Neuro-fuzzy resource forecast in site suitability assessment for wind and solar energy: a mini review

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Abstract

Site suitability problems in renewable energy studies have taken a new turn since the advent of geographical information system (GIS). GIS has been used for site suitability analysis for renewable energy due to its prowess in processing and analyzing attributes with geospatial components. Multi-criteria decision making (MCDM) tools are further used for criteria ranking in the order of influence on the study. Upon location of most appropriate sites, the need for intelligent resource forecast to aid in strategic and operational planning becomes necessary if viability of the investment will be enhanced and resource variability will be better understood. One of such intelligent models is the adaptive neuro-fuzzy inference system (ANFIS) and its variants. This study presents a mini-review of GIS-based MCDM facility location problems in wind and solar resource site suitability analysis and resource forecast using ANFIS-based models. We further present a framework for the integration of the two concepts in wind and solar energy studies. Various MCDM techniques for decision making with their strengths and weaknesses were presented. Country specific studies which apply GIS-based method in site suitability were presented with criteria considered. Similarly, country-specific studies in ANFIS-based resource forecasts for wind and solar energy were also presented. From our findings, there has been no technically valid range of values for spatial criteria and the analytical hierarchical process (AHP) has been commonly used for criteria ranking leaving other techniques less explored. Also, hybrid ANFIS models are more effective compared to standalone ANFIS models in resource forecast, and ANFIS optimized with population-based models has been mostly used. Finally, we present a roadmap for integrating GIS-MCDM site suitability studies with ANFIS-based modeling for improved strategic and operational planning.

Keywords: ANFIS-based modeling; GIS; MCDM; Site suitability; Solar energy; Wind energy.

Contents

1. Introduction

The global paradigm shift from the non-renewable energy sources (non-RES) to the renewable energy sources (RES) has placed more demands on the RES to ensure maximum resource conversion using different resource-specific conversion technologies (Adedeji et al., 2019; Ajagekar and You, 2019). Optimality of the resource conversion is largely dependent on the location of the conversion technologies, thus, emphasizing the relevance of site suitability analysis. This condition has consequentially made renewable energy (RE) resource location problems more complex as several criteria like environmental, technological, social and economic are required to be satisfied to achieve optimal geospatial location for RE projects (Bandoc et al., 2018; Jahangiri et al., 2016; Mao et al., 2015; Su et al., 2018). Hence, these problems are classified as multicriteria decision making (MCDM) problems. In the past few decades, the quest for sustainable clean energy sources has increased the penetration of RES in the energy mix of many countries. While many RESs are being explored globally, solar energy and wind energy have blazed the trail among these resources due to their capacity factor, availability, "degree of cleanliness", and investment cost compared to other renewable resources. In terms of investment cost, scalability, and ease of maintenance, solar and wind energy harvesting remains preferable. It has been observed that the capacity factors of solar and wind is fast increasing due to more inclinations to their utilization for power generation. For example, the global average wind power capacity factor increased from less than 22 % in 2010 to over 24 % in 2017 and offshore wind power gradually approaches a capacity factor of 50 % (IEA, 2018). Also, in 2017, solar resource uptake experienced tremendous growth far above the aggregate of fossil fuels (Evans, 2018).

The geographical information system (GIS)-based land suitability technique had its footings from the late nineteenth to the early twentieth century where American landscape architects use hand-drawn overlay techniques, a technique which was further improved upon by mapping data on natural and human-made attributes in the environment of a study area (Malczewski, 2004). These information are further presented in individual transparent maps using light and dark shades which depict high suitability and low suitability respectively. These individual transparent maps are then superimposed over one another to create an overall suitability map for specific land use (McHarg, 1969). The advent of information technology has translated this technique of problem-solving to the virtual environment, thus giving birth to the GIS tool, which further increases the accuracy and precision of the process. The advancement and growth of internet connectivity have in turn influenced the current state of GIS modeling technique. This is seen in the development of data warehouse and the proliferation of spatial data both at national and global levels (Peng and Tsou, 2003). The geospatial dimension of location problems has attracted more relevance in location science, therefore two techniques have been developed in the identification of prospective viable sites. These methods are; Land suitability analysis and land screening process. While land suitability analysis scores each land area based on its ability to support specific land use, the land screening process spatially removes land areas from the feasibility region based on their attributes (Cova and Church, 2000). GIS-based location problems are multicriteria, thus, this tool has been used in congruence with MCDM tools most especially in RE facility location for ranking alternative viable areas.

Forecasting wind and solar resources in hotspot areas have taken a new turn from the traditional statistical methods to the use of intelligent techniques within the domain of artificial intelligence (AI). This giant stride has increased the level of data-driven decisions both for strategic and operational planning in wind and solar uptake and the RE sector at large. AI techniques have demonstrated increasing reliability in modeling complex and nonlinear relationships between a set of inputs and system response (output) and unravelling latent patterns that exist between datasets (Malekmohamadi et al., 2011). AI methodologies have been described as exhibiting human-like traits, which is acquired through a learning process (Joshi, 2020). The literature has established four learning types for AI models which include: supervised learning, unsupervised learning, reinforced learning and ensemble learning (Voyant et al., 2017). The supervised learning models require data labels for learning data and thus follow the input/output process. The unsupervised learning technique on the other hand does not require data labels to learn data but learns trends and historical patterns in the input. The reinforced learning technique learns dynamic data through continuous interaction and searching within the solution space; it also integrates feedback from the environment. The ensemble learning method consists of multiple base learners as ensemble learners whose predictions are combined into a single output for better performance than individual members of the ensemble with an uncorrelated error on the target dataset (Gala et al., 2016; Voyant et al., 2017). The adaptive neurofuzzy inference system (ANFIS) is an example of a supervised learning technique, which integrates the self-learning capabilities of artificial neural network (ANN) and the problem-solving prowess of fuzzy logic (FL) to effectively perform a function approximation especially when imprecision exist (Adedeji et al., 2019; Liu et al., 2017). This technique consists of five layers: three layers which consist of non-adaptive nodes and the other two layers consist of adaptive nodes that enable ANFIS to perform parameter adjustment according to the input/output data pairs. At first, ANFIS models are associated with gradient descent or backpropagation learning methods, however, the slow convergence rate and local minima problems of backpropagation techniques have necessitated the development of hybrid method for learning (Suparta and Alhasa, 2016) which will be further discussed in this study. The use of ANFIS and its variant models in wind and solar energy have tremendously increased in the past few decades after its development by Jang in 1993. The structure, classification and applications of ANFIS model will be extensively discussed later in this study.

GIS-based approach to site suitability analysis provides information about land areas that are not only viable for RE resource exploration but are also dispute-free in terms of specific constraints that need to be satisfied before the plant siting process. Its use with MCDM techniques offers flexibility in the decision-making processes for decision-makers. In the RE sector, the viability of the investment is highly essential if a low-carbon economy will be a reality. Consequent to this, resource forecast in the RE sector has often been performed in perceived resource-rich sites. The literature is replete with studies that have adopted data from the supervisory control and data acquisition (SCADA) system of RE plants. Such plants had passed through the site suitability analysis before site development. Hence, there exists a synergy between GIS-based approach to RE facility location and RE resource forecast.

1.1. Renewable Energy

The quest for a low-carbon economy on the global scale has necessitated the increase in the use of RESs as alternatives to fossil fuels. Contrary to the non-RES that are not easily replenished but become depleted over a period of time, the RES replenish themselves within a short period of time, and freely available in nature. On a global scale, the wind and solar energy resources are blazing the trail though biomass has been acknowledged to have a potential in liquid fuel production (Olatunji et al., 2020).This section presents a brief overview of the governing principles related to wind and solar energy exploration with an emphasis on power generation.

1.1.1. Wind Energy

Wind energy remains one of the potent RES largely harnessed globally asides solar energy. The wind has been the prominent means of sailing ships until the invention of the steam engine in the 18th century by James Watts (Johnson, 2006). Wind as a source of energy began in Denmark with the 23 m diameter wind turbine. The technology became commercially available in the American market around 1925 with the most common brands having two and three blades as propellers. They generate 200 to 1200 W (Wincharger model) and 1.5 to 3 kW (Jacob model) (Johnson, 2006). Over the last two decades, wind energy has been considered among the fastest-growing RE resources (GWEC, 2017; Katinas et al., 2014) and many countries presently consider harnessing this resource for energy generation due to its free, environmentally friendly, and inexhaustible nature (Mohammadi et al., 2015c). Murthy and Rahi (2017) refer to wind energy as the centerpiece of economical and efficient energy. While fossil fuels have a finite time for which they are abundant for exploration in a particular location, the wind energy does not suffer this constraint. Asides the mentioned attributes, wind energy is considered the cheapest among the RES whose efficiency is highly dependent on the geographical location of the wind turbine. A poor location of the technology results in investment loss.

Wind energy is available as kinetic energy produced from large masses of air moving across the earth's surface. The harvesting technology receives the kinetic energy through the blades and the efficiency of its conversion largely depends on the efficiency of the rotor interaction with the wind.

1.1.1.1. Power available in the wind spectra

The kinetic energy (K.E) in a stream of air with mass m moving at a speed V can be calculated using:

$$K.E = \frac{1}{2} m V^2 \qquad (1)$$

During wind energy harvesting, a rotor of cross-sectional area, A_r exposed to the stream of air with volume, v and air density, ρ_a receives the kinetic energy. The kinetic energy available to the turbine can be expressed as:

$$E = \frac{1}{2}\,\rho_a\,v_a\,V^2 \qquad (2)$$

since $m = \rho_a v_a$

However, the air parcel with constant interaction with the rotor in real-time possess a cross-sectional area equivalent to that of the rotor (A_r) and a thickness equal to the wind velocity, *V*. Therefore, the energy available per unit time (Power, *P*) then becomes (Mathew, 2006):

$$P = \frac{1}{2}\,\rho_a\,A_r\,V^3 \qquad (3)$$

From Eqn. (3), the power available in the stream of air is directly proportional to the air density, the area of the rotor and the cube of the wind velocity. Wind velocity, however, has a predominant effect on the power available for the harvesting equipment due to its cubic relationship. From the general gas equation, certain factors affect air density. These include air temperature, elevation, atmospheric pressure, and air constituents as expressed by:

$$pv_a = n\,RT \qquad (4)$$

where p is the air pressure, v_a is the volume of air, n represents the number of moles of air, R represents the universal gas constant and T is the air temperature.

From $\rho_a = \frac{m}{v_a}$ and Eqn. (4), air density can be calculated by:

$$\rho_a = \frac{m\,p}{R\,T} \qquad (5)$$

For a known site elevation, *Z* and air temperature, *T*, its air density then becomes:

$$\rho_a = \frac{353.049}{T}\,e^{\left[-\,0.034\frac{Z}{T}\right]} \qquad (6)$$

Hence, air density decreases with increasing site elevation and temperature.

Eqn. (3) gives the theoretically available power which can be extracted by the turbine. However, wind turbines do not extract the available power completely. While the power harvested the by rotor is determined by the kinetic energy of the air stream that reaches the rotor, the rest is carried away by the moving stream of air. Thus, the actual power produced by the rotor is a function of the efficiency of the energy conversion that takes place within the rotor and the stream of air, called the power coefficient (C_p). This can be expressed as the ratio of the power developed by the rotor to the theoretical power available in the wind as shown in Eqn. (7).

$$C_p = \frac{2\;P_T}{\rho_a\,A_r\,V^3} \qquad (7)$$

where P_T represents the turbine power. It is also essential to note that several factors affect the power developed by the turbine. Some of these factors include the arrangement of the blades, the rotor profile, etc. Thus, maximum power coefficient is designed for in the rotor such that for a thrust force of:

$$F = \frac{1}{2}\,\rho_a\,A_r\,V^2 \qquad (8)$$

the maximum theoretical torque transmitted by the rotor of radius, R_r can be expressed as:

$$Torque = \frac{1}{2}\,\rho_a\,A_R\,V^2\;\;R_r \qquad (9)$$

However, in practice, the rotor only transmits a fraction of this torque due to transmission losses. The torque coefficient, C_T can then be expressed as the ratio of the actual torque, T_T transmitted by the rotor and the theoretical torque expressed as:

$$C_T = \frac{2\ T_T}{\rho_a\ A_R\ V^2 R_r} \tag{10}$$

1.1.1.2. Wind resource characterization

Characterization of available resource is highly essential for wind energy resource location to determine resource abundance, its persistence, availability, and intermittency. The reliability of the results from the characterization metrics is highly dependent on data resolution, data integrity, and recency. Some studies use the wind power density as a measure of the resource and not wind speed because the wind power density accounts for variation in air density. The two-parameter Weibull distribution, $f(V)$ has been used over time for fitting wind resource distribution. This probability density function consists of two parameters; the shape parameter, k, and the scale parameter, c such that the wind speed, V is expressed as:

$$f(V) = \left(\frac{k}{c}\right)\left(\frac{V}{c}\right)^{k-1} exp\left[-\left(\frac{V}{c}\right)^{k}\right] \tag{11}$$

The shape parameter accounts for the skewness in the Weibull distribution and thus significantly influences the fits of the wind speed with an inverse relationship between its value and the tail of the Weibull distribution (Gunturu and Schlosser, 2012). Due to the cubic relationship between the wind power density and the wind speed, a small perturbation in the wind speed can translate into a large increase in wind power density (Gunturu and Schlosser, 2012). It is reported that daytime winds are near-Weibull than the night time winds which are notable to show positive skewness than the Weibull distribution (He et al., 2010). Interestingly, it was discovered that some wind regimes defies the two-parameter Weibull distribution and so its generalization may not be accurate (Jaramillo and Borja, 2004; Morrissey et al., 2004).

In wind resource characterization, it is expected that the variation between cycles of uptime and downtime also called intermittency, be determined for a specific location. Intermittency integrates the availability and persistence of the wind resource. Further to this, one significant metric for measuring the reliability of power generation is the persistence of the wind power density. As proposed by Gunturu and Schlosser (2012), this involves determining the statistics of wind power episode lengths, the statistics of no-wind power episode lengths, availability/ unavailability of wind power, the probability distribution of wind power episode lengths, and the probability of no-wind power episode lengths. By wind power episode length, we refer to the length of time where wind power is harvestable (above the set threshold) for successive hours.

Persistence is a measure of the consistency of wind power above the threshold for which power generation occurs. It is a measure of median wind power episode length which is the median of all continuous harvestable periods when the wind power is above the threshold value. This can be estimated using:

$$Persistence = median\big(\infty(P_i)\big) \tag{12}$$

where $\infty(P_i)$ is the duration of times when wind power density, P_i is greater than the threshold (200 W/m^{-2}).

The availability metric is one of the measures of the reliability of the wind energy harvesting system. The degree to which wind power is available in a specific location can be expressed Eqn. (13). The metric is calculated relative to wind power density of 200 W/m^{-2} because it is assumed that power density less than a threshold of 200 W/m^{-2} is a no-power condition.

$$Availability = \frac{Total\ no\ of\ hours\ wind\ power\ density\ \geq 200\ W/m^{-2}}{Total\ number\ of\ hours} \tag{13}$$

This can be expressed mathematically as:

$$Availability = \frac{1}{n}\sum_{t=1}^{n} \infty(P_i) \quad \ni \quad \infty(P_i) = \begin{cases} 1, & P_i \geq \ 200\ W/m^{-2} \\ 0, & otherwise \end{cases} \tag{14}$$

Constant wind power is the most desirable, however, from the nature of the resource, variability is unavoidable. Variability of the resource calculated in terms of the robust coefficient of variation (RcoV) can be estimated using (Yip et al., 2016):

$$RcoV = \frac{P_{median}\,|P_i - P_{median}|}{P_{median}} \tag{15}$$

where P_{median} is the median of the wind power density and P_i is the observed wind power density.

1.1.2. Solar Energy

Solar energy is one of the clean and inexhaustible energy sources in the universe. Solar power becomes more useful for electricity generation by two conversion approaches: photovoltaic (PV) and concentrated solar power (CSP). While the first converts solar power directly to electricity the second converts solar power first to heat and then to electricity using a heat engine (Ren et al., 2015). In these two conversion methods, the solar irradiance index *G*, which is the amount of solar energy a surface receives per unit area per unit time on the earth, plays a vital role. The solar irradiance index can be affected by the time of the day, spatial location, and cloud/haze cover. Eqn. (16) gives a mathematical expression for the solar irradiance index (Wang et al., 2012):

$$G = \ \alpha G_0 \left[1 + 0.033 \cos\left(\frac{360d}{365}\right)\right] sin\theta_\mathrm{s} \tag{16}$$

$$sin\theta_\mathrm{s} = \cos h \cos\delta \cos\phi + \sin\delta \sin\phi \tag{17}$$

where θ_s = solar angle

h= solar hour angle

δ = local latitude

d = date sequence of the year

α = cloud/haze cover index

G_0 = solar irradiance constant (1367 W/m^2)

The solar irradiance can be categorized into three: direct, diffuse, and global. The direct normal irradiance (DNI) is the solar irradiance directly incidence on a surface from the sun, the diffused horizontal irradiance (DHI) is the scattered solar irradiance and the global horizontal irradiance (GHI) is the aggregate of the DNI and DHI. Shown in Figure 1 is a representation of the DNI and DHI. The GHI is relevant for solar resource harvesting through PV technologies (Prăvălie et al., 2019). On the other hand, a sufficiently high DNI is of interest in harvesting solar resource through concentrated solar power (CSP) technologies (Clifton and Boruff, 2010). Solar energy is not available in an explorable amount in all parts of the world either for solar PV or CSP conversion technologies, thus a suitability classification based on annual sunshine, location and geospatial characteristics as presented by Qui et al. (2019) are summarized in Table 1.

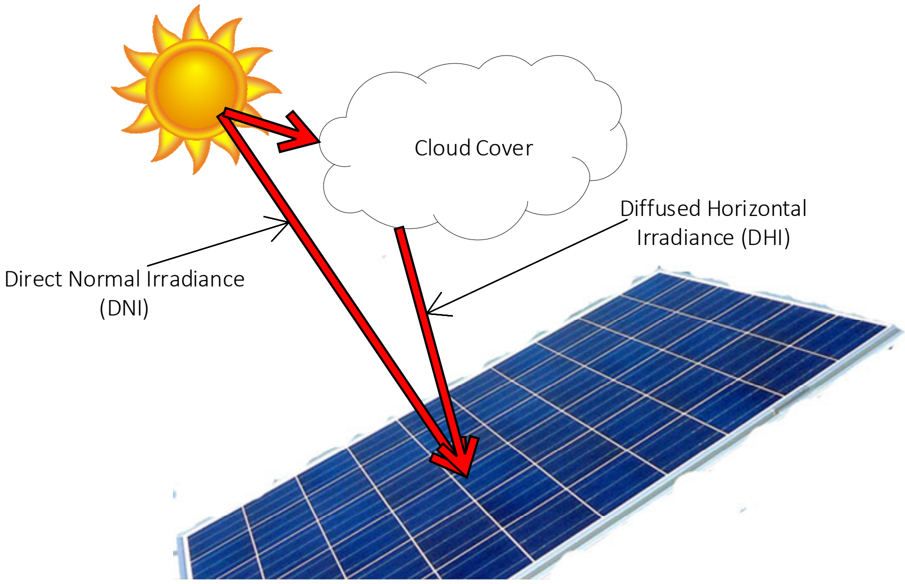

Figure 1. Schematic diagram showing the direct and diffuse irradiance

One of the pioneer studies on the spatial distribution of solar energy across the 7 continents established the gap in the availability of sufficient representative data and accuracy of instruments of measurement at available meteorological stations per continent (Löf et al., 1966). However, advancements in technology and the discovery of more usefulness of these data have provided a more reliable distribution of solar energy across the continent. The solar resource space has experienced a proliferation of data and increased access in recent years. Certain websites now make solar energy resource maps available for the public. For example, PVGIS and SOLARGIS websites.

Table 1. Global solar resource classification

Class	Latitude	Annual sunshine	Characteristics
Highly favourable	15º N to 35º N and 15º S to 35º S	> 3000 hours	Semi-arid, limited cloud cover, less rainfall, high direct radiation.
Moderately favourable	0 and 15º N	> 2500 hours	High humidity, frequent cloud cover, high scattered radiation.
Less favourable	35º N to 45º N and 35º S to 45º S		Solar radiation in winter is less than other seasons of the year.
Least favourable	< 45º N		About 50% of total radiation being diffused and largely occurs in the winter season than summer, extensive cloud cover.

The global transition from the non-RES to RES has increased the uptake of wind and solar energy ranging from small to large-scale investments; standalone, embedded generation and grid-connected systems. Recent developments at component and systems levels have improved energy harvesting equipment associated with these two sources. For instance, for wind turbines, there has been reliability improvement in the gearbox (Musial et al., 2007), blades (Mohle, 2009), method of operation (Amit Kumar and Anshuman, 2012), vibration isolation systems (Van der Woude and Narasimhan, 2014) and so on. Wind turbine capacity has also improved significantly with significant growth in the capacity factors of the turbines. Typical wind turbines in 1985 have rated capacity of 0.05 MW with a rotor diameter of 15 m, however, in recent times, wind turbine capacities now range between 3 to 5 MW for offshore wind turbines and about 2 MW for onshore types and some commercial wind turbines are rated 8 MW (IRENA, 2019a). For solar energy, recent developments in this field has shown different technological improvements in the solar cells, solar modules trackers, mounting structures, inverters and electrical components.

With the expansion in the solar PV markets and the fall in price of its associated components, more players are being involved in the manufacturing of its polysilicon (which is often the most costly), like Apple and Tesla (IRENA, 2019b). Recent developments in the cell material with transition from the crystalline silicon to advanced silicon cells like passivated emitter and rear cell/contact (PERC), tandem cells, perovkites and thin film technologies some of which are silicon-based and non-silicon based have provided excellent absorption of light, higher internal reflectivity among many other advantages (Fraunhofer ISE, 2019). These advancements have increased the percentage of solar radiation which can be converted to electricity, thus reducing dependency on non-RES. The trend of investment on solar technologies as a whole still tops the list when compared with wind energy as shown in Figure 2 some of which is due to reduction in price of its highly priced components.

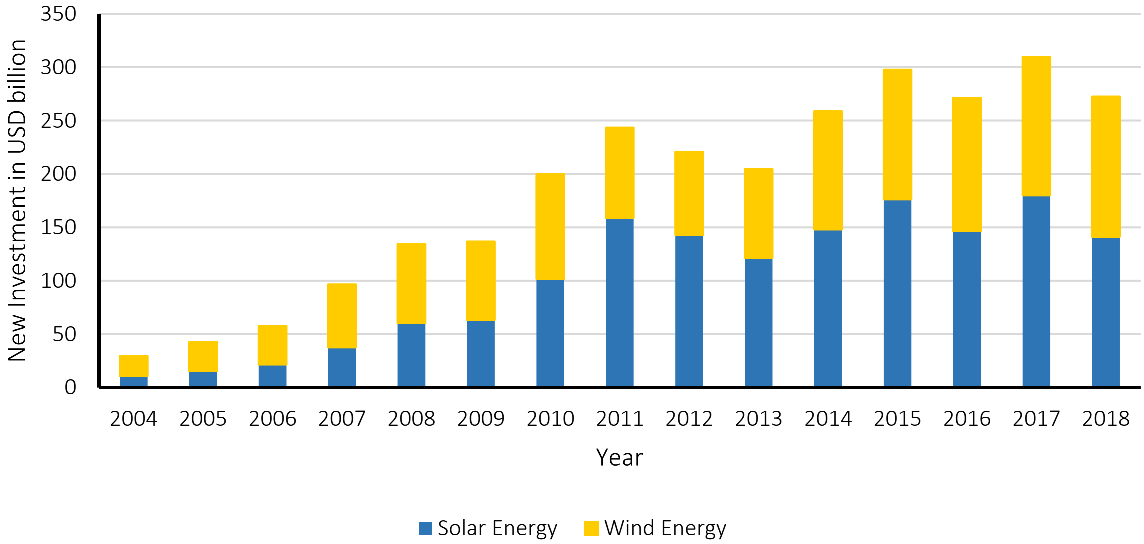

Figure 2. Global trends in renewable energy investments (Frankfurt School-UNEP Centre, 2018)

1.2. Geographical Information System

Geographical Information system (GIS) is a potent tool in location science, which collects, manages, manipulates and analyzes map geospatial data for effective decision-making process (Bruno and Giannikos, 2015; Nematollahi et al., 2016). The GIS tool takes two data representation formats: the raster/image and vector. The raster/image files contain rectangular grids known as pixels with each cell in the grid containing a single-valued attribute of the cell. Attribute data are stored in relational database models in the form of tables consisting of rows and columns. The vector files, however, hold a geometric figure in the form of lines, polygons and points and defines a limit associated with a georeferencing system. A geodatabase houses these information to maintain order, structure and standard for the data. To store these spatial data, the computer is expected to be able to successfully hold both the locational and the attribute dimensions of data (Wise, 2014). Unlike other data types, geographical data are seemingly complex in that they subsume information about position, likely topological associations, and attributes of displayed objects (Crosetto et al., 2000). GIS tool offers capabilities that enable geospatial analysts to analyze topology and spatial, spatial attributes, and a combination of spatial and non-spatial data attributes (Burrough and McDonnell, 1998). Significant to the result of the analysis in the GIS tool is the condition of the data. Data to be used must be up-to-date, accurate, and reliable. Most GIS applications are data-hungry and computationally intensive depending on the size of the data being analyzed. For raster files, large cell sizes could resort to an unnecessarily generalized data, however, a very small cell size resorts into humongous data size, thus leading to high data processing time. For vector files, however, data representation in its original resolution without generalization is just sufficient. Regarding GIS-based analysis, it is noteworthy that the data quality assurance process is often more cost than procurement of the tool (Bruno and Giannikos, 2015).

GIS has found its usefulness in site selection problems including land suitability analysis for RES. The tool can be used to screen a large area of land against a list of criteria to determine which areas are suitable for a specific purpose. In conjunction with the GIS tool are the MCDM tools, which further screen suitable land areas against a ranking methodology for criteria ranking and for determining the most suitable sites. Simply put, the GIS technique for land suitability analysis proceeds by applying restrictive criteria for the elimination of unsuitable land areas and a classification metrics to order the useful land areas according to their suitability (Yushchenko et al., 2018). Weight assignment is carried out based on the relative importance of the considered factors. After the nomination of suitable sites by the software, it is expedient that a ground verification be carried out, which involves a physical investigation of the location proposed to be highly suitable for RE exploration.

1.3. Artificial intelligence in renewable energy resource forecast

A paradigm shift from the statistical forecasting methods to empirical data-driven artificial intelligent models has been observed in the literature. The statistical forecasting models are based on mathematical principles of recognizing relationships and patterns in historical data. Many of these models are based on time series data studies with significance on the time dimension of data. Examples include smoothing techniques, moving average and autoregressive moving average models (Ahmed and Khalid, 2019). The persistence model is also one of the elementary forecasting techniques against which the performances of other advanced model are compared. These statistical-based models have less computational time due to less model complexity and could perform exceptionally better than the AI-based models in simple non-complex datasets. A comparison between the statistical-based and AI-based models by Makridakis et al. (2018) confirms this. However, these models chiefly rely on their history and, thus have difficulty comprehending latent intricate patterns when non-linearity exists in the data. Also, they are inefficient when big data are to be learned. Further to this, statistical forecasting models could fit data effectively rather than learning the future.

On the contrary, AI models leverage their fast computational ability, near-accuracy nature without the need for an internal knowledge of a nonlinear complex system (Hossain et al., 2018). For RE resource forecasting, deterministic input variables with high correlation to the output variable or autocorrelated variables must be considered in order to reflect reality. For example, in forecasting solar irradiance or solar power output, dependent variables like solar irradiance, atmospheric pressure, atmospheric temperature, cloud cover, the conversion efficiency of the panels, installation angle, surface impurity like dust on the panel, and other random influential variables are highly important as they affect the power output from the solar panel (Kumar and Kalavathi, 2018).

Empirical models are data-driven models, which unravel the latent patterns in an avalanche of data for informed decision-making (Adedeji et al., 2019). They are often referred to as black-box models because they do not explicitly explain their internal input-output mapping or data learning process (Adedeji et al., 2019). Large-scale exploration of RES is associated with an avalanche of time series data from which data-driven decisions can be made either at the operational level or strategic level of management.

With technological growth in RE harvesting, the five dimensions of data (volume, variety, veracity, velocity and value) are observed to increase on daily-basis and an increase in resource exploration also adds to the data pool, hence the associated storage concern. Thanks to artificial intelligence and the evolving quantum computing technologies (Ajagekar and You, 2019) which have assisted in data archiving. Often, the nature of the big data generated through RE exploration requires further processing in preparation for use by the AI model to enhance the performance and improve forecast accuracy (Okumus and Dinler, 2016). Such processing includes; the removal of outliers, handling missing data, filtering, de-noising, dimensional reduction, normalization and so on. This is as shown in Figure 3. Furthermore, it is expedient that features of interest be extracted from the pre-processed data for effective use by the AI model. Like in other data sources, data obtained from RE systems like wind and solar systems can also be associated with imbalances. The use of ensemble learners like bootstrap aggregation (Bagging) and adaptive boosting (AdaBoost), which have the capability of accounting for imbalance in data provides a good solution to this (Ren et al., 2015).

The prowess of deep learning techniques in understanding complex relationships in unstructured/unlabeled data has also been harnessed in RE resource forecast. One of the notable advantages of deep learning models is its ability to combine low-level features to generate high-level features in an input data across each step in its execution (Peng et al., 2020; H. Wang et al., 2019). Several deep learning models like simple recurrent neural network (RNN), long short-term memory (LSTM) neural network, convolutional neural network (CNN), gated recurrent unit (GRU) have been used in the RE space with prominence in the wind and solar resource forecasting. For example, in wind energy prediction, Chen et al. (2019) developed a two-layer model comprising a nexus of integrated deep learning models (ELM, Elman Neural Network, LSTM) for short-term predictions of wind speed. Also, Hu and Chen (2018) used a hybrid of LSTM, differential evolution (DE), hysteretic extreme learning machine (HELM), and nonlinear combined mechanism for wind speed forecasting. The study comprises of parameter optimization in LSTM using DE, and performance improvement of ELM by integrating hysteresis. Similarly, predicting wind power using an integration of isolated forest (IF) and deep learning was performed by Lin et al. (2020). In their study, the authors used related features of wind power obtained from the supervisory control and data acquisition (SCADA) to forecast wind power in which laudable results were obtained when compared with conventional predictive models. The use of deep learning models is also gradually gaining traction in solar resource forecasts. For example, Kaba et al. (2018) used astronomical variables like extraterrestrial radiation, sunshine duration, cloud cover, maximum and minimum temperature to forecast global solar radiation. Also, a forecast of solar resource using deep learning integrated with portfolio theory was performed by Lima et al. (2020) and a hybrid model aggregating the prowess of machine learning models and statistical methods to forecast solar power was investigated in a hybrid model of the two by Alkandari and Ahmad (2019). Deep learning models have suffered some setbacks in their longer training time, large memory requirement and the need for a large dataset for training compared to other AI algorithms (Kamilaris and Prenafeta-Boldú, 2018). Further to this, the learning technique is generally nonconvex, hence training deep networks and optimizing its parameters is difficult (H. Wang et al., 2019).

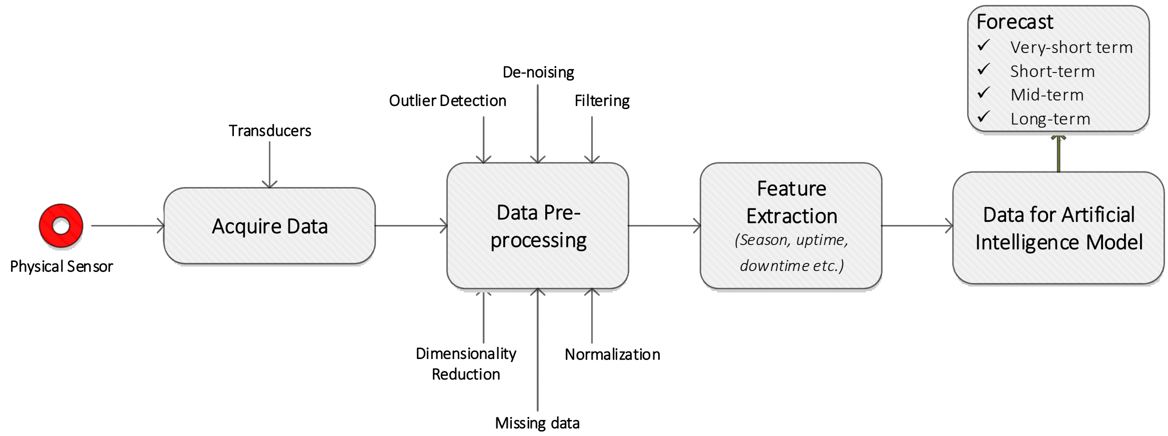

Figure 3. Data flow from "cradle to grave" for AI forecasting models

Several other AI techniques applied in RE forecasting have recorded significant success. Some of these models are either regressive or classification models. Examples of these models include artificial neural network (ANN) (Al-sbou and Alawasa, 2017; Buga et al., 2018; Mellit et al., 2013), adaptive neuro-fuzzy inference system (ANFIS) (Chauvin et al., 2014), particle swarm optimization hybrid with adaptive neuro-fuzzy inference system (PSO-ANFIS) (Douiri, 2019; Semero et al., 2018), support vector machine (SVM) (Dong et al., 2015), support vector machine hybrid (Mohammadi et al., 2015b; Olatomiwa et al., 2015), support vector regression (SVR) (Mohammadi et al., 2015a), recurrent neural network (RNN) and so on. Based on their strengths and weaknesses, while some perform well on large dataset, some others do not. Some can be computationally efficient while some are computationally intensive. However, these models have demonstrated a divergence from the traditional forecasting models with laudable efficiencies in the resource forecast compared to the conventional statistical models. ANFIS model has recently received more attention and its hybrid has been noticeably used for solar resource forecast (Kumar and Kalavathi, 2018; Perveen et al., 2019). While ANN shows prowess in learning numeric data obtained from non-linear systems but limited when handling linguistic variables, the FL model on the other hand demonstrates capability in unravelling systems represented by linguistic variables through a rule-based system (Mohandes et al., 2011). The FL, however, is unable to learn knowledge stored in numerical form. These two models (ANN and FL) infuse to form the ANFIS model with each leveraging the strengths of the other.

A concentrated focus on the status of research in the use of ANFIS model and its hybrids for forecasting solar and wind resources is presented in section 4.4.

1.4. Significance of the review

Several studies have applied the GIS-MCDM technique for site suitability towards increased RE uptake both in resource hotspot areas and areas with perceived potentials for power generation. Also, the use of artificial intelligent methods for RE resource forecast is fast increasing with hybrid models gaining traction. However, to the best of our knowledge, there have not been studies that integrate the two themes and establish a synergistic relationship between them. Further to this, several review articles have presented the current state of knowledge on GIS application in wind and solar resource location (Choi et al., 2019; Jahangiri et al., 2016; Malczewski, 2004) and intelligent forecast of solar and wind energy resource (Ahmed et al., 2020; Guermoui et al., 2020; Shihabudheen and Pillai, 2018; Suganthi et al., 2015; Suganthi and Samuel, 2012), however, in isolation. To the best of our knowledge, there has been no review article that presents the state of knowledge in the application of GIS-MCDM techniques for site suitability analysis and synergistically the prospect of integrating a soft computing technique like ANFIS for wind and solar resource forecast in a potentially viable site. Also, authors are not aware of any framework presented in the literature, which integrates these two themes. Further to this, this mini review presents the state of knowledge in the choice of criteria parameters for wind and solar site suitability analysis, which is essential for developing a common framework for site suitability analysis for prospective upscaling of wind and solar resource harvesting. Resource variability and intermittency are inherent characteristics of wind and solar energy, hence the choice of ANFIS modeling approach in this study. ANFIS model as a soft computing technique capable of modeling uncertainties, and imprecisions, can self-learn and adapt in fuzzy environments towards obtaining near-optimal solutions in systems where precision could be costly and complex. Hence, this mini-review (i) presents the state of knowledge in GIS-MCDM-based site suitability analysis and resource forecast with focus on wind and solar resources; (ii) presents the state of research in ANFIS-based modeling for wind and solar resource forecast (iii) motivates for the integration of the two themes to set a pace for a paradigm shift in GIS-MCDM-based site suitability analysis through the development of a framework for its integration.

An outline of the succeeding sections is as follows. Section 2 presents the state of knowledge in GIS-MCDM site suitability and ANFIS-based modeling for wind and solar energy uptake among key players across the globe. The current state of different MCDM techniques, an integral of GIS-based site and several studies where they have been used were also presented (section 3). Section 4 presents a review of ANFIS architecture, suitable performance measures and the state of research in its use for solar and wind resource forecasting. Section 5 presents a framework for the integration of GIS-MCDM-based site suitability and ANFIS-based resource forecast, section 6 concludes the study and section 7 presents recommendations for future studies.

2. Review Methodology

This section presents the methodology adopted in selecting the most appropriate articles that are significant to this study. First, representative countries tagged as the "key players" in wind and solar exploration were selected from six continents (Africa, Asia, North America, South America, Australia and Europe) of the world based on their power generation from wind and solar energy in their continent. The selection was not based on resource abundance as there are many countries with more resource than the selected, but rather on a fifty-three (53) years report of cumulative solar PV and wind power generation as obtained from www.ourworldindata.org/renewable-energy (Ritchie and Max, 2019), a database which houses global data of sustainable development goals (SDGs). The representative countries and their location on the global map are shown in Figure 4 created using ArcGIS 10.4.1. Table 2 also presents which of the countries is considered for wind and solar-based on their statistic of power generation from wind and solar in 2018 as obtained from www.ourworldindata.org/renewable-energy (Ritchie and Max, 2019).

From Figure 5 and Figure 6, China, representing the Asian continent, leads on the global scale in both solar and wind power with 366.6 GWh and 177.5 GWh generation respectively. It should be noted that presently in the African continent, the largest wind farm is in Kenya with an installed capacity of 310 MW (Gabisch et al., 2011) however, the database used in this review does not have historical data for the country.

Also, from Figure 5 and Figure 6, a comparison between the power generation from solar PV and wind energy shows that more power is generated from the wind than solar PV. This can be due to many factors some of which could include the power factor, the installed capacity, the resource availability, and so on. Also, while power generation from wind experienced an increase in the last two decades in all representative countries, power generation from the solar PV only received significant attention in less than two decades ago.

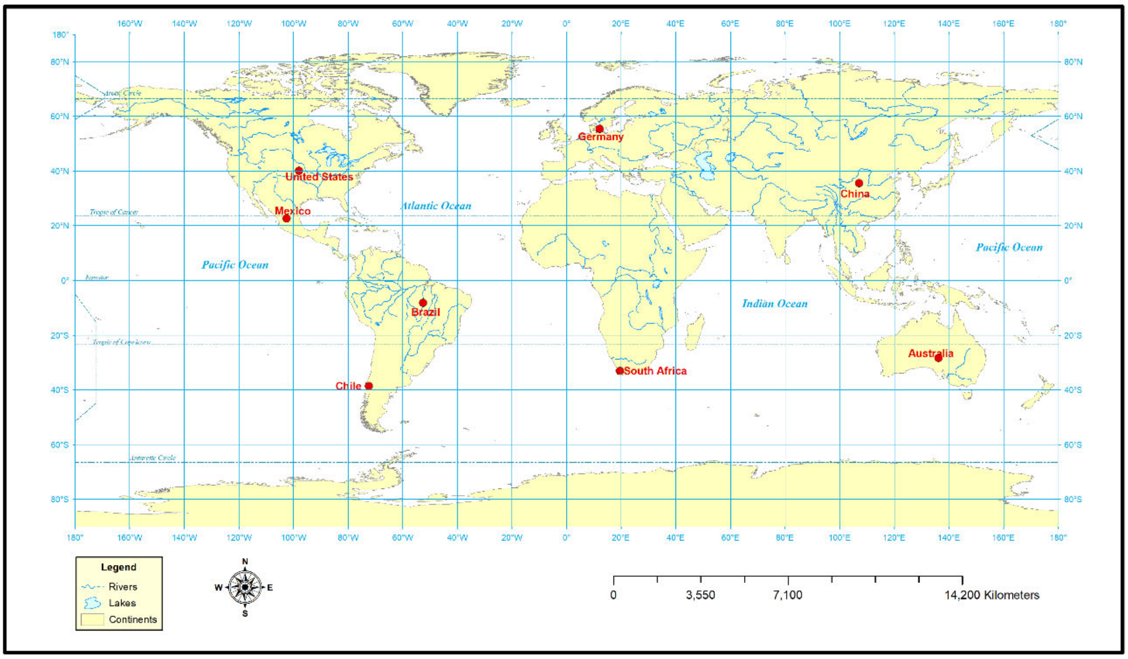

Figure 4. Location of representative countries in the six continents.

Table 2. Power generation from representative countries in 2018.

	Wind Energy		**Solar Energy**	
Continent	Country	Power generation (TWh)	Country	Power generation (TWh)
Africa	South Africa	6.895	South Africa	4.935
Asia	China	366.600	China	177.500
Australia	Australia	16.267	Australia	12.081
Europe	Germany	111.590	Germany	46.164
North America	United States	277.729	Mexico	2.243
South America	Brazil	48.480	Chile	5.119

Source: (Ritchie and Max, 2019)

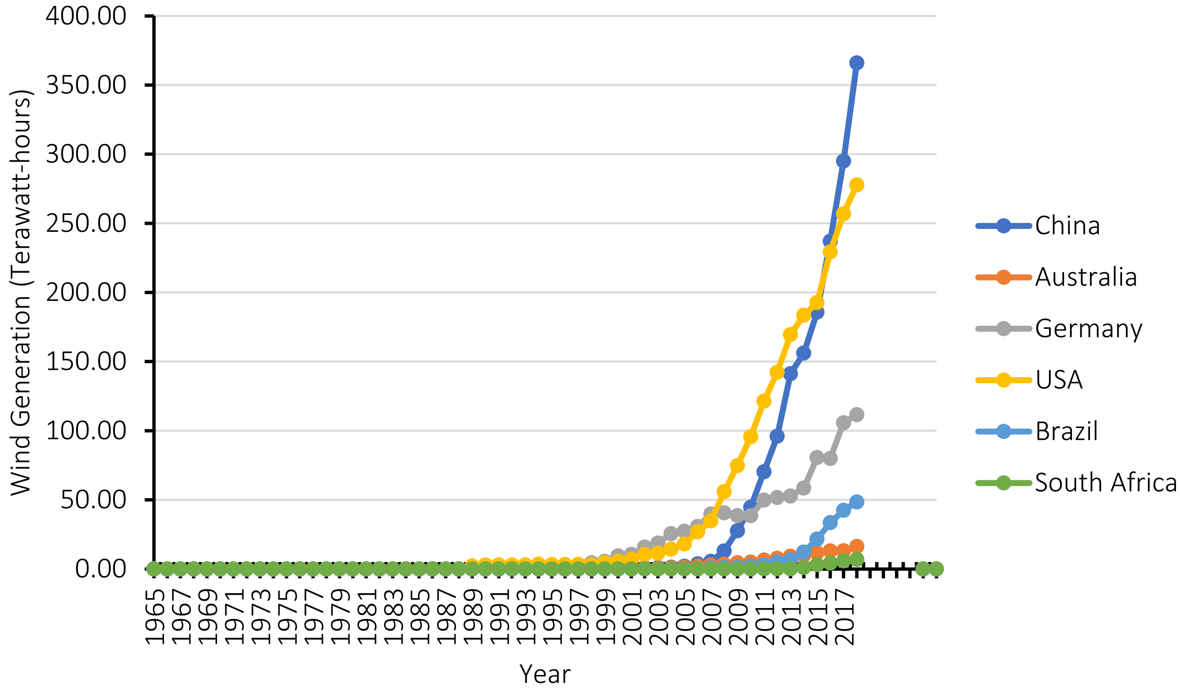

Figure 5. Trend of wind energy generation in representative countries from 1965 to 2018. (Ritchie and Max, 2019) .

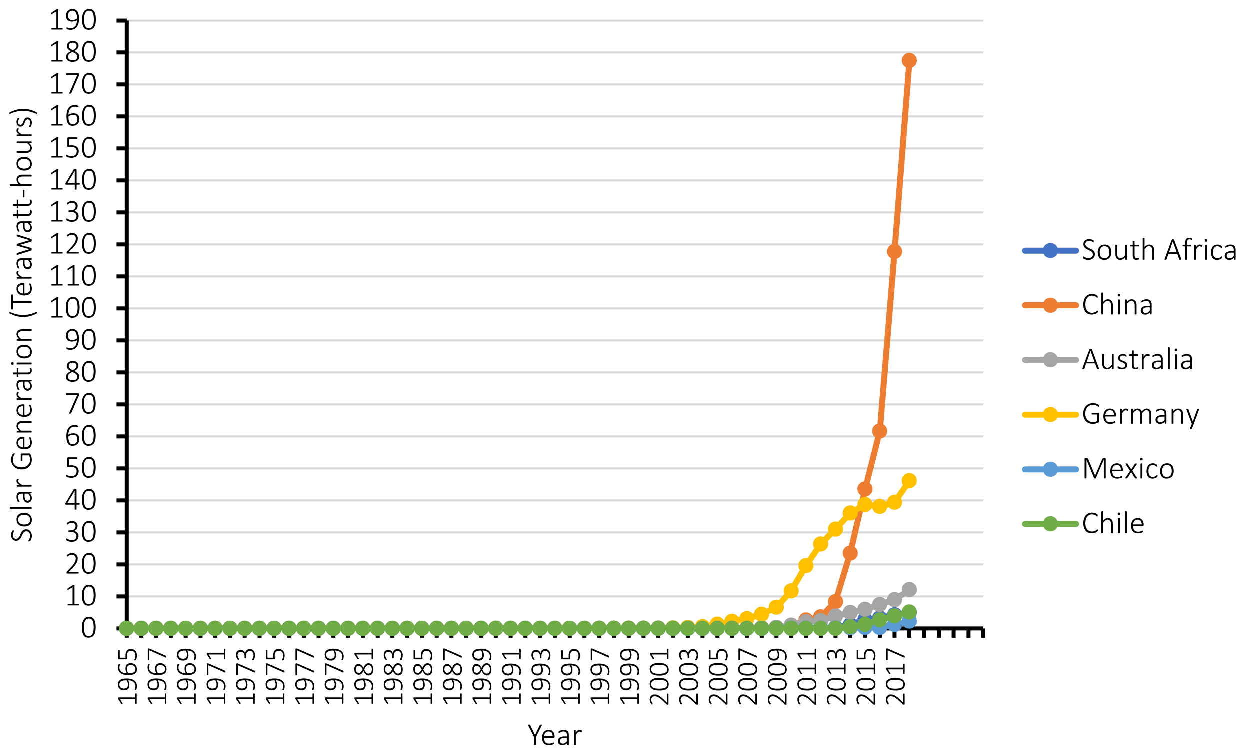

Figure 6. Trend of power generation from solar PV in representative countries from 1965 to 2018 (Ritchie and Max, 2019) .

Scopus database was used to search for credible articles (conference proceedings and journal articles) in both themes of this study: GIS-based wind and solar resource assessment and ANFIS-based solar and wind resource forecast. Search operators were used for exactness and similarity between search keywords. These operators include the AND, OR, and " ". In this regard, "GIS-based site suitability for wind", "GIS-based site suitability for solar" were two keywords used to investigate the trend of GIS-based studies in both resources. From Figure 7, within the last decade, the studies in solar resource site suitability were observed to increase gradually with the highest increase experienced in 2019. Similarly, the wind resource site suitability analysis also experienced a significant increase in the same year. The increase in the number of studies shows that more prospective areas for wind and solar exploration are been unveiled for developers to explore, hence an increase in the percentage of RE in the energy mix of the countries concerned may likely occur in the future. From the previous list of the studies, further criteria were spelled out in selecting which article to further review. These criteria include explicitness of exclusion criteria, and the use of the MCDM technique for optimal site selection. These criteria are further explained in section 4. Studies in representative countries selected in the six continents were given preference. This is to determine whether more areas are been unveiled in these countries.

Furthermore, for the second theme of this study which is concerned with ANFIS-based forecasting of wind and solar energy, two keywords were selected vis-à-vis: "ANFIS-based wind resource forecast" and "ANFIS-based solar resource forecast" were queried from the Scopus database. From Figure 8, wind energy forecast using ANFIS-based technique experienced significant attention compared to the solar resource forecast using the same technique. This skewness can be due to the proliferation of wind farms and data availability. From Figure 9 and Figure 10, India leads in the number of studies which use ANFIS-based techniques for solar and wind resource forecast. Even though the country was not listed among the big players in the exploration of the two resources, it is given that development and awareness of intelligent models are being created in the country for use to enhance strategic and operational decision-making.

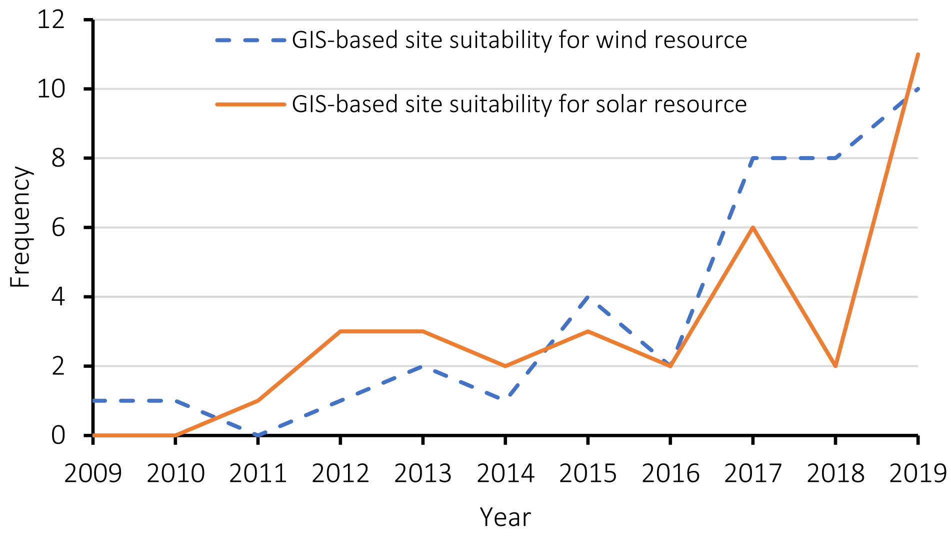

Figure 7. Trend of GIS-based solar and wind resource forecast from 2009 to 2019.

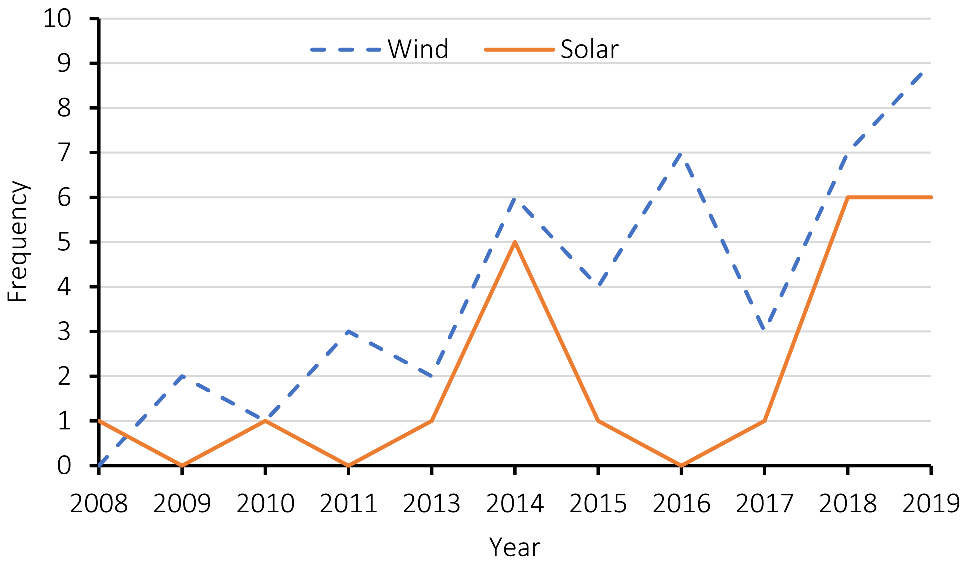

Figure 8. Trend of ANFIS-based wind and solar forecast from 2008 to 2019.

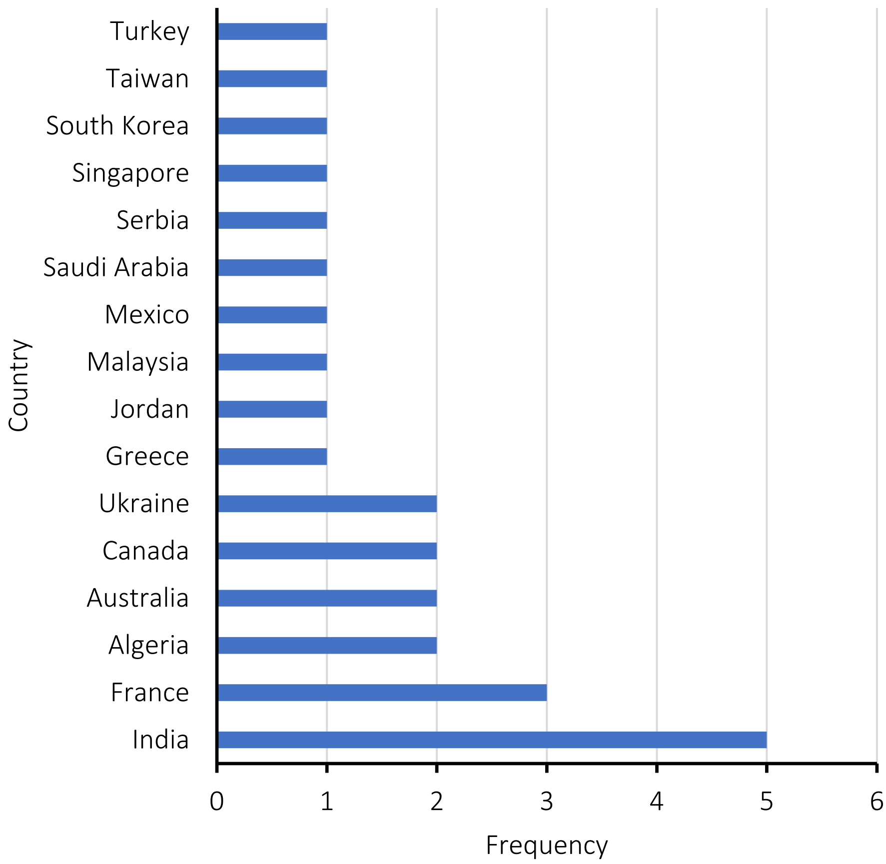

Figure 9. Country-based analytics of ANFIS-based solar resource forecast studies

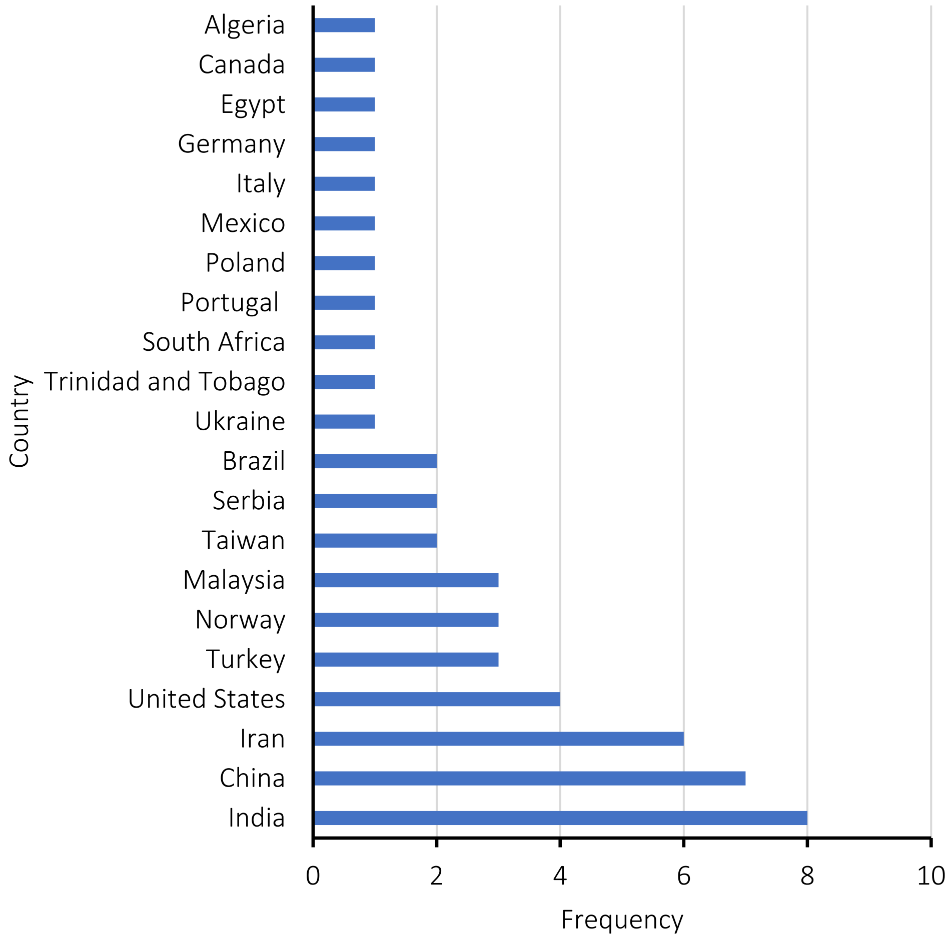

Figure 10. ANFIS-based wind resource forecast by country.

3. Multicriteria Decision Making Techniques in Renewable Energy Exploration

Variety of MCDM tools have emerged in recent times to aid decision-making both at strategic and operational levels of organization. Decisions are often dynamic and increasingly becoming complex owing to different criteria to be considered and a near-balance to be established. Decision making becomes more complex when subjectivity in criteria ranking and selection of alternative is relatively high and final decisions can make or mar the system under consideration. In real-life applications, variables within the decision space are often a mix of tangible/quantitative criteria and the intangible/qualitative criteria. MCDM problems can be broadly classified into two vis-à-vis multi-objective decision making (MODM) and multi-attribute decision making (MADM). While MODM finds suitability in evaluating alternatives with continuous data type where constraints integrating decision variables are specified, MADM considers system characteristics/attributes (Kumar et al., 2017). The MADM problem selects the best alternative from a set of alternatives with specific criteria for the selection process but the MODM problem extends the mathematical programming approach to finding an optimal solution to a problem design with a set of constraints (Jankowski, 1995). Most GIS-based problems often apply MADM approaches for problem-solving.

There exist several MCDM techniques in the literature with each having its strengths and weaknesses. Some are improvements on some others (e.g. ANP, ELECTRE, PROMETHEE). Therefore, a wide literature survey of common MCDM techniques used in RE exploration was performed through a random search, and their strengths, weaknesses and concise procedures were further outlined and presented in Table 3.

Table 3. Common MCDM techniques, their concise procedures, strengths, and weaknesses

Method	Procedure	Strength	Weakness	Reference
Weighted Product	$X_i = \prod_{j=1}^{M} \left[(m_{ij})_{normal}\right]^{w}$ where X_i is the overall score of the alternative and m_{ij} is the normalized value of the alternative	1. Applies relative values to avoid homogeneity problems. 2. It solves MCDM problems with the same criteria.	It prioritizes or deprioritizes alternative which his far from average, thus leading to undesirable results.	(Carbonneau and Vahidov, 2016; Chang and Yeh, 2001; Triantaphyllou and Mann, 1989)
Weighted Sum/ Weighted Linear Combination (WLC)	$J_{weighted\ sum} = w_1 J_1 + w_2 J_2 + \cdots w_m J_m$ where J is a function of the design vector and w_1 ($i = 1,2,3, \ldots m$) is a weighting factor for ith objective. The best alternative becomes max ($J_{weighted\ sum}$).	1. Computational simplicity. 2. Suitability for a single dimensional problem.	1. It does not integrate multiple preferences 2. Difficulties in weight allocation to objective functions 3. It does not achieve Pareto optimal solution in non-convex problems.	(El Amine et al., 2014; Kim and De Weck, 2006, 2005; Odu and Charles-Owaba, 2013)
Ordered weighted averaging (OWA)	$OWA(a_1, a_2, \ldots a_m) = \sum_{i=1}^{m} w_i J_i$ where J_i is the *ith* largest of a_i and $\sum_{i=1}^{m} w_i = 1$.	1. Provides alternative aggregation through adjustment of "and" and "or" extreme criteria satisfaction. 2. Coefficients are associated with ordered positions rather than attributes. 3. Addresses uncertainties in the interaction of criteria. 4. It can integrate heterogeneous datasets.	1. Non-optimal weight determination has an effect on the operator's output.	(Gorsevski et al., 2012; Khodadadi et al., 2017; Kiavarz and Jelokhani-Niaraki, 2017; Yager, 1988)
Occupational Competitiveness Rating Analysis (OCRA)	1. Create criteria and alternative matrix 2. Calculate the preference rating relative to non-beneficial criteria. 3. For each criterion, compute linear preference rating. 4. Calculate the preference rating relative to each beneficial criterion. 5. Compute output preference rating. 6. Compute the overall preference and ranking the preference order.	1. The procedure is robust. 2. Intuitively accounts for the preferences of decision-makers. 3. It is a non-parametric method. 4. It separately treats alternatives with respect to maximization and minimization. 5. It can integrate both qualitative and quantitative criteria.	1. It allows for crisp data. An enhanced version is needed for a fuzzy situation. 2. Performance rating is calculated only by applying a single scalar measurement to inputs and outputs.	(Madić et al., 2016, 2015; Parkan, 1994; Wang and Wang, 2005)
TOmadao de Desicao Interactiva Multicriterio	1. Calculate the relative weights of one criterion to a reference criterion	1. Simplicity of implementation.	1. It is sensitive to new weight vector.	(Llamazares, 2018; S. M. Yu et al.,

(TODIM) (Portuguese acronym for Interactive and Multicriteria Decision Making)	2. Calculate the dominance of one alternative over another with respect to a criterion. 3. Calculate the overall dominance degree of one alternative over the other alternatives. 4. Calculate the overall performance of each alternative. 5. Calculate the overall normalized performance of each alternative. 6. Rank all alternatives according to the normalized overall performance index.	2. Accounts for decision maker's behavior. 3. Ability to reflect risk preferences through gains and losses.		2018; Zhang and Xu, 2014; Zhou et al., 2020)
Analytical Hierarchical Process (AHP)	1. Decompose the problem into hierarchical elements. 2. Develop a pairwise comparison matrix using the Saaty scale. 3. Normalize matrix and obtain individual priorities for each criterion. 4. Model synthesis. 5. Sensitivity analysis.	1. Computational simplicity 2. Method adaptability and applicability. 3. Evaluates qualitative and quantitative criteria and alternatives on a similar preference scale. 4. It follows the intuitive method of problem-solving.	1. Suffers from rank reversal problem. 2. Results are affected by the interdependency between objectives and criteria. 3. Model complexity occurs when more decision-makers are involved.	(Anwar et al., 2019; Ishizaka and Labib, 2011; Mu and Pereyra-Rojas, 2017; Yang and Lee, 1997)
Analytical Network Process (ANP)	1. Detailed problem description 2. Determine control criteria and subcriteria for benefits, opportunities, costs, and risks. 3. Determine a global network of model components as applicable to all control criteria. 4. Determine feedback with influence and approach for the analysis of influences 5. Supermatrix construction 6. Pairwise comparison of elements and clusters based on their influences. 7. Compute priority vectors for supermatrix and synthesize for each of the four benefits. 8. Calculate overall synthesis and perform sensitivity analysis.	1. It accommodates interdependencies and feedback between criteria and alternatives. 2. Useful in solving complex decision problems involving feedbacks and interdependence based on benefits, opportunities, cost, and risks. 3. Decisions are descriptive and not normative.	1. Judgment could be subjective but based on a garbage-in-garbage-out principle.	(Melani et al., 2018; Saaty, 2006, 2004)
Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS)	1. Calculate the decision matrix and create a weighted normalized decision matrix	1. It makes use of all attribute information. 2. The interdependency of attribute preferences is not required.	1. All attribute values must be numeric. 2. Attribute values must increase or	(Lee and Chang, 2018; Wang et al., 2016; Zyoud and Fuchs-

	2. Determine the ideal positive and negative solutions. 3. Calculate the distance of each alternative from the ideal positive and negative solutions. 4. Calculate the relative closeness to the ideal solution 5. Rank alternatives by sorting the results from (4).		decrease monotonically. 3. It is built on Euclidean distance function and so does not consider the difference between negative and positive values.	Hanusch, 2017)
VIseKriterijumska Optimizacija I KompromisnoResenje (VIKOR)	1. Determine the ideal positive and negative solutions. 2. Calculate the normalized Manhattan and normalized Chebyshev distances. 3. Compute Q_i based on calculations in (2). 4. Rank all alternatives by sorting Q_i in increasing order.	1. It provides a complete ranking of alternatives. 2. It takes into significance the relative distances and not farthest distance.to ideal solutions 3. It proffers a compromise solution close to the most decision-makers' choice. 4. Computational simplicity.	1. It becomes challenging in case of conflicting problems. 2. Ranking alternatives relative to criteria is crisp which inadequately models real-life situations.	(Çalı and Balaman, 2019; Chatterjee and Chakraborty, 2016; Lee and Chang, 2018; Quijano et al., 2012; Tavana et al., 2016)
ELimination Et Choix Traduisant la REalite - ELimination and Choice Expressing the REality (ELECTRE)	1. Construction of one or more outranking relations. 2. Development of an exploitation procedure based on the problem (either choice, ranking, or sorting problem).	3. It solves the problem of choice making (ELECTRE-I, ELECTRE-Iv, ELECTRE-IS), ranking problems (ELECTRE-II, ELECTRE-III, ELECTRE-IV) and sorting problems (ELECTRE-TRI). 4. Integrates both qualitative and quantitative features of criteria. 5. Intuitive validation of final results.	1. Strong heterogeneity should exist among criteria, thus making aggregation in a unique and common scale difficult. 2. Less adaptable.	(Danila and Roy, 1986; Figueria et al., 2005; X. Yu et al., 2018)
Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE)	1. Obtain an evaluation matrix and perform a pairwise comparison of them with each criterion. 2. Assign preference function based on the difference between pairs with values from 0 to 1. 3. Calculate the global matrix and its rank through the addition of column which expresses the significance of one alternative over the other.	1. Applicable in partial ranking (PROMETHEE I), complete ranking (PROMETHEE II), ranking according to intervals (PROMETHEE III), continuous situations (PROMETHEE IV). 2. It supports group-level decision making.	1. It has no formal guidelines for weight assignment and so this depends on the decision-maker. 2. It has complicated preference information processing which is hard	(Brans and Mareschal, 2005; De Keyser and Peeters, 1996; Kumar et al., 2017)

		3. It can integrate both qualitative and quantitative criteria and heterogeneous criteria scores.	for a novice to understand. 3. The clarity in problem definition and result interpretation could be difficult in the case of many criteria.	
Decision Making Trial and Evaluation Laboratory (DEMATEL)	1. Formulate group direct influence matrix 2. Compute normalized direct influence matrix. 3. Determine the total influence matrix. 4. Create the influential relation map for decision making.	1. The capability of solving cause and effect relationship between criteria. 2. Visualization of interrelationships between factors for a clear understanding of mutual influences is possible. 3. Critical evaluation criteria and their weights can be easily deduced.	1. Ranking of alternatives is based on interdependent relationships without considering other criteria in the decision making. 2. In culminating personal judgments of experts into group assessment, the relative weights of experts are not considered. 3. It does not take into account the aspiration levels of alternatives. 4. Often hybridized with other MCDM techniques for better performance	(Chen et al., 2014; Ren and Sovacool, 2014; Si et al., 2018; Vinodh et al., 2016)
Multi-Attributive Border Approximation area Comparison (MABAC)	1. Compute decision matrix 2. Normalize matrix elements according to cost and benefit criteria. 3. Calculate elements of weighted matrix 4. Determine the matrix of border approximation areas 5. Compute the distance of alternatives from border approximation areas. 6. Rank the alternatives.	1. Computational simplicity. 2. Stability of output results. 3. Reliability in rational decision making. 4. It accounts for latent gains and losses in the problem. 5. It is easily hybridized with other MCDM techniques.	1. All criteria are assumed compensatory.	(Gigović et al., 2017; Luo and Xing, 2019; J. Wang et al., 2019)

3.1. GIS-based MCDM techniques in solar and wind energy exploration

Unlike the non-RE facilities, the location of RE facilities strongly requires the concerned plants to be located in proximity to the energy resource for effectiveness and investment viability. Hence, RE power plants must be sited in geographical locations with an abundance of RE resource, or with at least resource availability higher than the threshold required for plant functionality. Asides plant location in resource-rich zones, there exist several factors needed to be considered in the choice of specific locations (Tuler et al., 2014; Villacreses et al., 2017). Hence this becomes a multi-criteria optimization problem. These criteria differ from one resource to another. Presented in Table 5 is a resource-based (wind and solar) review of applications of GIS-based MCDM techniques. The various criteria considered by authors and location where the study was carried out was specified. Studies that are not explicit with their criteria or values selection were not reviewed. Preference was first placed on the selected representative countries in each continent, however, studies from these countries are sparse in the literature and so, a wide literature survey was carried out on these two sources.

It is important to establish that wind energy resource exploration can be carried out in two different ways: offshore-based exploration and onshore-based exploration. While onshore wind energy exploration is concerned with wind resource on land, the offshore wind energy exploration is concerned with wind energy on the sea (either floating foundation (water depth ≥ 50 m) or fixed foundation (water depth ≤ 50 m)) (Arapogianni et al., 2013; Möller et al., 2012). The criteria for offshore-based exploration distinctly differs from onshore-based exploration. Table 4 presents the criteria for offshore-based exploration as found in the literature (Castro-santos et al., 2019; Mahdy and Bahaj, 2018; Saleous et al., 2016). However, for the course of this review, studies focussed on onshore-based wind energy exploration were considered as presented in Table 5.

Table 4. Criteria for offshore-based wind energy site suitability analysis.

Criteria	Desirability decision
Wind speed	Maximize
Oil exploration areas	Avoid
Fishing areas	Avoid
Water depths (bathymetry)	Minimize
Soil status, type and depth	Sandy sedimentary areas close to the
Distance from submerged cable paths	Maximize
Distance from protected areas	Maximize
Distance to shoreline	Minimize
Distance to military base/zones	Maximize
Distance to shipping routes	Maximize
Distance to the national grid	Maximize
Distance from seismic fault lines	Maximize
Distance from supply pipes	Maximize
Anchorage areas	Avoid
Buoys for tanker vessels	Avoid
Distance from ports, shipyards, docks	Maximize

Table 5. Applications of GIS-based MDCM techniques in solar and wind energy site suitability analysis.

Resource	MCDM Method	Reference	Criteria (suitable)	Location
Solar-PV	AHP/TOPSIS	(Sánchez-Lozano et al., 2013)	*(Authors here specified percentage weights for all criteria)* ***Climatic*** 1. Solar radiation potential [23.802] 2. Average Temperature [4.7604] ***Location*** 3. Distance to main road [4.291]	South-eastern Spain

		4. Distance to power lines [32.539] 5. Distance to villages [2.849] 6. Distance to substations [8.946] ***Geomorphological*** 7. Slope [11.203] 8. Orientation [4.815] 9. Area [1.241] ***Environmental Capacity*** 10. Agrological Capacity [5.553]	
Fuzzy-AHP	(Asakereh et al., 2017)	***Techno-economic*** 1. Solar Intensity $\left[x \leq \frac{0kWh}{m^2}/day \in 0; x \geq \frac{6kWh}{m^2}/day \ \in 1\right]$. ***Human and environmental*** 2. Slope [$x \leq 3 \in 1; x \geq 10 \ \in 0$]. 3. Distance from wetlands, rivers and conservation areas [$x \leq 100m \in 0; x \geq 400m \ \in 1$]. 4. Distance from lakes [$x \leq 300m \in 0; x \geq 500m \ \in 1$]. 5. Distance from urban areas [$x \leq 1000m \in 0; x \geq 5000m \ \in 1$]. 6. Distance from rural area [$x \leq 300m \in 0\ ; x \geq 700m \ \in 1$]. 7. Distance from dense forest [$x \leq 100m \in 0; x \geq 500m \ \in 1$]. 8. Distance from vegetation cover [$x \leq 100m \in 0; x \geq 400m \ \in 1$]. 9. Distance from flood zones [$x \leq 100m \in 0; x \geq 400m \ \in 1$].	Khuzestan Province, Iran
AHP	(Ali et al., 2019)	***Physiographic*** 1. Global Horizontal Irradiance $\left[> \frac{3.5\ kWh}{m^2}/day\right]$. 2. Slope s [$0 - 1$ %] 3. Elevation [$0 - 50\ m$] ***Environmental*** 4. Distance from urban areas [$> 1500\ m$]. 5. Distance from rural area [$> 1500\ m$]. 6. Distance from wetlands [$> 1000\ m$]. 7. Distance from airports[$> 2000\ m$] 8. Distance from Forest [$> 1500\ m$] 9. Distance from main roads [$> 500\ m - 2000\ m$] 10. Distance from transmission lines [$0 - 2000\ m$] 11. Land area [$> 1500\ m^2$]	Songkhla, Thailand
AHP	(Doorga et al., 2018)	***Climatological*** 1. GHI $\left[> \frac{17.84\ MJ}{m^2}/day\right]$. 2. Sunshine duration [$> 225.25$ hrs] 3. Temperature [< 19.80 ℃] 4. Relative humidity [> 72.03 %] ***Topography*** 5. Elevations [$> 816\ m$] 6. Slope [< 1.1 %] 7. Aspect [$North$ (%)] ***Location*** 8. Proximity to road [$< 433.3\ m$] 9. Proximity to grid [$< 998.0\ m$]	Mauritius
AHP	(Doljak and Stanojević, 2017)	***Climate*** 1. GHI $\left[> \frac{1412.311\ kWh}{m^2}/year\right]$ 2. Sunshine duration [$< 2000.174\ hrs$] 3. Air temperature [< 2.277 ℃]	Serbia

			4. Relative humidity [< 75.372 %] ***Orography*** 5. Slope [< 2 °] 6. Aspect [Horizontal and south] ***Vegetation*** 7. Normalized difference vegetation index (NDVI) [< 0]	
	Fuzzy-AHP	(E. Noorollahi et al., 2016)	***Climatology*** 1. Solar Radiation $\left[> \frac{1300\ kWh}{m^2}/year\right]$ 2. Average annual temperature [~] ***Location*** 3. Distance from power transmission lines [< 50 km] 4. Distance from major roads [> 0.1 km ; $<$ 50 km] 5. Distance from residential areas[City $<$ 2 km; villages < 0.5 km] 6. Distance from faults [> 0.5 km] 7. Distance from lake and waterbodies [> 1 km] 8. Distance from protected areas [> 2 km] ***Environment*** 9. Elevation [$< 2.2.$ km] 10. Slope [< 10 %] 11. Land use [~] ***Meteorology*** 12. Average annual cloudy days [~] 13. Average annual humidity [~] 14. Average annual dusty days [~]	Iran
	AHP	(Al Garni and Awasthi, 2017)	***Technical feasibility criteria*** 1. Solar Irradiation [N/S] 2. Air temperature [N/S] ***Economic criteria*** 3. Slope [$\leq 5^o$] 4. Land aspect [$south - facing$] 5. Proximity to power lines [< 50 km] 6. Proximity to urban areas [> 1.5 km ; $<$ 50 km] 7. Proximity to highways [< 500 m] 8. Protected lands [< 1000 m]	Saudi Arabia
	TOPSIS/ ELECTRE TRI	(Sánchez-Lozano et al., 2016)	1. Agrological capacity [N/S] 2. Slope [N/S] 3. Area [N/S] 4. Field orientation [N/S] 5. Distance to main roads [N/S] 6. Distance to power lines [N/S] 7. Distance to cities [N/S] 8. Distance to electricity transformer substation [N/S] 9. Potential solar radiation [N/S] 10. Average temperature [N/S]	Spain
Wind (Onshore)	AHP	(Ali et al., 2019)	1. Wind speed $\left[> 6\frac{m}{s}\right]$ 2. Slope [$0 - 7$ %] 3. Elevation [$> 50\ m$] ***Environmental*** 4. Distance from urban areas [$> 3000\ m$]. 5. Distance from rural area [$> 2000\ m$].	Songkhla, Thailand

		6. Distance from wetlands [$> 1000\ m$]. 7. Distance from airports[$> 4000\ m$] 8. Distance from Forest [$> 3000\ m$] 9. Distance from main roads [$> 500\ m - 2000\ m$] 10. Distance from transmission lines [$0 - 2000\ m$] 11. Land area [$> 6000\ m^2$]	
AHP	(Jangid et al., 2016)	1. Wind speed $\left[2.6 - 3\frac{m}{s}\right]$ 2. Distance from residential houses [$> 500\ m$]. 3. Land use and land cover Wind speed [$fallow\ and\ bare\ land$] 4. Distance from roads [$> 100\ m$] 5. Slope [$> 10\ \%$]	Rajasthan, India
Type II fuzzy AHP	(Ayodele et al., 2018)	***Economic /Technical*** 1. Wind speed $\left[> 4.4\frac{m}{s}\right]$ 2. Slope [$< 15\ \%$] 3. Proximity to gridlines [$250\ m$] 4. Proximity to roads [$< 500\ m$] ***5.*** ***Environmental/Social*** 6. Distance from urban areas [$> 2000\ m$]. 7. Distance from waterbodies [$> 200\ m$]. 8. Distance from airports[$> 5000\ m$] 9. Distance from important bird areas (IBA) [$> 300\ m$] 10. Distance from protected areas [$> 500\ m$] 11. Land cover [$exclude\ forests, woodlands, wetlands$]	Nigeria
AHP	(Baseer et al., 2017)	***Climatic*** 1. Wind speed $\left[> 5\frac{m}{s}\right]$ ***Economic*** 2. Proximity to gridlines [$< 10,000\ m$] 3. Proximity to highway and roads [$< 10,000\ m$] ***Planning*** 4. Distance from settlements [$> 5000\ m$]. 5. Distance from airports[$> 2500\ m$]	Saudi Arabia
WLC and Borda count	(Gorsevski et al., 2013)	***Environmental factors*** 1. Wind speed $\left[7 - 7.5\frac{m}{s}\right]$ 2. Distance from important bird areas (IBA) [$> 30,000\ m$] 3. Land use [$baren, shrub, pasture, cropland$] ***Economic factors*** 4. Proximity to gridlines [$< 1000\ m$] 5. Proximity to major transportation [$< 1000\ m$] 6. Soil type [$Gravel$]. 7. Population density [$> 200/\ km^2$].	Northwest Ohio
WLC and AHP	(Latinopoulos and Kechagia, 2015)	***Economic /Technical*** 1. Wind speed $\left[> 7.5\ \frac{m}{s}\right]$ 2. Slope [$< 5\ \%$] ***Economic***	Greece

		3. Distance to road network [$200\ m$] ***Environmental*** 4. Distance from Natura 2000 areas [$> 3000\ m$] ***Environmental/Economic*** 5. Current land use [$5 - point\ Likert\ Scale$] ***Environmental/Social/ Economic*** 6. Distance from specific sites (archeological, tourism, historical and protected landscape) [$> 3000\ m$].	
WLC	(Y. Noorollahi et al., 2016)	***Techno-economic*** 1. Wind speed $\left[> 9.5\ \frac{m}{s}\right]$ 2. Distance from electric power lines [$> 250\ m$]. 3. Distance from highway and roads [$> 1000\ m$] ***Physiological*** 4. Digital elevation [$< 2000\ m$]. 5. Slope [< 15 %]. ***Environmental*** 6. Distance to cities [$> 1000\ m$] villages [$> 500\ m$] 7. Distance from railway lines [$> 300\ m$] 8. Distance from airports: military airports [$> 15{,}000\ m$], commercial airports [$> 2{,}500\ m$]. 9. Distance from ancient and cultural monuments [$> 700\ m$]. 10. Distance from rivers [$> 500\ m$]. 11. Distance from coast lines and wetlands [$> 500\ m$]. 12. Distance from environmental protected areas [$> 2000\ m$]. 13. Distance from lakes and water bodies [$< 1000\ m$]. 14. Distance from faults [$> 500\ m$].	Western Iran
AHP. OWA, OCRA, VIKOR and TOPSIS	(Villacreses et al., 2017)	*(Authors specified weights for all criteria)* ***Meteorological*** 1. Wind speed [0.3982]. 2. Air density [0.1327]. ***Relief*** 3. Slope [0.2151]. ***Location*** 4. Distance to substation [0.1009]. 5. Distance road network [0.0432]. 6. Distance to urban areas [0.0432]. 7. Distance to transmission lines [0.0185]. 8. Distance to charging ports [0.0092]. ***Environmental*** 9. Vegetation coverage and land use [0.0390].	Continental Ecuador
DEMATEL, ANP and MABAC	(Gigović et al., 2017)	1. Wind speed [$> 3.5\ m/s$] 2. Land use [$non - wet\ areas$] 3. Distance to urban areas [$500\ m$] 4. Distance to protected areas [$2000\ m$] 5. Distance to electricity network [$200\ m$] 6. Slope [< 7 %] 7. Distance to roads [$200\ m$]	Vojvodina, Serbia

	8. Distance to telecommunication network [250 m] 9. Distance to airports [3000 m] 10. Distance to tourists cites [1000 m] 11. Distance to military facilities [5000 m].

* ~ means the criterion has varying classes with each class having distinct values. Readers should see the referenced articles for further details on such criterion. Also, N/S means not specified. Studies with such did not specify the values of the criteria used in explicit terms.

The trend of studies in solar exploration as presented in Table 5 unveils some criteria which are very vital to the solar resource assessment like solar radiation (GHI or DNI), slope, elevation, aspects, air temperature, distance from transmission/ power lines, distance from residential areas, distance from airports, distance from protected areas, distance from transportation network, and distance from waterbodies. It is expected that site suitability analysis be as robust and possible with several criteria considered to ensure that seemingly viable land areas are free from environmental and social related conflicts. However, many studies have used less data due to unavailability of necessary data in their national database . Rather than complete dependence on national database for country-specific data, international geographical database with high data integrity and accuracy can be consulted in such case. Examples of global databases from which credible data can be obtained are presented in Table 6.

Table 6. Examples of global databases from which criteria data can be accessed

Name	Available data	Web address
Food and Agricultural organization of the United Nations	Global terrain and aspect, slope, land cover, elevation	http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/
The World Bank	Wind speed, Transportation network, transmission line network	https://datacatalog.worldbank.org/search/field_wbddh_data_type/geospatial--fbcb7053-4dc3-4748-8ed7-2d4ed86ec71a?sort_by=changed&f%5B0%5D=field_wbddh_data_type%3A295
Birdlife International	Important Bird Areas	http://datazone.birdlife.org/site/requestgis
SolarGIS	Solar irradiation	https://solargis.com/maps-and-gis-data/overview

A critical look into the studies reviewed shows that AHP and its fuzzy variant have been mostly applied for criteria ranking and selection of the best site among feasible locations.

Also, from the trend of study in Table 5, certain criteria are observed to be vital to wind and solar resource site suitability analysis. For wind energy exploration, the wind speed, slope, distance from transmission/ power lines, distance from road networks, distance from the airport, distance from waterbodies, and distance from protected areas of all kinds are observed to be highly essential for the analysis. This further reveals the multicriteria nature of the wind resource site suitability process. The buffer values and criteria were observed to vary from one author to another based on their personal literature search and more skewed to subjectivity of decision-makers. Up till now, there has not been any standard values for these criteria. One of the reasons could be because of geospatial variations in the degree of each of these criteriaAlso, from all the studies reviewed, among several MCDM techniques for selecting the optimal site, the AHP method is prominently used. This can be due to its computational simplicity. Other MCDM techniques which avoid subjectivity (Table 3) as much as possible have been less used in the literature.

It can be observed that there exists a point of integration between the criteria for solar and wind energy exploration. This point of integration is observed in the distance-related criteria. Also, the slope and elevation of the land area form another point of integration even though the values to be selected for solar and wind energy exploration might slightly differ. It should be stated that the values of these criteria may significantly vary depending on the size of the wind/solar farm under consideration. While large farms could require higher values in exclusion criteria to avoid conflict with the environment and higher energy resource values for economic viability, the small-scale farms stand on the contrary. Also, the annual review of specific criteria like protected areas and important bird areas require that land suitability for future exploration should be reviewed relative to these criteria maps. This will prevent encroachment into such areas and further enhance viability of the investment.

4. Adaptive neurofuzzy inference system modeling

The ANFIS model integrates ANN and Fuzzy Inference System (FIS) such that optimal distribution of membership function is obtained from input-to-output mapping (Jang, 1993; Olatunji et al., 2019a). Based on the literature survey in this study, we can classify ANFIS models by two metrics: (a) by structure (b) by algorithm as shown in Figure 11.

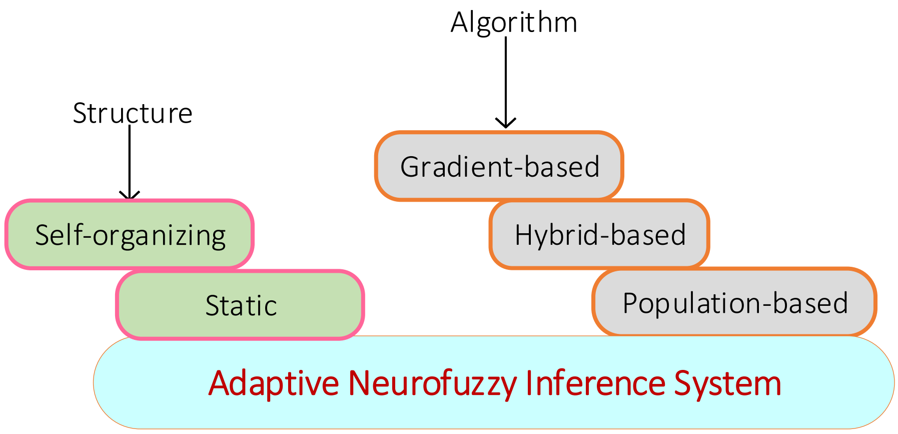

Figure 11. Classification of ANFIS model based on structure and algorithm.

4.1. Classification by structure

Self-organizing ANFIS models are notable for their self-tuning ability both in structure and parameters during the training process. Nodal learning with self-adaptation towards developing an optimal rule base by deleting and adding of rules according to the learning method. This structure of ANFIS is associated with on-line learning technique which characteristically allows for dynamic rule update by an aligned clustering-based algorithm (Juang and Lin, 1998).

The static-structured ANFIS model is the most common ANFIS structure. This structure of the ANFIS entails the number of rules, the inputs and outputs, the antecedent and consequent parameters (Adedeji et al., 2020). These structure remains constant during the training process. A good number of gradient-based, and population-based ANFIS models belong to this category by structure.

4.2. Classification by Algorithm

a. ***Gradient-based ANFIS models:*** These are built on steepest descent method for nonlinear function minimization. Notable merits of this technique are its ease of computation and low storage requirement. One of the most important build-ups of the gradient technique is the backpropagation-based learning methods. The backpropagation methods have been widely used in neuro-fuzzy techniques for deployment in different fields (Meza, 2010; Petković, 2015). For building reasoning capability, three fuzzy models are prevalent: the zero order Takagi-Sugeno-Kang (TSK) which has constant consequent parameter, the first order TSK whose consequent is a first order linear equation and the Mamdani fuzzy systems whose consequents are fuzzy variables (Shihabudheen and Pillai, 2018). Generally, gradient descent-based ANFIS models are relatively slow with likelihood of convergence to local minima. It has been observed that initial setting of fuzzy rules is often difficult in neurofuzzy models based on gradient descent technique alone when large dataset is involved and also, training ANFIS model with gradient descent technique alone can result in weak firing strength (Shi and Mizumoto, 2000).

b. ***Hybrid-based ANFIS models:*** Models under this category uses two or more learning technique for ANFIS parameter estimation such that fast convergence and model stability is enhanced. The need for hybrid learning method in neurofuzzy inference system is a result of the problems associated with models with single learning technique. Single learning methods often gives less optimal outputs when very large datasets are involved and training the model when large parameter and model structure prevails becomes a great challenge (Shihabudheen and Pillai, 2018).

c. ***Population-based ANFIS models:*** These models are improvements on the generalized ANFIS structure where parameter estimation of both antecedent and consequence are optimally determined by a population-based optimization model. Some of the commonly used population-based optimization techniques are genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and artificial bee colony (ABC) (Olatunji et al., 2019b, 2019c; Sarkar et al., 2019; Zainuddin et al., 2019). Here, the initial parameters specific to optimization model are supplied. These data are used across the solution space to determine optimal values for the antecedents and consequence of the ANFIS model. The membership function values are determined in this process. One of the merits of population-based neurofuzzy models is their independence of differentials which makes them more effective in cases where differentials are difficult or not present (Shihabudheen and Pillai, 2018).

The ANFIS structure in sequential order consists of the fuzzy layer, the product layer, the normalized layer, the de-fuzzy layer and the total output layer (Adedeji et al., 2018; Jang, 1993; Rosadi et al., 2013) as shown in Figure 12. A brief description of each of the layers are presented as follows:

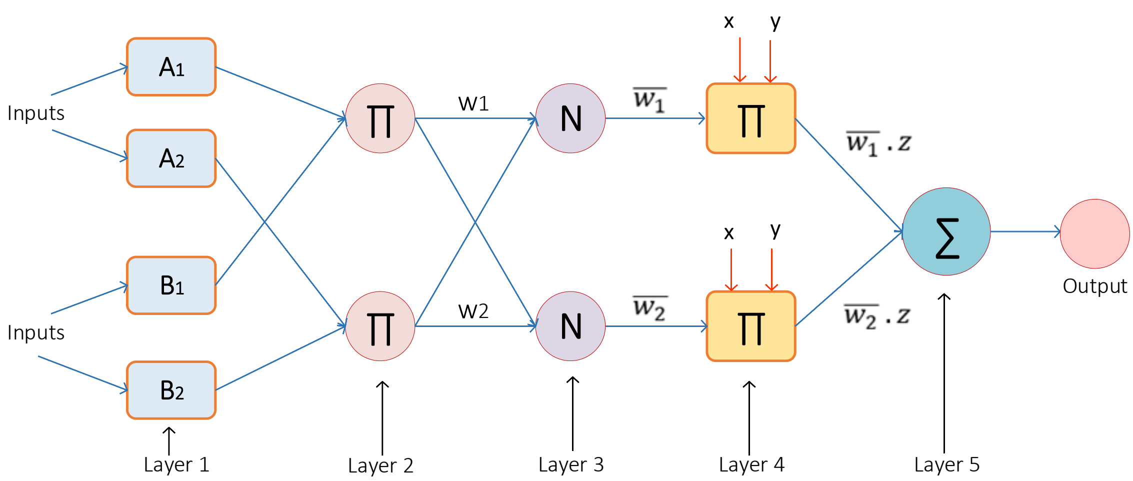

Figure 12. The ANFIS architecture.

First layer: The first layer has every node as adaptive node and so each adapts to a function parameter. The layer output consists of fuzzy membership functions with output functions for each node represented by eqn. (3) and (4).

$$O_j^1 = \mu_{A_j}(I_1), j = 1, 2 \quad (3)$$

$$O_j^1 = \mu_{B_j}(I_2), j = 1, 2 \quad (4)$$

Second layer: The second layer consists of nonadaptive nodes, which computes the firing strength of a rule using multiplicative operator as presented in eqn. (5).

$$O_j^2 = w_j = \mu_{A_j}(I_1) \, . \, \mu_{B_j}(I_2) \quad , j = 1, 2 \qquad (5)$$

Third layer: This layer also consists of fixed/nonadaptive nodes. Here, the ratio between the firing strength in the jth node and the sum of all firing strengths from all the rules (eqn. 6) is used to normalize the firing strength at the jth node of the ANFIS structure.

$$O_j^3 = \overline{w_j} = \frac{w_j}{w_1 + w_2} \qquad j = 1, 2 \qquad (6)$$

Fourth layer: All nodes in this layer are adaptive. The effect of jth rule towards the output is expressed by a node function in eqn. (7):

$$O_j^4 = \overline{w_l}\left(p_j I_1 + q_j I_2 + r_j\right) = \overline{w_l} z_j \qquad (7)$$

where p_j, q_j, r_j is a parameter set of the node and $\overline{w_l}$ is the normalized firing strength of the third layer.

Fifth layer: The fifth layer has nonadaptive nodes, which compute a summation of all in-coming signals from the previous node through a summing function (Suparta and Alhasa, 2016) expressed in Eqn. (8):

$$O_j^5 = \sum_j \overline{w_l} z_j = \frac{\sum_j w_j z_j}{\sum_j w_j} \qquad (8)$$

Fuzzy rules
From Figure 12, the first order Takagi-Sugeno fuzzy model has fuzzy rules with the structure:

Rule 1: If I_1 is A_1 AND I_2 is B_1 then $f_1 = p_1 I_1 + q_1 I_2 + r_1$.

Rule 2: If I_1 is A_2 AND I_2 is B_2 then $f_2 = p_2 I_1 + q_2 I_2 + r_2$.

4.3. Performance Metrics for ANFIS-based models

Model evaluation is expected in forecasting to assess how well the model performs on unfamiliar data and performance metrics used differ depending on the problem type. For example, performance metrics for classification models differ from those of data fitting models. Since the focus of this study is the use of ANFIS-based models for data fitting, performance evaluation metrics reviewed will be limited to the same.

Over the years, statistical metrics have been used in ANFIS-based techniques for model performance evaluation to determine the accuracy and deviation of the forecast. Table 7 presents a list of common performance evaluation metrics, their formulae, significance of the metrics and their desirability measurement.

Table 7. Common performance metrics for ANFIS-based techniques

Performance Metrics	Formula	Significance	Evaluation
Mean square error (MSE)	$MSE = \frac{\sum_{k=1}^{N}[y_k - \widehat{y_k}]^2}{N}$	Measures the average degree of the forecasting error.	Lower value is most preferred.
Root mean square error (RMSE):	$RMSE = \sqrt{\frac{\sum_{k=1}^{N}[y_k - \widehat{y_k}]^2}{N}}$	Determines model precision.	Lower value is most preferred.

Relative root mean square error (RRMSE)	$RRMSE = \frac{\sqrt{\frac{1}{N}\sum_{k=1}^{N}(\widehat{y_k} - y_k)^2}}{\frac{1}{N}\sum_{k=1}^{N} y_k} \times 100$	Determines model precision.	Lower value is most preferred.
Mean Absolute Deviation (MAD)	$MAD = \frac{1}{N}\sum_{k=1}^{N}\lvert y_k - \bar{y}\rvert$	Measures the average degree of the forecasting error.	Lower value is most preferred.
Mean Absolute Percentage Error (MAPE) also average absolute percentage relative error (AAPRE)	$MAPE/\ AAPRE = \frac{1}{N}\sum_{k=1}^{N}\left\lvert\frac{y_k - \widehat{y_k}}{y_k}\right\rvert \times 100\%$	Measures model accuracy.	Lower value is most preferred.
Mean Absolute Error (MAE) also known as Mean absolute bias error (MABE)	$MAE/MABE = \frac{1}{N}\sum_{k=1}^{N}\lvert\widehat{y_k} - y_k\rvert$	Measures the average prediction error.	Lower value is most preferred.
Standard Deviation (St.D)	$St.D = \sqrt{\frac{\sum_{k=1}^{N}(y_k - \bar{y})^2}{N-1}}$	Measures dispersion/variation	Lower value is most preferred.
relative Mean Bias Error (rMBE):	$rMBE = \frac{1}{N}\sum_{k=1}^{N}\left(\frac{\widehat{y_k} - y_k}{y_k}\right)$	Measures model capability.	Value closer to zero is most preferred.
Coefficient of correlation (R)	$R = \frac{\sum_{k=1}^{N}(\widehat{y_k} - y_k)}{\sqrt{\sum_{k=1}^{N}\widehat{y_k}^2}}$	Measures the relationship between observed and predicted values	Values close to unity (1) are most preferred.
Coefficient of determination (R^2)	$R^2 = 1 - \left(\frac{\frac{1}{N}\sum_{k=1}^{N}(\widehat{y_k} - y_k)^2}{\sum_{k=1}^{N}(\widehat{y_k} - y_k)^2}\right)$	Measures the relationship between observed and predicted values.	Values close to unity (1) are most preferred.
Variance accounted for (VAF)	$VAF = 1 - \left[\frac{var(\widehat{y_k} - y_k)}{var(y_k)}\right] \times 100$	Measures the proportion of variance in the prediction that is associated with the predictor. *(fundamentally the same as R^2).*	Value close to 100 % is most preferred.
Computational time (CT)	N/A	Measures the model efficiency	Lower value is most preferred/

where y_k is the observed data, $\widehat{y_k}$ is the predicted data, N is the number of observations, $\bar{y}$ is the mean of observed data. From Table 7, it can be observed performance metrics for evaluating the forecast are either measuring the level of dispersion, the variance between the observed and the predicted, the reliability of the model and its prospect when used for further forecast, and model precision. One of the performance metrics used in recent times for evaluating the efficiency of the model is the computational time (CT). This measures the speed with which the computation was performed from training to testing phase. However, this metric suffers some limitations to its use and so, it must be carefully interpreted with all surrounding premises clearly stated. For instance, CT strongly depends on the computational power of the computing machine being used. The CT also varies with the data size as a model which is executed in short period in a scenario involving small dataset might take a longer time to execute another when a large dataset is involved. The presence of loops in the model can also affect the CT, hence the experience of the programmer can influence its value. CT is highly useful when different models are to be compared with one another, thus providing more information on the computational intensity of each model. It should also be noted that the longer the CT the more the machine utilization time. Hence, an increase in CT is not economically viable in time and space.

4.4. ANFIS in wind and solar energy resource forecast

This survey was made to largely cut across the representative countries and other countries in the continents with applications of these techniques for solar PV and wind energy forecast. For each study, the location of study or data collection, explicitness in the input and output model variables, model type, and the results of the model are reported. Any literature outside these criteria was not considered in Table 8. Further to this, few studies presented in Table 8 further considered other models, however, results of ANFIS and ANFIS-based models were reported in this study. Emphasis was also placed on the input and output variables for input/output (I/O) models and the input in the case of self-organizing techniques.

The study area of an article does not necessarily depict the affiliations of the authors. This clear distinction was also carefully put into consideration. Therefore, the report in Table 8 for forecasting is based on the study area and not the affiliation of authors. For each study considered, the data size and results obtained in the form of metrics used for model performance evaluation were also reported. Model comparison was made based on the results from their performance metrics. Also, the data resolution reported is based on the collected data but in cases where this is not reported, the resolution of the forecast was reported. Furthermore, the performance evaluation metrics reported are for the hold-out data and not the training datasets.

Table 8. ANFIS modeling in wind and solar resource forecast.

Resource	Technique	Reference	Continent/ Location	Data Size	Model Configuration	Performance metrics
Wind Energy	ANFIS	(Makhloufi et al., 2019)	Algeria	30 days	***Inputs:*** i. Wind speed ii. GHI iii. Temperature iv. Humidity ***Output:*** Active power	i. MSE= 0.0031 ii. RMSE 0.0558 iii. MAE= 0.0175 iv. St.D= 0.0531
	ANFIS-PSO	(Pousinho et al., 2011)	Portugal	384 data points (data resolution = 15mins)	***Inputs:*** Historical wind power ***Output:*** wind power	Winter: i. MAPE= 6.71 ii. $\sqrt{SSE}$= 432.57 iii. SDE= 26.86 Spring: i. MAPE= 7.22 ii. $\sqrt{SSE}$= 382.98 iii. SDE= 25.34 Summer: i. MAPE= 4.59 ii. $\sqrt{SSE}$= 168.80 iii. SDE= 11.29 Fall: i. MAPE= 3.13 ii. $\sqrt{SSE}$= 179.80 iii. SDE= 11.29
	ANFIS-FNN*	(Okumus and Dinler, 2016)	Turkey	2 years (data resolution =1 hour)	***Input:*** Historical wind speed ***Output:*** wind speed	Site 1: i. MAE= 0.1868 ii. MSE= 0.0595 iii. MAPE= 3.3530

					Site 2: i. MAE= 0.1178 ii. MSE= 0.0270 iii. MAPE= 2.2598 Site 3: i. MAE= 0.0774 ii. MSE= 0.0133 iii. MAPE= 3.8589
ANFIS-GA-PSO	(Mbuvha et al., 2018)	Norway	7384 data points	***Inputs:*** i. Wind speed ii. Humidity iii. Windfarm online capacity iv. Temperature ***Output:*** Wind power	RMSE: 2941.02 kWh
ANFIS ANFIS-FCM SSA-ANFIS-FCM	(Moreno and dos Santos Coelho, 2018)	Brazil	1000 datapoints (data resolution= 10 mins)	***Input:*** Wind speed	ANFIS-FCM i. MAE= 0.51360 ii. MSE= 0.46828 iii. RMSE= 0.68431 iv. St. D= 0.66950 v. R^2= 0.85195 SSA-ANFIS-FCM i. MAE= 0.20583 ii. MSE= 0.08776 iii. RMSE= 0.29625 iv. St. D= 0.29646 v. R^2= 0.97261
ANFIS GA-ANFIS PSO-ANFIS Krill-ANFIS	(Hassanien et al., 2017)	Egypt	1500 datapoints	***Inputs:*** i. Low temperature ii. Out temperature iii. Humidity iv. Rain index ***Output:*** Wind speed	ANFIS i. RMSE= 0.5442 ii. AAPRE= 1.6147 iii. R^2= 0.98 PSO-ANFIS i. RMSE= 0.3723 ii. AAPRE= 1.6262 iii. R^2= 0.99 GA-ANFIS i. RMSE= 0.3736 ii. AAPRE= 1.5843 iii. R^2= 0.99 Krill-ANFIS i. RMSE= 0.3617 ii. AAPRE= 1.6294 iii. R^2= 0.99
ANFIS-PSO	(Khosravi et al., 2018a)	Iran	15,624 datapoints (data resolution = multi-resolution)	***Inputs:*** i. Local time ii. temperature iii. Pressure iv. Relative humidity ***Outputs:*** i. Wind speed ii. Wind direction iii. Wind turbine power output	ANFIS-PSO 5-mins interval i. RMSE= 23.7135 ii. MSE= 562.3316 iii. R= 0.9612 10-mins interval i. RMSE= 0.37068 ii. MSE= 1374.0433

						iii. R= 0.9074 30-mins interval i. RMSE= 61.2601 ii. MSE= 3752.7941 iii. R= 0.7201 1-hr interval i. RMSE= 87.9549 ii. MSE= 7736.056 iii. R= 0.5368
	DSA	(Zheng et al., 2017)	China	1 year (data resolution)	***Inputs:*** i. Wind speed ii. Wind direction iii. Air pressure iv. Air temperature v. Humidity ***Output:*** Wind power	Winter i. MAPE= 7.6979 ii. $\sqrt{SSE}$ = 190.2974 iii. RMSE= 38.8443 iv. SDE = 38.7981 Spring i. MAPE= 13.304 ii. $\sqrt{SSE}$ = 25.7918 iii. RMSE= 5.2647 iv. SDE = 5.2130 Summer i. MAPE= 8.232 ii. $\sqrt{SSE}$ = 32.5989 iii. RMSE= 6.6542 iv. SDE = 6.6092 Fall i. MAPE= 3.2197 ii. $\sqrt{SSE}$ = 49.0784 iii. RMSE= 10.0181 iv. SDE = 8.8529
	ANFIS	(Morshedizadeh et al., 2017)	Canada	20 months	***Inputs:*** i. Wind speed ii. Rotor speed ***iii.*** Gear temperature ***Output:*** Turbine active output power	MAE= 0.0102
Solar Energy						
	ANFIS ANFIS-PSO ANFIS-GA ANFIS-DE	(Halabi et al., 2018)	Malaysia	108 months	***Inputs:*** a. Sunshine duration b. Maximum air temperature c. Minimum air temperature d. Monthly rainfall e. Clearness index ***Output:*** a. Solar radiation	ANFIS i. RMSE=0.3667 ii. RRMSE= 2.1453 iii. r= 0.9945 iv. R^2= 0.9887 v. MABE= 0.2957 vi. MAPE=1.7186 ANFIS-PSO i. RMSE=0.3065 ii. RRMSE= 1.7933

					iii. r= 0.9963 iv. R^2= 0.9921 v. MABE= 0.2482 vi. MAPE=1.4097 ANFIS-GA i. RMSE=0.3228 ii. RRMSE= 1.8886 iii. r= 0.9954 iv. R^2= 0.9912 v. MABE= 0.2618 vi. MAPE=1.5146 ANFIS-DE i. RMSE=0.3701 ii. RRMSE= 2.1654 iii. r= 0.9942 iv. R^2= 0.9885 v. MABE= 0.3133 vi. MAPE=1.7980
ANFIS	(Makhloufi et al., 2019)	Algeria	30 days	***Inputs:*** a. GHI b. Wind speed c. Temperature d. Humidity ***Output:*** a. Active power	PV Plant 1 i. MSE= 0.2284 ii. RMSE 0.4601 iii. MAE= 0.1952 iv. St.D= 0.4370 PV Plant 2 i. MSE= 0.0023 ii. RMSE 0.0479 iii. MAE= 0.0110 iv. St.D= 0.0467
ANFIS	(Perveen et al., 2019)	India	15 years (data resolution= hours)	***Inputs:*** a. Sunshine duration b. Wind speed c. Ambient temperature d. Relative humidity e. Dew point ***Output:*** Clearness index	
ANFIS PSO-ANFIS GA-ANFIS	(Salisu et al., 2019)	Nigeria	132 months (data resolution= months)	***Inputs:*** ***a.*** Relative humidity b. Sunshine hours c. Relative humidity d. Minimum temperature e. Maximum temperature ***Output:*** Solar radiation	ANFIS i. RMSE= 1.6954 ii. R^2=0.7363 GA-ANFIS i. RMSE= 1.3008 ii. R^2=0.8385 PSO-ANFIS i. RMSE= 1.3838 ii. R^2=0.8058

ANFIS PSO-ANFIS	(Yadav et al., 2019)	India	1 month (data resolution= 15mins)	***Input:*** PV power output	ANFIS Week 3 i. RMSE= 0.0185 ii. MAPE= 4.2765 iii. sMAPE= 6.3387 Week 4 i. RMSE= 0.0335 ii. MAPE= 4.2765 iii. sMAPE= 9.3187 PSO-ANFIS Week 3 i. RMSE= 0.0174 ii. MAPE= 3.5196 iii. sMAPE= 3.3094 Week 4 iv. RMSE= 0.0285 v. MAPE= 8.11917 vi. sMAPE= 7.8313
ANFIS-GP ANFIS-SC ANFIS-FCM	(Khosravi et al., 2018b)	Iran	7 years (data resolution= N/A)	***Inputs*** i. Pressure ii. Temperature iii. Wind speed iv. Relative humidity v. Local time ***Output*** Solar irradiance	ANFIS-GP i. R= 0.94938 ii. RMSE= 86.1513 ANFIS-SC i. R= 0.9456 ii. RMSE= 84.8125 ANFIS-FCM i. R= 0.95279 ii. RMSE= 83.1365
ANFIS	(Chauvin et al., 2014)	USA	12 years (data resolution= 40 mins)	***Inputs*** i. Day of the year ii. Minute of the day iii. Atmospheric turbidity. ***Output*** Direct normal irradiation	Single block (t+ 5h) NRMSE= 3.84

* ANFIS-FNN= ANFIS- Feedforward artificial neural network; DSA= Double-Stage ANFIS; PSO- Particle Swarm Optimization; DE= Differential Evolution; GA= Genetic Algorithm; GP= Grid Partitioning; SC= Subtractive Clustering; FCM= Fuzzy c-means; SSA= Singular Spectrum Analysis.

From Table 8, ANFIS models have been used either as standalone or hybrid for forecasting in solar and wind energy studies. Good results have been recorded from standalone ANFIS models, however, studies that compared standalone with hybrid models reveal that hybrid models outperform the standalone models. This is because of the parameter tuning capacity of the supporting model such that local optimal is not reached, the loss function is reduced during the learning process, and the optimization converges at a satisfactory solution.

By model structure, it was observed that solar or wind resource forecast can be performed either by historical univariate means or through the use of meteorological or climatological data which has a close relationship with the resource to be forecast. In both resources, it was observed that in all the literature reviewed, which forecast power generated, the active power has been considered while the reactive power was not. This is because reactive power does not translate into financial yield for the investors. Based on performance metrics for model evaluation, it was observed that statistical performance metrics that measure the relationship between the observed values and the predicted values of the hold-out data and those metrics that evaluate the model accuracy are seldom used complimentarily. Hence, evaluation of the model can be skewed to a statistical measure of dispersion and variance, thereby leaving out a measure of model accuracy. Among all the literature reviewed, studies that compare two or more ANFIS-based models did not evaluate the computational time of the models. This is observed to be essential, most especially when two or more models are involved. This further amplifies the influence of the hybridizing model on the base model. Based on the horizon of the forecast, ANFIS-based models have been used for very short term, short-term, mid-term and long-term forecasts with a significant level of accuracy recorded across these horizons.

5. The integrated framework

GIS-MCDM-based site suitability process for wind and solar energy studies is aimed at obtaining extremely viable sites, which satisfy technical, environmental, location, orographic, and economic criteria. However, integrating ANFIS-based models for virtual investigation of prevalent resource variability of a selected site before ground investigation offers cost-saving and improved reliability on resource planning for operational and strategic processes. This further enables wind and solar energy developers to better understand characteristic randomness and variability of the resource in the proposed site before site development. The framework for achieving this is presented in Figure 13.

With the established effectiveness of hybrid ANFIS models, they can be efficiently applied to viable sites obtained from GIS-MCDM-based models for wind and solar investigations. Prior to the application of ANFIS-based model for resource forecast, a virtual investigation of the viable site is performed using historical time series data of the selected location. These data can be virtually obtained from reputable databases like the National Aeronautics and Space Administration (NASA). The accuracy of the forecast can be significantly improved and data complexity reduced by preprocessing the data inputs (Nelles, 2001). Inherent in real-time data collected from data acquisition instruments is missing data, outliers due to unexpected events, noise, and distortion, which must be eliminated to enable the learning algorithm to learn the right data. Some of the commonly used preprocessing techniques which can be useful in solar and wind resource forecasting include; window length technique, historical lag identification, wavelet transform, and normalization and unsupervised learning techniques like self-organizing maps (SOMs) (Moosavi et al., 2014). The preprocessed data then forms an input to the ANFIS-based model. The built intelligent model is evaluated with performance metrics identified in Table 7 for effectiveness and efficiency prior to the use of new datasets for day-ahead forecasts for the wind or solar farm.

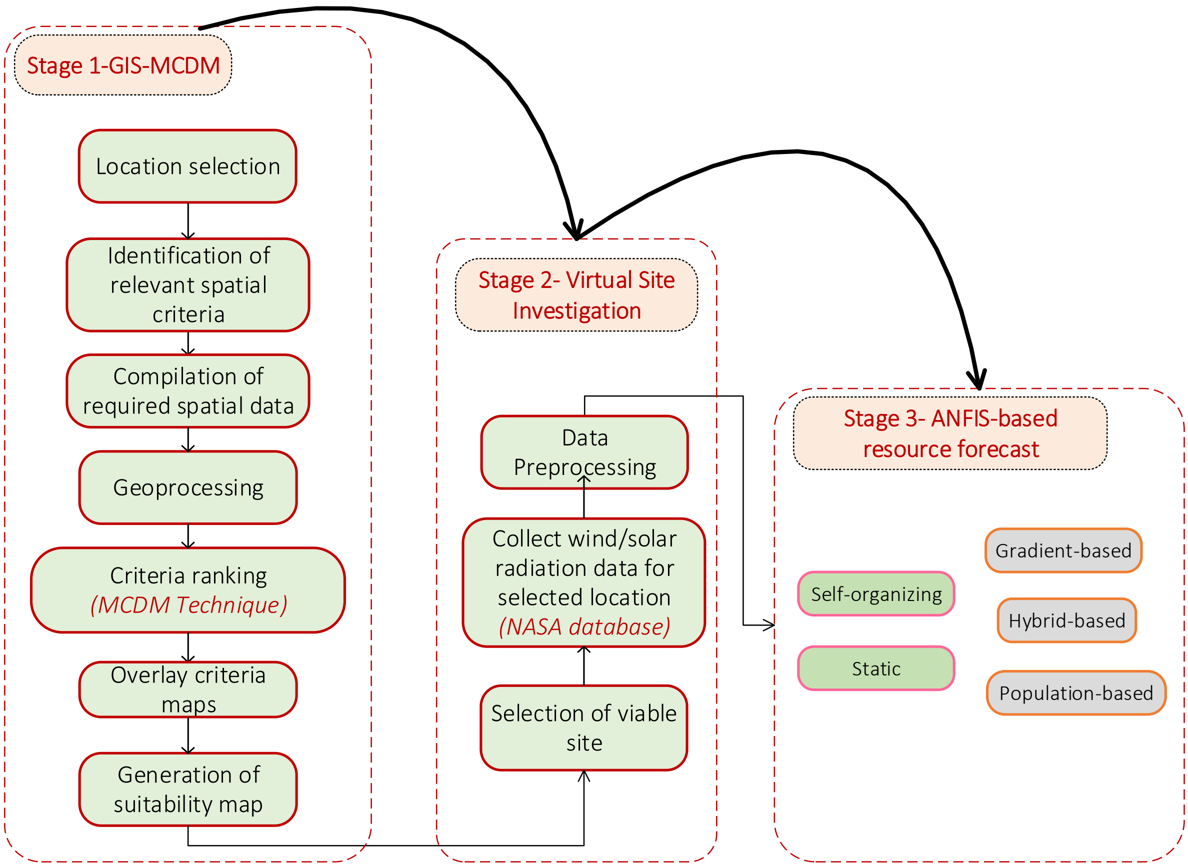

Figure 13.The integration framework for GIS-MCDM and ANFIS-based modeling for wind and solar exploration

6. Conclusions

GIS-based model for suitability analysis is highly effective in solar and wind energy exploration and its preference is rapidly increasing based on its spatial data-archiving and processing, visualization, and analytical abilities. While studies to open up new areas for wind and solar exploration are evolving from developing countries, developed countries are further increasing the percentage of renewables in their energy mix. In this study, a mini-review of two complementary themes: GIS-based site suitability analysis and ANFIS-based solar and wind resource forecast were carried out. The site suitability analysis predicates the intelligent resource forecast as data for the intelligent forecast is obtained from viable sites, hence a need to establish the state of research in these two and motivate for a point of integration. The status of countries in six continents considered as key players in the wind and solar energy exploration based on the available data was also presented. The Scopus database was used in this study owing to its credibility and search was conducted based on keywords dominant in the two themes of this review. The following conclusions were drawn based on our findings:

i. Certain criteria are common to both wind and solar energy resource exploration in new sites. These criteria are exclusion criteria, which could make co-location of solar and wind resources in geographical locations with an abundance of both resources possible. The choice of values for these exclusion criteria was observed to vary across the literature and choices per author are substantiated with previous studies in the same domain. However, to date, there has been no standard distance measures per exclusion criteria. This non-standardization, however, could be based on the differences in geospatial characteristics across countries. Resource-based criteria often classified as technical criteria also do not have standard values, however, a wind speed above 5 m/s is considered as viable for small wind farms. Solar farm on the other hand has three basic components; the DNI, DHI, and GHI, whose selection depends on the mode of exploration: solar PV or CSP. For solar PV the DHI and DNI are suitable with a minimum of 1800 kWh/m^2/year (Yushchenko et al., 2018) required for viable power generation. However, for CSP, the DNI is of interest with a minimum of 2000 kWh/m^2 required for power generation (Al Garni and Awasthi, 2017; Clifton and Boruff, 2010).

ii. It was observed that among many MDCM techniques for decision making, the AHP has been preferred due to its computational simplicity and its intuitive approach to problem-solving despite its propensity to be complex when more decision-makers are involved. Few studies have used TOPSIS, WLC, DEMATEL, OCRA methods, or a combination of different techniques. These other techniques have remained less explored in GIS-based site suitability studies.

iii. Hybrid ANFIS models are overly more effective than the standalone ANFIS models both for wind and solar resource forecasts. This is due to parameter tuning of both antecedence and consequence of the ANFIS model by non-standalone ANFIS models, most especially the population-based architectures, such that high loss function during model training and model convergence at local optimal are avoided. In this regard, population-based ANFIS which uses GA, DE, or PSO, has been observed to record high accuracy. Further to this, the PSO-based ANFIS model is less computationally intensive compared to other population-based ANFIS models. On the overall, a trade-off between accuracy and CT of hybrid models exists. Statistical evaluation methods that measure dispersion/variance between the observed and the predicted values have been solely used in some studies. This might not be sufficient to evaluate model performance. Hence, a combination of measure of variance, accuracy, and computational intensity (when two or more algorithms are compared) is essential.

7. Recommendations for future studies

Artificial intelligence integrated GIS-based site suitability methodology is still at its infant stage. However, based on our findings, the following recommendations are made for further studies:

i. Asides AHP, other MCDM techniques like ELECTRE, PROMETHEE, and VIKOR can be explored and their performances compared with the commonly used AHP method for criteria ranking and site selection in site suitability process.

ii. Presently, with no generally valid range of criteria for GIS site suitability analysis due to geospatial variations that could occur, a hemispherical range of values for these criteria and other resource-based criteria in wind and solar studies is feasible and thus open for further research.

iii. Site suitability analysis and resource forecast using artificial intelligence have been performed in isolation. To the best of the authors' knowledge, there has been no study that harnesses the two. Thus, creating a projection into resource viability in areas classified as most suitable from GIS technique using the proposed framework in this study is open for further studies.

Nomenclature		Abbreviations	
$\boldsymbol{A_r}$	Rotor cross-sectional area, *m*^{2}	ABC	Artificial bee colony
$\boldsymbol{c}$	Scale parameter	ACO	Ant colony optimization
$\boldsymbol{C_p}$	Power coefficient	AHP	Analytical hierarchical process
$\boldsymbol{C_T}$	Torque coefficient	ANN	Artificial neural network
$\boldsymbol{d}$	Date sequence of the year	ANFIS	Adaptive neurofuzzy inference System
$\boldsymbol{F}$	Thrust force, *N*	ANP	Analytical network process
$\boldsymbol{\rho_a}$	Air density, kg/m^3	CSP	Concentrated solar power
$\boldsymbol{\theta_s}$	Solar angle, r*ad*	DE	Differential evolution
$\boldsymbol{h}$	Solar hour angle, r*ad*	DEMATEL	Decision Making Trial and Evaluation Laboratory
$\boldsymbol{G_0}$	Solar irradiance constant	DHI	Direct horizontal irradiance
$\boldsymbol{O_j^1}$	Output of adaptive node *k*	DNI	Direct normal irradiation

$\boldsymbol{I_i}$	Input of layer i	DSA	Double-stage ANFIS
$\boldsymbol{k}$	Shape parameter	ELECTRE	ELimination and Choice Expressing the REality
$\boldsymbol{m}$	Mass of air, *kg*	FCM	Fuzzy c-means
$\boldsymbol{n}$	Number of moles	FIS	Fuzzy inference system
$\boldsymbol{N}$	Number of observations	FL	Fuzzy logic
$\boldsymbol{p}$	Atmospheric pressure, N/m^2	FNN	Feedforward neural network
$\boldsymbol{P}$	Output power, kW	GA	Genetic algorithm
$\boldsymbol{P_i}$	Wind power density, W/m^{-2}	GHI	Global horizontal irradiance
$\boldsymbol{P_T}$	Turbine power, kW	GIS	Geographical information system
$\boldsymbol{R}$	Universal gas constant	GP	Grid partitioning
$\boldsymbol{R_r}$	Rotor radius, *m*	MABAC	Multi-Attributive Border Approximation area Comparison
$\boldsymbol{RcoV}$	Coefficient of variation	MCDM	Multi-criteria decision-making
$\boldsymbol{T}$	Air temperature, *K*	PROMETHEE	Preference Ranking Organization Method for Enrichment of Evaluations
$\boldsymbol{T_T}$	Actual torque, *Nm*	OCRA	Occupational Competitiveness Rating Analysis
$\boldsymbol{v_a}$	Air volume, *m*^{3}	PSO	Particle swarm optimization
$\boldsymbol{V}$	Wind speed, *m/s*	PV	Photo-voltaic
$\boldsymbol{\bar{y}}$	Mean of observed data	RE	Renewable energy
$\boldsymbol{\widehat{y_k}}$	Predicted data	RES	Renewable energy sources
$\boldsymbol{y_k}$	Observed data	RNN	Recurrent neural network
Z	Site elevation	SC	Subtractive clustering
$\boldsymbol{\alpha}$	Cloud/haze cover index	SSA	Singular spectrum analysis
$\boldsymbol{\delta}$	Local latitude	SVM	Support vector machine
$\boldsymbol{\mu_{A_j}}$	Membership function of fuzzy set *A*.	SVR	Support vector regression
		TOPSIS	Technique for order preference by similarity to ideal solution
		TODIM	TOmadao de Desicao Interactiva Multicriterio (Portuguese acronym for Interactive and Multicriteria Decision Making)
		VIKOR	VIseKriterijumska Optimizacija I KompromisnoResenje
		WLC	Weighted Linear Combination

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