Welcome to:

Machine Learning in Energy and Utilities

Unit objectives

After completing this unit, you should be able to:

- Learn about importance of smart grids
- Gain knowledge on smart grid technologies
- Understand characteristics of smart grid
- Gain knowledge on machine learning applications in smart grid
- Understand machine learning techniques for renewable energy generation
- Learn about the applications of machine learning in forecasting renewable energy generation

Introduction

- learning algorithms can revolutionize both the power, economy demand and supply side in the following ways:
  - Improve distributed generation management.
  - Asset management.
  - Outage management.
  - Customer engagement.

Smart grid

- It is a smart grid to incorporate ICT into electrical generation and delivery systems.

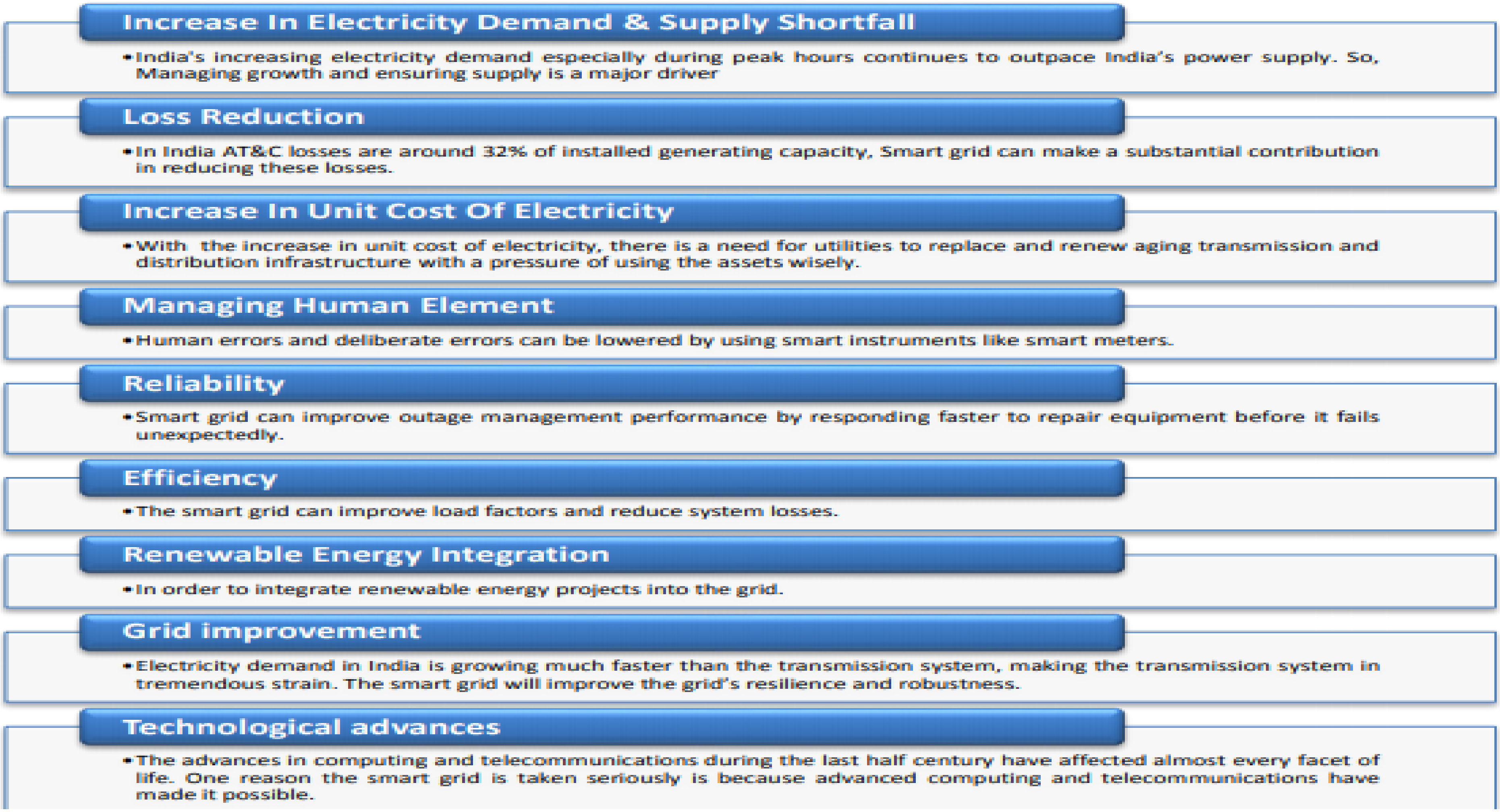

Figure: Smart grid driver

Source: https://www.slideshare.net/MirdulAminSarkar/india-smart-grid-can-it-become-a-reality-70236139

Smart grid technologies

IBM ICE (Innovation Centre for Education)

Technology Area	Hardware	Systems and Software	Implementation Area
Wide-range tracking and control	Phasor measurement units (PMU) and other sensor equipment	Supervisory control and data acquisition (SCADA), wide area monitoring systems (WAMS), wide-area adaptive protection, control and automation (WAAPCA), wide area situational awareness (WASA)	Generating and transmitting
Implementation of data and communications systems	Communication equipment (Power line carrier, WIMAX, LTE, RF mesh network, cellular), routers, relays, switches, gateway, computers (servers)	Enterprise resource planning software (ERP), customer information system (CIS)	Generation, Transmission, Distribution, Industrial, Service, Residential
Renewable And Distributed Generation Integration	Power conditioning equipment for bulk power and grid support, communication and control hardware for generation and enabling storage technology	Energy management system (EMS), distribution management system (DMS), SCADA, geographic Information system (GIS)	Energy management system (EMS), distribution management system (DMS), SCADA, geographic Information system (GIS)
Transmission Enhancement	Superconductors, FACTS, HVDC	Network stability analysis, automatic recovery system	Transmission

Key characteristics of smart grid

Self-healing and resilient:	Smart grid system performs real time self-assessment to detect, analyse and respond to subnormal grid conditions.
Asset optimization and operational efficiency	A smart grid will enable better asset utilization from generation to the consumer end points
Enable demand response	Extending the smart grid within the home, consumer appliances and devices can be controlled remotely, allowing for demand response
Integration of advanced and low-carbon technologies	A smart grid will exhibit "plug and play" scalable and interoperable capabilities. It permits a higher transmission and distribution system penetration of renewable generation, distributed generation and energy storage.
Improved Power quality	A smart grid will have high quality of power and reduces the occurrence of distortions of power supply
Market empowerment	A smart grid will provide greater transparency and availability of energy market information. It will enable more efficient, automated management of market parameters.
Customer inclusion	A smart grid involves consumers by engaging them as active participants in the electricity market.
Clean & Green	The energy conservation and improvements in end-use efficiency enabled by the smart grid reduce half of the emissions

Machine learning applications in smart grid

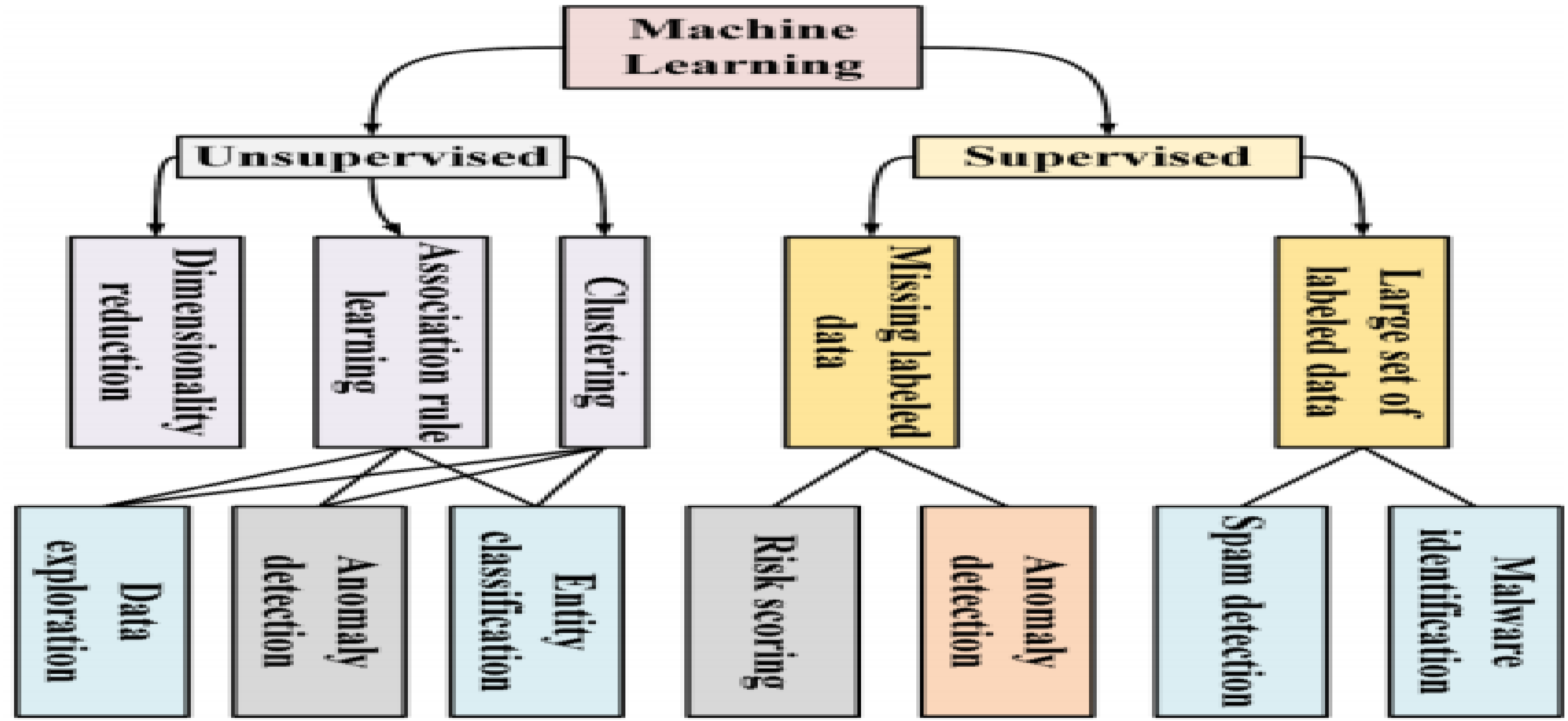

Figure: Application of machine learning in smart grid security. Unsupervised and supervised both approaches can be used to carry out an array of tasks including threat identification and data categorization

Source:
https://www.google.com/search?q=Application+of+machine+learning+in+smart+grid+security.+Unsupervised+and+supervised+%E2%80%93+both+approaches+can+be+used+to+carry+out+an+array+of+tasks+including+threat+identification+and+data+categorization.&rlz=1C1CHBF_enIN862IN862&source=lnms&tbm=isch&sa=X&ved=2ahUKEwjS1vyHjurnAhWxyjgGHcmHAy4Q_AUoAnoECA0QBA&biw=1366&bih=576#imgrc=ZCd3zbQOx_phHM

Machine learning techniques for renewable energy generation

- In the case of renewable energy, an essential usage for machine learning approaches is to determine the optimum distance, size and specification of renewable power plants.

- These framework depend on many parts, like:
  - The location of the population centre.
  - Local climatic conditions.
  - Weather.
  - Infrastructure.
  - Availability.
  - Costs of other facilities, and many others.

- One background for applying machine learning approaches is the total processes and maintenance of the smart network, i.e. concerns like detecting faults, energy, etc.,

Forecasting renewable energy generation

- Since this relies on many non-human supervision variables, like natural conditions, it is important to predict a renewable energy plant's power output.

- The power plant has certain characteristics that make it possible, based on the resource it utilizes, to use machine learning techniques for predictive purposes.

- Machine learning methods utilized in various forms of power plants like:
  - Wind power generation.
  - Hydro power generation.
  - Solar power generation.

Wind power generation

- Wind energy production is based on many features, and a wind turbine's power output can be determined utilizing equation 1.

- Equation 1:

$$P = \frac{A\rho V^3 C_p}{2}$$

Solar energy generation

- Photovoltaic (PV) solar power plants range from individual-household to huge solar photovoltaic (PV) plants with a capacity of 1–100 MW.
- Thermo siphon solar heater is a method of producing hot water for domestic use using renewable energy.
- The ANN has been educated with four forms of methods using performance data, all using the similar collector panel below different climate state.
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Hydro power generation

- Hydropower is one of the renewable energy sources most widely used and one of the most efficient.
- Since hydro power utilizes flowing water and accumulated water supplies that rely on the area's precipitation.
- It is naturally influenced by climate factors that require to be predicted for effective preparation and maintenance.
- An ensemble learning method was used to predict hydropower energy consumption.
- A Genetic Algorithm (GA) was used to support optimal ruler control in hydroelectric plants.

Determining plant location, size and configuration

- The area latitude and longitude are the inputs in this model, whereas the outputs are two parameter of hybrid size (f,u).

- Such factors are described by a basic correlation of the likelihood of lack of load (LLP) as indicated in equation 2.

- Equation 2: $f = f_1 + f_2 \log(LLP) \quad and \quad u = e^{(u_1 + u_2 \cdot LLP)}$

Managing renewable energy-integrated smart grid

- Users/stakeholders expect the grid to work and control more efficiently and effectively.

- Smart techniques are therefore required to provide for better smart grid management.

- We will describe some of the problems facing electrical grids in the section, including managing supply/demand, network services and processing, grid information maintenance, and strategies for machine learning.

Machine learning applications in wind energy forecasting

- The change in air velocity affects the production of the wind power plant to fluctuate, contributing to grid uncertainty.

- Correct wind-energy power grid forecasting is important and can help develop operating strategies.

- This prediction is complicated because the estimated time ranges from milliseconds to seconds to minutes or hours, from operating the wind turbine to uniting air energy into the energy system.

Case study: Wind power forecasting based on daily wind speed data

- In this analysis, machine learning algorithms depending on daily air velocity information were used to predict wind power.

- Techniques and architectures, especially for long-term forecast scenarios, cannot offer effective and satisfactory outcomes in terms of air velocity prediction.

- Regression analysis methods are utilized because of the statistical issue of ongoing air energy factors.

- The regression methods used in this analysis are:
  - Least Absolute Shrinkage Selector Operator (LASSO).
  - K-Nearest Neighbour (k-NN).
  - eXtreme Gradient Boost (XGBoost).
  - Random Forest (RF).
  - Supporting.

Wind energy output calculations based on hourly wind speed (1 of 2)

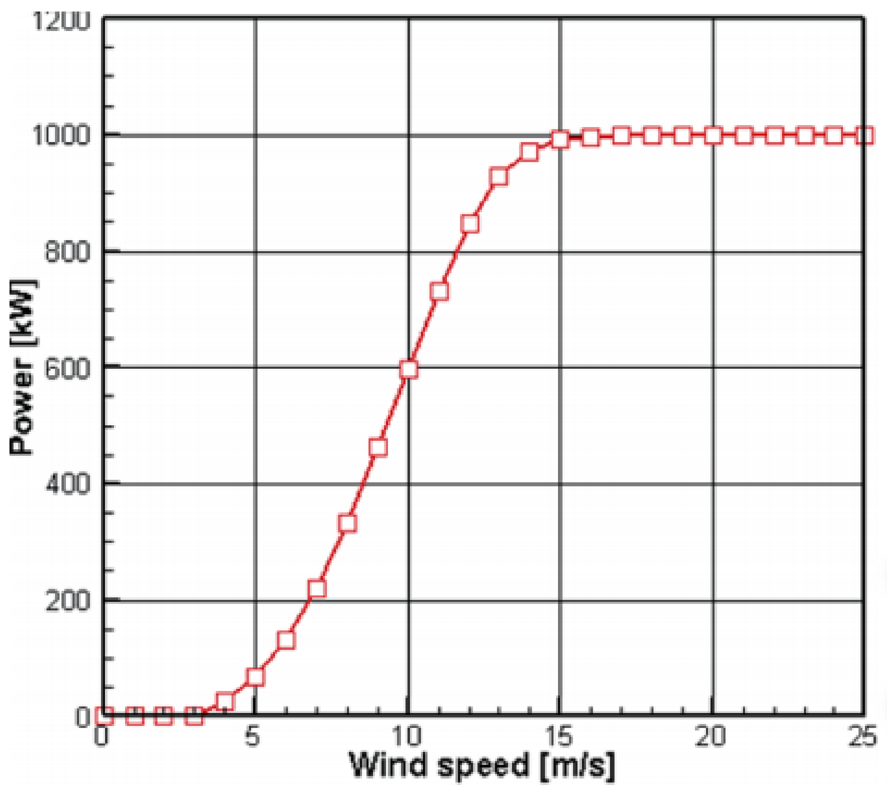

Figure: Power curve for a 1 MW wind turbine

Source: https://www.google.com/search?q=Wind+energy+output+calculations+based+++on+hourly+wind+speed&tbm=isch&ved=2ahUKEwjs8ty4pernAhXULisKHZvWDsMQ2-cCegQIABAA&oq=Wind+energy+output+calculations+based+++on+hourly+wind+speed&gs_l=img.3...31353.31353..32098...0.0..0.156.156.0j1......0....1..gws-wiz-img.CKU9TLRQTjw&ei=YM9TXuzCMtTdrAGbrbuYDA&bih=706&biw=1536&rlz=1C1SQJL_enIN794IN794#imgrc=m4ePRmQRTw8-3M

- Table: Technical specification of the considered with turbine.

Characteristics	Wind Machine
Rated power (kW)	1,000.0
Hub height (m)	50
Rotor diameter (m)	54.2
Swept area (m^2)	2,300.0
Number of blades	3
Cut-in wind speed (V_{ci}) (m/s)	3.0
Rated wind speed (V_R) (m/s)	15.0
Cut-off wind speed (V_{co})	25.0

Wind energy output calculations based on hourly wind speed (2 of 2)

- Equation 1:

$$P_i(v) = \begin{cases} 0, & v < v_{ci} \\ (a_n v^n + a_{n-1} v^{n-1} + \ldots + a_1 v + a_0), & v_{ci} \leqslant v < v_R \\ P_R, & v_R \leqslant v < v_{co} \\ 0, & v \geqslant v_{co} \end{cases}$$

- Equation 2:

$$E_c = \sum_{i=1}^{N} P(v_i) \Delta t$$

Machine learning techniques used

- LASSO regression.
- KNN regression.
- xGBoost regression.
- Random forest regression.
- Support vector regression.

LASSO regression

- Equation 3:

$$\left(\hat{\alpha}, \hat{\beta}\right) = arg\ min\left\{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \alpha - \sum_{j=1}^{p} x_{i,j}\cdot\beta_j\right)^2\right\}$$

- Equation 4:

$$\left(\hat{\alpha}, \hat{\beta}\right) = arg\ min\left\{\frac{1}{N}\ \|y - X\beta\|_2^2 + \lambda\ \|\beta\|_1\right\}$$

KNN regression

- Equation 5:

$$y' = \underset{v}{argmax} \sum_{(x_i, y_i) \in D_{neighbors}} I\left(v = y_i\right)$$

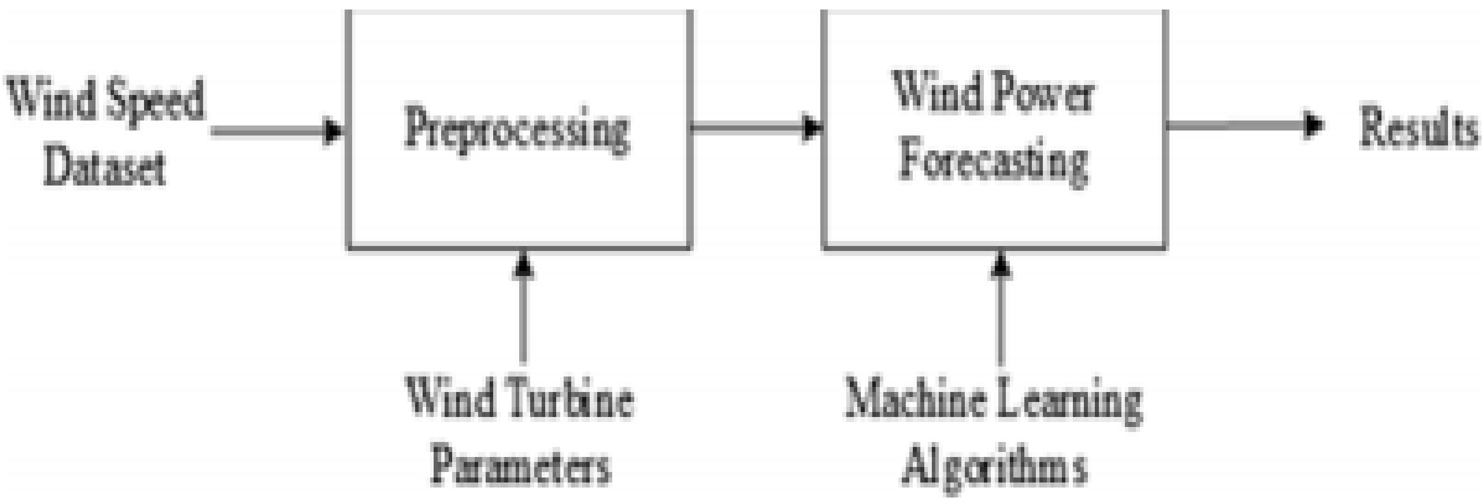

Figure: Experimental setup

Source: www.IBM.com

xGBoost regression

- Equation 6:

$$F_{obj}(\theta) = L(\theta) + \Omega(\theta) where\ L(\theta) = l(\hat{y}_i, y_i) and\ \Omega(\theta) = \gamma T + \frac{1}{2}\lambda \|w\|^2$$

- Fobj(θ) is the objective function.
- L(θ) is the loss function between prediction yi^ and real value.
- y ,Ω (θ) is the regularization term.
- λ is the learning rate.
- T is the number of leaves in the tree.
- λ is the regularization parameter.
- w is the weights of the leaves.

Random forest regression

- Equation 7:

$$PE^* = P_{X,Y}(mg(X, Y) < 0)$$

$$where\ mg(X, Y) = av_k I(h_k(X) = Y) - max_{j \neq Y} av_k I(h_k(X) = j)$$

Support vector regression

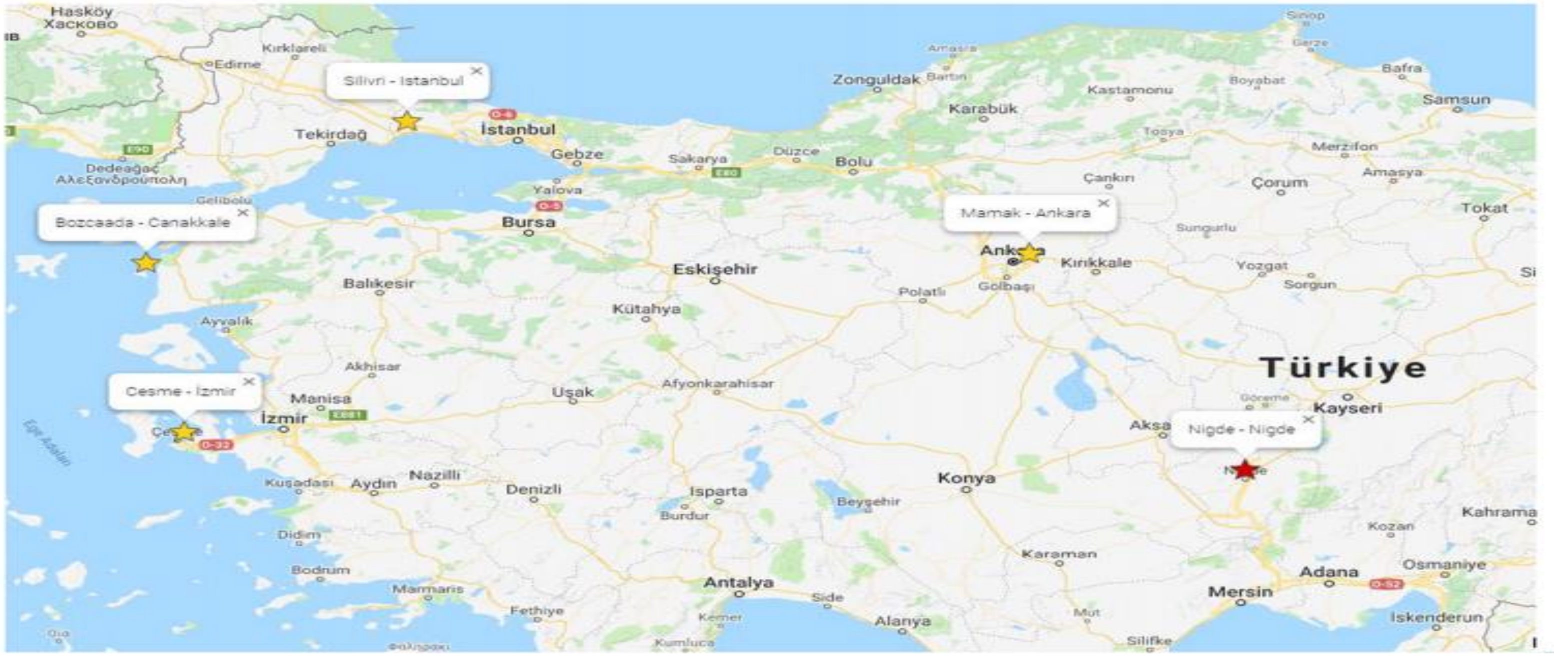

Figure: The locations of the meteorological stations shown on the map

- Equation 8:

$$\min \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{l} \xi_i + \xi_i^* \text{ subject to } \begin{cases} y_i - \langle w, x_i \rangle - b \leqslant \epsilon + \xi_i \\ \langle w, x_i \rangle + b - y_i \leqslant \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \geqslant 0 \end{cases}$$

Wind power forecasting method using machine learning algorithm

- Algorithm1 proposed wind power forecasting method.
- Input.
  - D: Dataset of 5 years of hourly wind observation.
  - Turbine specs: Wind turbine features.
  - Education ratio: Learning information instance ratio.

- Output:
  - Algorithm:
    - 1 hourly Power = calculate-hourly-power(D, turbine specs).
    - 2 [daily WS, daily SD] = pre-process-dataset(D).
    - 3 daily power = calculate-daily-total-power(hourly power).
    - 4 [daily WS Train, daily SD train, daily WS test, daily SD test, daily power train, daily power test] = split-train-test(training ratio).
    - 5 model = fit-algorithm(daily WS train, daily SD train, daily power train).
    - 6 forecasted Power = forecast-power(model, daily WS test, daily SD test).
    - 7 metrics = calculate-algorithm-performance(forecasted Power, daily power test).
    - 8 return forecasted power.

About data set (1 of 2)

- Equation 9:

$$v = v_0\left(\frac{h}{h_0}\right)^{\alpha}$$

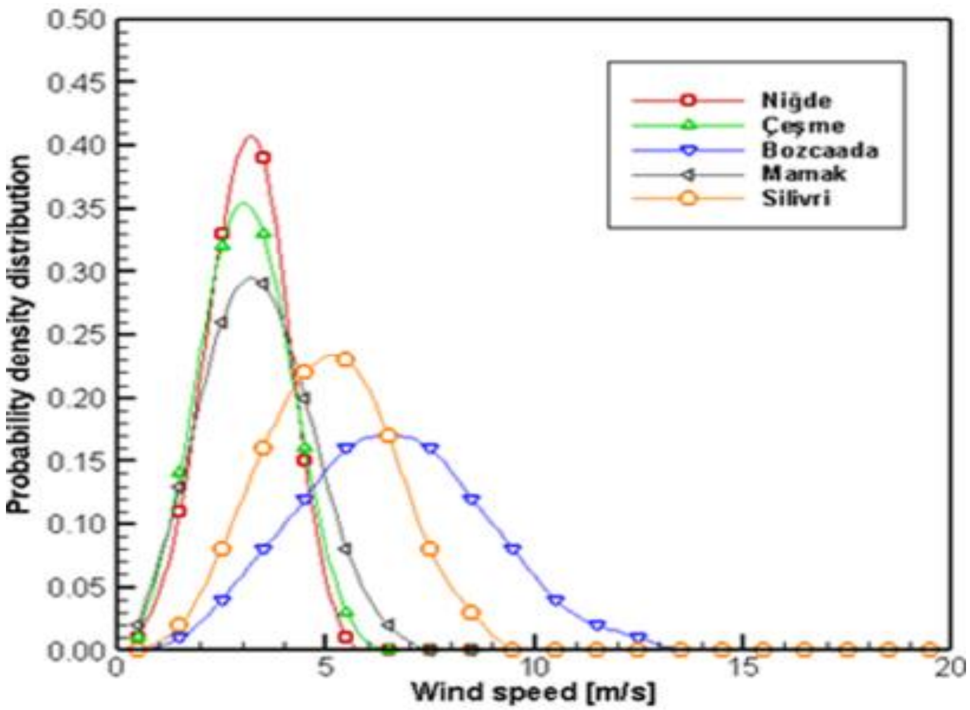

Figure: Wind speed frequency distributions in the selected locations

Source: https://www.google.com/search?q=Wind+speed+frequency+distributions+in+the+selected+locations&rlz=1C1CHBF_enIN862IN862&source=lnms&tbm=isch&sa=X&ved=2ahUKEwicqs35l-rnAhWBxTgGHVVxBWkQ_AUoAXoECA0QAw&biw=1707&bih=720#imgrc=w26URIRq4xcxVM

- Table: Calculated Weibull distribution parameter for selected location and 50m hub weight.

Location	k	c (m/s)
Nigde	3.69	3.45
Cesme	3.17	3.44
Bozcaada	3.20	7.28
Mamak	2.78	3.77
Silivri	3.44	5.60

Case studies

- The experimental results were provided for the algorithms of machine learning. For three cases, the tests are conducted.

- Case 1: Is performed utilizing the average regular air velocity and standard position variation to examine the output of machine learning methods for air power prediction.

- Case 2: Is performed when no standard deviation tests the efficacy of machine learning algorithms.

- Case 3: Is conducted to check the efficiency of machine learning systems constructing a prototype at a location and evaluating the system at various sites.

Case 1: Wind power forecasting based on daily mean wind speed and standard deviation

- In this scenario, with previous regular mean air velocity and standard deviation, the regular whole power produced was expected.

- The estimated wind power values have been compared with the fifth year's original power values.

Forecasting accuracy of algorithms

- Table 3: Forecasting accuracy of the algorithms for daily wind speed and standard deviation.

Algorithm/Metric	R^2	RMSE	MAE
LASSO	0.8619	164.61	88.85
kNN	0.9852	53.82	7.197
xGBoost	0.9939	34.40	6.528
SVR	0.992	38.52	**5.430**
RF	**0.995**	**30.224**	7.048

Case 2: Wind power forecasting based on only daily mean wind speed

- Only average mean wind speeds were used in this case to estimate the total daily wind power.

- The aim of this scenario is to illustrate the consequence of standard deviation on our system and see if there are any standard deviation values when the models generate reasonable results.

Case 3: Wind power forecasting for a different region

- Table 5: The bold values are the results that are observed as best performance.

Algorithm/Metric	Cesme			Mamak			Bozcaada			Silivri		
	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
LASSO (WS + STD)	0.7696	206.22	136.64	0.8970	200.71	119.84	0.7691	621.61	148.91	0.8135	450.41	124.17
LASSO (WS)	0.7462	216.44	166.24	0.8456	251.26	127.12	0.8415	514.92	177.01	0.8531	442.84	211.16
kNN (WS + STD)	0.9872	48.47	8.187	0.9778	93.145	10.128	0.9106	386.81	39.482	0.9579	213.92	124.17
kNN (WS)	0.9092	129.43	32.26	*0.9334*	*165.04*	64.450	0.9162	374.30	147.45	0.9199	326.90	127.40
xGBoost (WS + STD)	0.9922	37.83	7.942	**0.9851**	**76.148**	10.158	**0.9526**	**281.38**	24.490	**0.9845**	**129.49**	15.498
xGBoost (WS)	0.8993	136.34	26.653	0.9302	168.84	56.04	*0.9324*	336.32	138.04	0.9315	302.45	113.07
SVR (WS + STD)	**0.9992**	**11.487**	**6.4941**	0.9652	116.68	**7.7585**	0.8843	439.87	**12.83**	0.9766	159.32	**7.438**
SVR (WS)	*0.9362*	*108.46*	*22.310*	0.9260	173.90	*51.19*	0.9155	376.03	*130.49*	*0.9346*	*295.34*	*105.80*
RF (WS + STD)	0.9924	37.431	7.9680	0.9817	84.452	10.024	0.9509	286.49	28.339	0.9826	137.58	16.020
RF (WS)	0.8823	147.40	34.444	0.9242	176.00	72.41	0.9257	352.50	143.39	0.9230	320.67	128.74

Checkpoint (1 of 2)

Multiple choice questions:

1. Gradient of a continuous and differentiable function.
   a) Is zero at a minimum
   b) Is nonzero at a maximum
   c) Is zero at a saddle point
   d) Both b and c

2. Suppose you have trained a logistic regression classifier and it outputs a new example x with a prediction ho(x) = 0.2. This means:
   a) Our estimate for p(y=1 | x)
   b) Our estimate for p(y=0 | x)
   c) Our estimate for p(y=1 | x)
   d) Our estimate for p(y=0 | x)

3. In which of the following cases will k-means clustering fail to give good results? 1) data points with outliers 2) data points with different densities 3) data points with nonconvex denial of services (dos).
   a) 1 and 2
   b) 2 and 3
   c) 1,2, and 3
   d) 1 and 3

Checkpoint solutions (1 of 2)

Multiple choice questions:

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Checkpoint (2 of 2)

Fill in the blanks:

1. **------------** is an electrical grid which includes a variety of operation and energy measures including smart meters, smart appliances, renewable energy resources, and energy efficient resources.
2. **--------------** forecasting includes forecasting demand (load) and price of electricity, fossil fuels (natural gas, oil, coal) and renewable energy sources (RES; hydro, wind, solar).
3. **----------------- i**s a simple algorithm that stores all available cases and predict the numerical target based on a similarity measure (e.g. distance functions).
4. **---------------** is a decision-tree-based ensemble machine learning algorithm that uses a gradient boosting framework.

Checkpoint solutions (2 of 2)

Fill in the blanks:

1. **Smart grid** is an electrical grid which includes a variety of operation and energy measures including smart meters, smart appliances, renewable energy resources, and energy efficient resources.
2. **Energy** forecasting includes forecasting demand (load) and price of electricity, fossil fuels (natural gas, oil, coal) and renewable energy sources (RES; hydro, wind, solar).
3. **K nearest neighbours** is a simple algorithm that stores all available cases and predict the numerical target based on a similarity measure (e.g., distance functions).
4. **XGboos**t is a decision-tree-based ensemble machine learning algorithm that uses a gradient boosting framework.

Question bank

Two mark questions:

1. What are smart grids?
2. List the smart grid technologies.
3. How machine learning techniques can be used in energy forecasting.
4. Define smart grid drivers

Four mark questions:

1. Explain the key characteristics of smart grids.
2. Describe the machine learning techniques for renewable energy generation.
3. Explain the machine learning approaches for wind power forecasting.
4. How machine learning can be used for managing renewable energy integrated smart grids.

Eight mark questions:

1. Explain the machine learning application in wing energy forecasting.
2. Write a short note on application of machine learning in power generation and distribution.

Unit summary

Having completed this unit, you should be able to:

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- Gain knowledge on smart grid technologies
- Understand characteristics of smart grid
- Gain knowledge on machine learning applications in smart grid
- Understand machine learning techniques for renewable energy generation
- Learn about the applications of machine learning in forecasting renewable energy generation