of ensemblemodels is theinterpretability problem. ModelslikeRandomForest, XGBoost, andLightGBMoftenprovidehighaccuracy, but it is not easytoexplain how thepredictionsaregeneratedbywhichvariables. Therefore, in recentyears, theuse of explainableartificialintelligencemethodssuch as SHAP in conjunctionwithensemblemodels has gainedimportance (Lundberg& Lee, 2017; Molnar, 2022; Durap et al., 2025).

2.4. ArtificialNeural Networks, Deep Learning, and Time Series Models

Artificialneuralnetworkshavebeenusedfor a long time in windenergyforecastingduetotheircapacityto model nonlinearrelationships. Classicalartificialneuralnetworks can learnthecomplexrelationshipsbetweenpastwindspeed, temperature, pressure, humidity, andproduction data; however, theymay be limited in modellingtemporaldependencies. Therefore, in recentyears, LSTM, GRU, BiLSTM, CNN, andTransformer-baseddeeplearningmodelshavegainedmoreprominence in thewindforecastingliterature (Hochreiter&Schmidhuber, 1997; Cho et al., 2014; Wang et al., 2021).

LSTM modelsareone of themostcommonlyuseddeeplearningapproaches forwindspeedandwindpowerpredictionduetotheirabilitytolearnlong-termdependencies.
Theinfluence of past time steps on futureproduction in wind data enables LSTM-basedmodelstoperformstrongly in short- andmedium-termpredictions (Hochreiter&Schmidhuber, 1997; Wang et al., 2021; Akbal & Ünlü, 2024). However, LSTM modelshavelimitationssuch as high data requirements, longtrainingtimes, andlowinterpretability.
CNN-basedmodels, especially in multivariate data structures, provide an advantage in capturinglocalpatterns. Hybridarchitectureslike CNN-LSTM aimtoenhancepredictionaccuracybycombiningthefeatureextractionpower of CNN withthetemporaldependencylearningcapacity of LSTM (Wang et al., 2021; Akbal & Ünlü, 2024). Currentstudiesshowthatdeeplearningarchitecturessupportedbyattentionmechanisms can providemorestableresults in windenergyforecasting (Vaswani et al., 2017; Akbal & Ünlü, 2024).

Transformer-basedmodelsrepresent a newresearchdirection in time seriesforecasting.

Thankstoattentionmechanisms, Transformerstructures, which can model therelationshipsbetweendifferent time stepsmoreflexibly, holdsignificantpotential in representinglong-termdependencies (Vaswani et al., 2017; Yang et al., 2024). However, thewidespreadandmatureapplications of Transformermodels in windenergyforecastingarestill in thedevelopmentstage. Therefore, thesemodelsareconsideredmethodswithhighpotential but requiringfurthercomparativestudies.

2.5. Hybrid Machine Learning Approaches

One of themostnotabletrends in windenergyforecasting in recentyears has beenhybridmodellingapproaches. Hybridmodelsaimtoreducethelimitations of individualmodelsbyusing data preprocessing, signaldecomposition, featureselection, optimisation, andpredictionalgorithmstogether. Decompositionmethodssuch as wavelettransform, EMD, EEMD, CEEMDAN, and VMD areused in conjunctionwithmodelslike LSTM, SVR, XGBoost, or CNN toachievehigherpredictionaccuracy (Torres et al., 2011; Dragomiretskiy&Zosso, 2014; Karijadi et al., 2023).

The main advantage of hybridmodels is theirabilitytodecomposenon-stationaryandnoisywind data intomoremeaningfulsubcomponents. Inthisway, the model can producemorestablepredictionsthroughthedecomposedcomponentsinstead of directlylearningthecomplexfluctuations in theraw data (Torres et al., 2011; Karijadi et al., 2023). Especially, it has beenreportedthathybridapproachesbased on CEEMDAN, VMD, andWaveletimprove model performancebyreducinghigh-frequencynoise (Dragomiretskiy&Zosso, 2014; Kahveci et al., 2025).

However, thehighaccuracy of hybridmodelsdoes not alwaysmeanpracticalapplicability. Theuse of multiple model componentstogetherincreasescomputationalcost, training time, and model maintenancerequirements. Additionally, determiningwhichcomponent is responsibleforperformanceimprovement in hybridsystems is not alwayseasy. Thissituation can limit thetraceabilityandease of maintenance of the model in industrialapplications (Yang et al., 2024; Kandemir et al., 2024; Liu et al., 2025).

2.6. PerformanceMetricsandAccuracy Analysis

Inwindenergyforecastingstudies, model performance is generallyevaluatedusingmetricssuch as RMSE, MAE, MAPE, and R^2. Since RMSE givesmoreweighttolargererrors, it can moreaccuratelyreflect model performance in situationswheresuddenwindchangescannot be predicted. MAE, on theotherhand, is an easilyinterpretablemetricbecause it directlyshowstheaverageerrormagnitude. While MAPE providespercentageerrorinformation, it can producemisleadingresultswhentheactualvaluesareclosetozero (Hyndman&Koehler, 2006; Santhosh et al., 2020; Elmousalami et al., 2024).

Interms of accuracyanalysis, relyingsolely on a singleerrormetric is not sufficient. Forexample, a model mayhave a low RMSE value; however, it may not showthesamesuccess in differentseasons, differentwindregimes, ordifferentgeographicalregions. Therefore, thecurrentliteratureemphasisesthatmodelsshould be evaluated not only in terms of averagepredictionerror but also in terms of stability, generalisability, computationalcost, andexplainability (Dou et al., 2023; Liu et al., 2025; Rajaperumal et al., 2025).

Inprecisionanalysesconductedwithmachinelearningalgorithms, it is criticallyimportanttocorrectlyperformthetrain-test split, usecross-validation, prevent data leakage, andsystematicallycarryouthyperparameteroptimisation. Otherwise, thehighaccuracyvaluesreported in theliteraturemay not reflecttheactualapplicationperformance. Therefore, recentstudieshaveplacedgreateremphasis on model reliabilityandrepeatabilityalongside model accuracy (Elmousalami et al., 2024; Zabihi et al., 2025; Rajaperumal et al., 2025).

2.7. ResearchGaps in theLiterature

Whentheliterature is generallyevaluated, it is observedthatmachinelearningalgorithmshaveachievedsignificantsuccess in windenergyforecasting. However, a significantportion of theexistingstudies is limitedtoreportingtheperformance of a specificalgorithm on a specificdataset. Studiesconductinggeneralisabilityanalysisacrossdifferentdatasets, differentclimateconditions, anddifferentforecastinghorizonsarestilllimited (Yang et al., 2024; Liu et al., 2025).

Thesecondsignificantgap is theissue of explainability. High-accuracymodelssuch as XGBoost, LightGBM, LSTM, andhybriddeeplearningmodelsoftenhave a blackboxstructure.

Infieldsrequiringhighreliability, such as energysystems, beingabletoexplainwhy a model produced a certainprediction is as important as predictionaccuracy (Lundberg& Lee, 2017; Molnar, 2022; Durap et al., 2025).

Thethirdgap is real-time applicability. Manymodelsthatachievehighaccuracy in academicstudiesare not testedundertherequirements of real-time data flow, lowlatency, limitedcomputationalcapacity, andcontinuous model updates in industrialfields. Therefore, futureresearch is expectedtofocus on newapproachessuch as AutoML, Edge AI, digitaltwins, federatedlearning, andphysics-informedartificialintelligence (Kandemir et al., 2024; Bošnjaković et al., 2025; Liu et al., 2025).

Overall, theliteratureindicatesthatmachinelearningalgorithmshavestrongpotential in windenergyforecasting; however, thesuccess of thealgorithmsshould be evaluated not onlybyerrormetrics but alsobycriteriasuch as data quality, model transparency, computationalcost, generalisability, andindustrialapplicability. Thisliteraturereviewshowsthatmachinelearningalgorithms in windenergyforecastingoffermoreflexibleandpowerfulmodellingcapabilitiescomparedtostatisticalmethods. However, thekeyfinding in theliterature is that a singlealgorithm is not thebestsolutionforallscenarios. While SVR can yieldstrongresultswithlimiteddatasets, RandomForestandXGBoost can provideadvantageswithnoisyandhighlyvariabledatasets. LSTM anddeeplearningmodelsofferhighaccuracypotential in large time seriesdatasets, whilehybridmodels can enhanceperformancebycombining data preprocessingandmodellingprocesses.
However, highaccuracyalonedoes not determinethepracticalvalue of the model. Futureresearchshouldfocus on explainable, generalisable, computationallyefficient, andreal-time applicablemachinelearningsystems. Therefore, in windenergyforecasting, accuracyanalysisshould not be limitedtothecomparison of RMSE or MAE values; it should be evaluatedtogetherwiththemodel'sreliability, transparency, stability, andindustrialapplicability.

3. Methodology

3.1. Research Design

Thisstudywas conductedusing the Systematic Literature Review (SLR) methodtocomprehensivelyevaluatetheperformanceandpredictionaccuracy of machinelearningalgorithmsused in windenergyforecasting. Systematicliteraturereviewsare a researchapproachthatenablesthesystematiccollection, evaluation, synthesis, andinterpretation of theexistingscientificknowledge in a specificresearchfieldaccordingtopredefinedmethods (Snyder, 2019; Page et al., 2021).

Inthisstudy, unliketraditionalnarrativereviews, researchquestionswerepredetermined, theliteraturereviewprocesswasconductedsystematically, studieswereevaluatedaccordingtopredeterminedselectioncriteria, andthefindingsweresynthesisedusing a thematicanalysisapproach. Thus, thetransparency, reproducibility, andscientificreliability of thestudyhavebeenenhanced.

3.2. ResearchQuestions

Theliteraturereview has beenplannedtoaddressthefollowingresearchquestions.
AS1. Whichmachinelearningalgorithmsaremostcommonlyused in windenergyforecasting? Whichmachinelearningalgorithmsaremostcommonlyused in windenergyforecasting?
AS2. Whatperformancemetricsareusedtoevaluatethepredictionaccuracy of algorithms?
AS3. Whatarethestrengthsandweaknesses of machinelearningalgorithms?
AS4. How do data preprocessingprocessesaffectalgorithmperformance?
AS5. Whatadvantages do ensemble, deeplearning, andhybridmodelsprovidecomparedtotraditionalmachinelearningmethods?
AS6. Whatarethecommontrends in theliteratureregardingtheprecisionanalysis of algorithms?
AS7. Whichresearchareasareexpectedtostandout in thefuture?

3.3. LiteratureReviewStrategy

Theliteraturereviewwasconducted in internationallyrecognisedscientificdatabases in thefields of energysystems, artificialintelligence, andmachinelearning. Duringthescanningprocess, thefollowingdatabaseswereutilised:

- Web of ScienceCore Collection
- Scopus
- IEEE Xplore
- ScienceDirect
- SpringerLink
- Google Scholar

Duringthescreeningprocess, thefollowingkeywordsweresearchedeitherindividuallyor in combinationusingBooleanoperators (AND, OR).

• WindEnergyPrediction

• WindPowerPrediction

• WindSpeedPrediction

• Machine Learning

• ArtificialIntelligence

• SupportVectorRegression

• RandomDecisionTrees

• XGBoost

• LightGBM

• CatBoost

• ArtificialNeural Networks

• LSTM

• Deep Learning

• HybridModels

• ForecastAccuracy

• Performance Evaluation

Thescreeningprocessparticularlyfocused on studiespublishedbetween 2020 and 2026; somekeyclassicworkswerealsoincluded in theevaluationtodemonstratethedevelopment of thefield.

3.4. InclusionandExclusionCriteria

Specificselectioncriteriahavebeenappliedtoenhancethescientificqualityofthestudies.

InclusionCriteria:

• Studiesfocusing on windenergyorwindspeedprediction.

• Researchusingmachinelearning, deeplearning, orhybridalgorithms.

• International articlesthathaveundergonepeerreview.

• Publications withaccessiblefulltexts.

• Studiespublished in English.

• Studiesthatreportperformancemetrics in detail.

ExclusionCriteria:

• Studies in the form of conferenceabstracts.

• Editorials.

• Technical reports.

• Repeatedpublications.

• Studieswhosefulltextsare not accessible.

• Researchstudiesthat do not usemachinelearning.

• Studiesthat do not includeperformanceevaluation.

Thestudiesselectedaccordingtothesecriteriahavebeensubjectedtodetailedexamination.

3.5. Data ExtractionandCodingProcess

Eachstudy has beensystematicallyexamined in terms of thefollowingvariables.

• Year of publication

• Datasetused

• Type of prediction (windspeed / windpower)

• Machine learningalgorithm

• Data preprocessingmethod

• Performancemetrics

• Validationmethodused

• Keyfindings

• Advantages

• Limitations

Thisinformation has beencodedusing a standardevaluationframeworkandused in comparativeanalyses.

3.6. Performance Evaluation Approach

Thealgorithmsused in thereviewedstudieswere not evaluatedsolely in terms of predictionaccuracy; a multidimensionalanalysisapproachwasadopted. Algorithmswerecomparedconsideringthefollowingcriteria:

• Predictionaccuracy

• RMSE

• MAE

• MAPE

• R^2

• Computationalcost

• Training time
• Data requirement
• Robustnesstonoisy data
• Generalisability
• Interpretability
• Real-time applicability

Thankstothisapproach, a meaningfulperformanceevaluation has beenconducted not onlybased on errorvalues but also in terms of application.

3.7. Thematic Analysis

Theselectedstudieshavebeenclassifiedunderthefollowingthemes.
• Supervisedmachinelearningalgorithms
• Ensemblelearningalgorithms
• Deeplearningmethods
• Hybridpredictionmodels
• Data preprocessingtechniques
• Performanceevaluationmethods
• Precision analysis
• Explainableartificialintelligence
• Currentresearchtrends Withineachtheme, thestudieshave not onlybeensummarised; thestrengths, limitations, andcommontrends in theliteraturehavebeencriticallyevaluated.

3.8. Limitations of theStudy

Thisstudy has somelimitations. Thereview is limitedtoscientificarticlesthathaveundergonepeerreview. Books, graduatetheses, technicalreports, andnon-peer-reviewedpublicationshavebeenexcluded. Additionally, duetothestudiesusingdifferentdatasets, differentmeteorologicalconditions, anddifferentperformancemetrics, commontrendsandmethodologicaldifferenceswereevaluatedinstead of determining a directnumericalsuperiorityamongthealgorithms.

Nevertheless, it is believedthatthestudyprovides a comprehensive, reliable, andreproducibleevaluation of machinelearningalgorithmsused in windenergyforecasting, thankstothesystematicreviewstrategy, clearselectioncriteria, andthematicanalysisapproach.

4. Findings and Discussion from the Systematic Literature Review

4.1. Trends in theUse of Machine Learning Algorithms

Thereviewedstudiesindicatethatthemachinelearningalgorithmsused in windenergyforecastinghavesignificantlydiversifiedoverthepastdecade. Inearlystudies, SupportVectorRegression (SVR), DecisionTrees, andArtificialNeural Networks wereprominent, while in recentyears, it has beenobservedthatensemblelearningalgorithmssuch as RandomForest, XGBoost, LightGBM, andCatBoosthavestartedto be usedmorewidely. Inaddition, duetotheirabilityto model long-termdependencies in time series data, there has been a significantincrease in theuse of LSTM, GRU, andTransformer-baseddeeplearningmodels (Santhosh et al., 2020; Yang et al., 2024; Liu et al., 2025).
This trend indicatesthatresearchersare not onlyaimingtoachievehigherpredictionaccuracy but alsoturningtomethodsthat can workwithlargedatasetsand model complexmeteorologicalrelationships. However, it standsout as a commonfinding in theliteraturethatnoalgorithm is universallysuperiorforalldatasetsandallforecastinghorizons.

4.2. Comparison of Algorithms in Terms of PredictionAccuracy

A general evaluation of theliteratureshowsthat, comparedtoclassicalstatisticalmethods, mostmachinelearningalgorithmsachievelowererrorrates in variousapplications. Especially, it has beenreportedthatXGBoost, RandomForest, and LSTM-basedmodelsexhibithighperformance in short- andmedium-termwindforecasting (Chen&Guestrin, 2016; Rajaperumal et al., 2025).

However, it is understoodthatthesuccess of thealgorithms is not solelydependent on themethodused. The size of thedataset, samplingfrequency, diversity of meteorologicalvariables, and data preprocessingstrategiesdirectlyaffectpredictionaccuracy. Forexample, while SVR orRandomForest can yieldsuccessfulresultswithlimiteddatasets, deeplearning-basedmodels can demonstratehigherperformancewithlargeandhighlyvariabledatasets (Elmousalami et al., 2024; Yang et al., 2024).

Therefore, it is concludedthattheselection of thealgorithmshould be based on thecharacteristics of the problem, and a singlealgorithmcannot be consideredthebestsolutionforallscenarios.

4.3. TheImpact of Data Preprocessing on PredictionPerformance

One of thecommonfindings of thereviewedstudies is that data preprocessingprocesseshave a decisiveimpact on predictionperformance. It is observedthatmodelsdevelopedwithoutapplyingtechniquessuch as handlingmissing data, cleaningoutliers, normalisation, featureselection, andsignaldecompositionoftenproduceloweraccuracyvalues (Dou et al., 2023; Elmousalami et al., 2024).

Especially, it has beenreportedthatsignaldecompositionmethodssuch as CEEMDAN, VMD, andWavelettransformationenhancethesuccess of machinelearningalgorithmsbyseparatingnoisywind data intomoremeaningfulcomponents (Dragomiretskiy&Zosso, 2014; Karijadi et al., 2023). Thissituationdemonstratesthatthesuccess of the model is stronglydependent not only on thechoice of algorithm but also on thequality of the data preparationprocess.

4.4. Advantages of EnsembleandHybridModels

Recentstudieshaveshownthatensembleandhybridapproaches can providehigheraccuracyandmorestableresultscomparedtoalgorithmsusedalone. Especiallyhybridapproachesthatcombineboosting-basedalgorithmssuch as XGBoost, LightGBM, andCatBoostwithdeeplearningmodelsthatinclude LSTM, CNN, andattentionmechanismsstandout in theliterature (Akbal & Ünlü, 2024; Rajaperumal et al., 2025).

However, theincreasingcomputationalcost, longertrainingtimes, andmorecomplex model structures of hybridmodelsposesignificantlimitations in practicalapplications. Therefore, in model selection, not onlyaccuracy but alsocomputationalresources, applicationenvironment, andease of maintenanceshould be considered.

4.5. Evaluation of PerformanceMetrics

Intheliterature, RMSE, MAE, MAPE, and R^2 standout as themostcommonlyusedperformancemetrics. However, thesystematicreviewshowsthatevaluationsbased on a singleperformancemetricareinadequate. Forexample, while RMSE is moresensitivetolargeerrors, MAE reflectstheaverageerrormagnitudemoreevenly. MAPE, despiteprovidingpercentageerrors, can yieldmisleadingresultswithlowactualvalues (Hyndman&Koehler, 2006).

Therefore, currentstudiesrecommendevaluatingalgorithmstogetherusingdifferenterrormetricsandsupportingthemwithcross-validationmethodswheneverpossible. Thus, the model performance can be evaluated not only on a specificdataset but alsounderdifferentconditions.

4.6. Evaluation in Terms of Precision Analysis

Thissystematicreviewdemonstratesthattheprecisionanalysis of machinelearningalgorithmscannot be explainedsolelybylowerrorrates. Thehighpredictionaccuracy of an algorithmdoes not mean it willshowthesamesuccess on differentdatasets. Inaccuracyanalysis, data diversity, model stability, generalisability, hyperparameteroptimisation, andvalidationstrategiesshould be evaluatedtogether (Elmousalami et al., 2024; Liu et al., 2025). It is observedthat a significantportion of thehighaccuracyvaluesreported in theliteraturearespecifictocertaindatasets; thesameperformance is not alwaysachieved in differentgeographicalregionsandunderdifferentclimaticconditions. Therefore, it is recommendedthatfuturestudiesusemulticenterdatasetsandstandardisedevaluationprotocols.

4.7. CurrentTrendsandResearchGaps

Thereviewedstudiesindicatethattheresearchfocus in thefield of windenergyforecasting is increasinglyshiftingtowardsexplainableartificialintelligence, digitaltwintechnologies, AutoML, federatedlearning, andphysics-informedartificialintelligencemodels (Kandemir et al., 2024; Yang et al., 2024; Liu et al., 2025). Inparticular, theability of modelsthatprovidehighaccuracytoexplaintheirdecision-makingprocessesandto be integratedintoreal-time energysystems is amongthe main objectives of futureresearch.

However, threesignificantresearchgapsarenoteworthy in theliterature. Firstly, there is a limitednumber of studiesevaluatingthegeneralisability of algorithms in differentgeographicalregions. Secondly, practicalcriteriasuch as computationalcostandenergyconsumptionare not sufficientlyconsidered in model comparisons. Thethird is thatevaluations of explainabilityandreliabilityareoftensecondary in moststudies.

Thefindingsobtainedfromthesystematicliteraturereviewrevealthatmachinelearningalgorithmsh avemadesignificantadvancements in windenergyforecasting. However, it is understoodthatnoalgorithm is thebestsolutionforallscenarios; predictionaccuracyshould be evaluated in conjunctionwith data quality, preprocessingstrategies, hyperparameteroptimisation, andapplicationconditions. Therefore, it is expectedthatthemodelsdeveloped in thefuturewill not onlyfocus on lowererrorrates but also on explainability, generalisability, computationalefficiency, andreal-time applicability.

5. RESULTS AND FUTURE RESEARCH

5. 1. Results

Inthissystematicreview, machinelearningalgorithmsused in windenergyforecastinghavebeenevaluatedwithintheframework of a comprehensiveliteraturereview; thealgorithms' predictionaccuracy, performancecharacteristics, strengthsandweaknesses, andapplicationareashavebeenanalysedcomparatively.

Thereviewedstudiesrevealthatthehighlyvariablenature of windenergy, which is dependent on atmosphericconditions, makesthedevelopment of accuratepredictionmodels indispensablefor thereliability of energysystems.

As a result of theliteraturereview, it has beenobservedthat classicalstatisticalmethodsmaintaintheir importance in certainapplication areasduetotheirlowcomputationalcostsandinterpretabilityadvantages; however, machine learning algorithmsareseento be moresuccessful in terms of theircapacityto model nonlinearrelationships. It has beendeterminedthatalgorithmssuch as RandomForest, XGBoost, LightGBM, andSupportVector Regression providehighpredictionaccuracy in manyapplications, while LSTM andotherdeeplearning-basedapproachesyieldstrongerresults in largedatasets.

However,thesystematicreviewrevealsthatnosinglealgorithmdemonstratesthebestperformancea cross all datasets, all prediction horizons, and all application conditions. It is understoodthatthesuccess of thealgorithm is influencedby a number of factorssuch as data quality, sample size, diversity of meteorologicalvariables, data preprocessingstrategies, hyperparameteroptimisation, andperformanceevaluationapproach. Therefore, in model selection, it is necessarytoevaluate not onlyerrormetrics but alsocriteriasuch as computationalcost, interpretability, generalisability, andreal-time applicabilitytogether.

One of theimportantfindings of thestudy is thesignificantincrease in theadoption of hybridmachinelearningapproaches in recentyears. Hybridapproachesthatintegrate data preprocessingtechniqueswithensembleanddeeplearningmodelshavethepotentialtoenhancepredictionaccuracy. However, issuessuch as model complexity, training time, andmaintenancecostareamongthe main limitations of thesemethods in practice.

5.2. ImplicationsforResearchers

Thisstudyoffersthreekeyimplicationsforresearchersworking in thefield of windenergyforecasting. Firstly, instead of solelyfocusing on accuracyvalues in algorithmselection, data structure, applicationpurpose, andcomputationalrequirementsshould be evaluatedtogether. Secondly, data preprocessing, featureselection, andhyperparameteroptimisationprocessesare an integral part of model successandshould be treated as independentvariables. Thirdly, it would be scientificallymorevaluablefornewstudiestofocus on testingthegeneralisabilityandexplainability of existingmethods on differentdatasetsratherthanmerelyproposingnewalgorithms.

5.3. RecommendationsforIndustrial Applications

Whenevaluatedfromtheperspective of energyproductioncompanies, transmissionsystemoperators, andwindfarmmanagers, it is of greatimportancethatmachinelearningalgorithmsaretested not only in laboratoryenvironments but alsounderreal-time operatingconditions. Intheselection of algorithms, in additiontopredictionaccuracy, training time, ease of model updating, hardware requirements, andmaintenancecostshouldalso be considered. Additionally, theregularmonitoring of real-time data obtainedfrom SCADA systemsanditsuse in model updates is considered a criticalrequirementforthesustainability of predictionperformance.

5.4. RecommendationsforPolicymakers

Focusingsolely on theincrease in installedcapacity is not sufficientfortheeffectiveimplementation of renewableenergypolicies. Thedevelopment of reliableforecastingsystems, balancing of energymarkets, enhancement of gridreliability, andplanning of energystorageinvestmentsarealso of strategicimportance. Therefore, it is recommendedthatpublicinstitutionsandenergyregulatorybodiesdeveloppoliciesthatsupportope n data sharing, promotestandardperformanceevaluationcriteria, andencouragethedevelopment of AI-baseddecisionsupportsystems.

5.5. FutureResearchAreas

Based on thereviewedstudies, theresearchtopicsexpectedtogainimportance in thefield of windenergyforecasting in thefuturearesummarisedbelow:

ExplainableArtificialIntelligence,AutoML,DigitalTwin-BasedPrediction Systems, GraphNeural Networks,Transformer-Based Time Series Models,Physics-Informed AI , Federated Learning,Edge AI,Multimodal AI Approaches, Real-Time DecisionSupportSystems.

Thecommongoal of theseresearchareas is not onlytoachievelowererrorrates but alsotodevelopnext-generationwindenergyforecastingsystemsthatarereliable, explainable, scalable, andeasilyintegrableintoindustrialapplications.

5.6. General Evaluation

Inconclusion, thisstudy has criticallyevaluatedthemachinelearningalgorithmsused in windenergyforecasting not only in terms of performancemetrics but also in terms of data requirements, model complexity, computationalcost, interpretability, andapplicability. Theholisticanalysis of theliteratureindicatesthatfutureforecastingsystemsshouldfocus on integratedartificialintelligenceapproachesthataddress data quality, model transparency, andreal-time applicabilitytogether, ratherthanconcentrating on a singlealgorithm. Inthisrespect, thestudyaimstoprovide a comprehensivereferencesourceforresearchers, industryrepresentatives, andpolicymakers, goingbeyondthesystematicsummarisation of theexisting body of knowledgetoserve as a decisionsupporttool.

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