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A Survey on Learning System Applications in Energy System Modeling and Prediction

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Abstract:Learning Systems (LS) such as machine learning, statistical pattern recognition and neural networks are computer programs that can learn from sample data and develop a prediction model that makes prediction for new cases. The most important think related with a prediction model is to achieve results as closer as to real situation while making predictions. This is important because being closer to real results help to reduce the costs of feasibility studies in system installation. The performance of Learning Systems has been raised in latest years such as it sometimes exceeds the performance of humans. That's why the applications of Learning Systems have been increased in many areas. This paper reviews the present applications of Learning Systems in energy system modeling and prediction especially in renewable energy systems such as wind and solar. The aim of this paper is to create a vision for researchers by gathering the present applications and outline their merits and limits and the prediction of their future performance on specific applications.

Keywords:*Energy efficiency, Source installation, Estimation, Artificial intelligence*.

1. Introduction

Learning Systems (LS) are research areas of computer science that are used to extract information from large data stores [1, 2]. It includes concepts such as machine learning, statistical pattern recognition and neural networks. In everyday life in many areas such as education, health, telecommunication, transportation, marketing, meteorology, earth sciences and etc. a large quantity of data have been collected. Due to the growth in these data, extracting valuable information from large data stores has become an engineering discipline. This valuable information than is used for developing prediction models that can learn from sample data and develop a prediction model that makes prediction for new cases [3-5]. The objective of this paper is to gather and argue the studies that are related to Learning System techniques in modeling and prediction for renewable energy systems. The following of the paper is organized as follows: In the second part the learning system is explained briefly. While wind energy applications of learning system are given in the third part, solar energy applications are given in the fourth part. Finally conclusion is given.

2. Learning Systems

Learning systems are the computer programs that can learn from the sample data and can predict for the future [1, 2]. While there are many learning system methods and applications in the literature, this paper is focused on the presentation of some of the learning system applications on energy system modeling and prediction. Since energy sources are not abundant predictions for appropriate and satisfactory use of these energy sources are essential. Some of the most common methods of learning systems, used in the field of energy system modeling and prediction, are linear regression, artificial neural networks (ANN), support vector machine (SVM), decision trees and etc. [6]. In the literature many studies can be found related to the solar irradiation, wind speed, production of energy from wind and solar and reducing the operating costs with the realization of economic dispatch [7]. In design of wind farms, solar plants and power generators, wind and solar characteristics such as distribution of wind speeds and solar irradiation of the location have to be known. As this information is not always available Learning System algorithms are used to predict this information according to the historical data.

Learning System algorithms are the samples of supervised classification algorithms. A supervised classification algorithm uses a database which includes attributes and the class information. The sample of a database, which is given in Table1, has *m* data that each one has *n* attributes, called as predictors, and class information, called as target.

A supervised classification includes two steps which are the training and the testing steps. First of all the database is split into two parts according to some criterion. First part of the database, training set, is used in the training step and the second part, test set is used in the testing step. In the training step, a model is constructed by using the training set of which the class information is known.

Than using the test set the performance of the constructed classification model is evaluated. Once the model is constructed, a sample data with its known attributes and unknown class information can be classified into a class. In the following part some of the popular Learning System algorithms that are used in renewable energy systems are explained briefly.

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Table 1. A sample database

Case ID	Attributes (Predictors)					Class information (Target)
	X_1	X_2	.	.	X_n	
1						
2						
.						
.						
.						
m						

2.1. Linear Regression

Features Linear regression model is a very popular mathematical classification model that is used for making predictions, and has many applications in various fields including sciences such as social sciences and physical sciences [8]. In the regression analysis it is used a database that is based on observed data over a period of time. In this database attributes would be the predictors and the class information would be the target (Table1). As this is a supervised classification model, it has a training step in which the database, which's target values are known is used and a regression model is constructed. Than the model is tested using the part of the database that is not used for the training process. At the end, once the model is constructed it can be used to predict the target value of a case which's target value is unknown.

Basically a linear regression model explains the relationship between the predictor and the target with a straight line. In some applications there is only one predictor but in some applications it could be more than one predictor, multivariate linear regression analysis [8]. The single predictor linear regression model can be expressed as in Eq.1 and the 2-Dimensional graphical representation is given in Fig.1.

$$y = ax + b + e \quad (2)$$

In Eq.1 the regression parameters a and b are the angle between a data point and the regression line, and the point where x crosses the y axis (x=0) respectively [9].

In multivariate linear regression analysis the regression equation has a form as given in Eq.2.

$$y = b + ax_1 + cx_2 + \cdots + zx_{n-1} + e \quad (11)$$

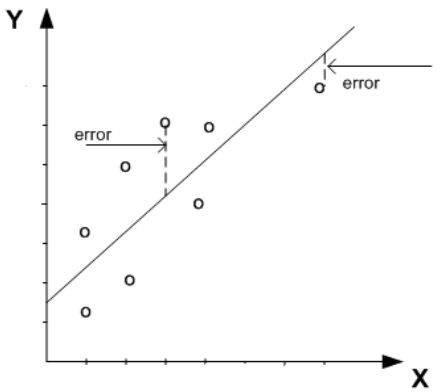

Figure1. Block diagram of proposed methodology

2.2. Artificial Neural Networks (ANN)

Artificial Neural Networks is a supervised learning algorithm which bases the working principle of human brain. It learns from data samples, and then develops a model which can learn from these data samples and can make predictions for the future. It consists of basically two layers that are called the input layer and the output layer. Each layer has different numbers of neurons which are associated with the neurons in the other layer with a weight. Working principle of an ANN is given in Fig 2. The output of the network is the application of the sum of the weighted inputs to an activation function.

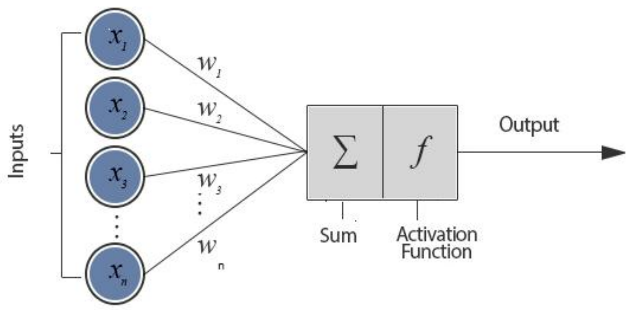

Figure 2. Working process of a simple neuron

There are some advantages of ANN compared to the conventional algorithms such as the speed, the simplicity, the capacity of the network to learn from examples and the realistic results due to the use of actual data for the training step of the network [10].

2.3. SVM

Support Vector Machine (SVM) is a tool for solving pattern recognition problems and it is based on the concept of finding the decision planes that define decision boundaries, and can separate a set of objects belonging to different classes (Fig.3.) In Fig.3.a a schematic example of a linear classifier can be seen. But however in most real classification problems, data points, belong to different classes, cannot be distinguished from each other linearly (Fig.3.b). Classification tasks given in Fig.3.b, are known as hyper plane classifiers and SVMs are particularly suited to handle such tasks. In other words with hyper plane classifiers, the data can be mapped into a higher dimensional feature space, and an optimal separating hyper plane can be constructed in this new space [11-13] (Fig.4).

a b

Fig. 3 A schematic example of a) A linear classifier, b) A nonlinear classifier [14]

SVM algorithm can cope with high dimensional data well although when the training samples are relatively small [15]. In the literature SVM algorithm is used for medium and long term wind speed predictions [16-18], and a few studies can be found in which SVM is used for short-term wind speed prediction [19].

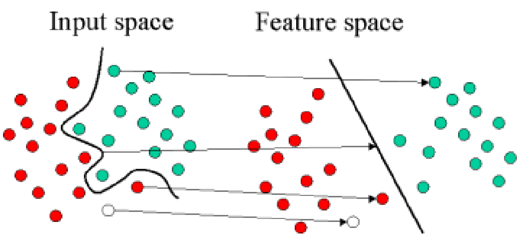

Fig. 4 The basic of a SVM classifier [14]

3. Wind Energy Applications

Wind speed predictions are performed for three different time scales such as short, medium and long terms. While the time intervals in short term are about 10 sec or 10 min [20-22] they become hourly predictions for medium term [23-25] and involve days for long term predictions [26-28]. Each time scale is indicative of different things. For example short term wind speed prediction is important to control of wind turbines, medium term supports unit commitment planning and the long term is used in determining generation mix and scheduled maintenance of power systems [29]. Wind speed prediction methods can be grouped into four categories such as statistical, physical-based, data mining and hybrid methods [30]. When the wind characteristics are examined, it can be seen that it has both linear and nonlinear characteristics that can be analyzed with the learning systems such as data mining methods that can model both the linearity and the nonlinearity of wind speed [30].

The frequently used data mining algorithms in wind speed prediction are tree-based regression algorithms [31-34], k-nearest neighbor [35], support vector machine (SVM) [36-37], Artificial Neural Networks [38-40] and ensemble data mining algorithms [41]. Among these prediction models prominent ones are developed from ANN and SVM algorithms [30]. The ANN wind speed prediction model is applied for short [20, 42-44] and the long term predictions [42]. The data mining models may suffer from the limited data in terms of accuracy [45]. The long term approaches of ANN model can be seen as monthly in [46] and as monthly and daily in [47]. ANN model has some advantages according to the conventional algorithms such that the speed, the simplicity and the capacity of the network to learn from examples. [48].

In [23] ANN is used for wind speed prediction that is the mean monthly wind speeds prediction in Cyprus where any data is not available. In [49] it is proposed multivariate time series models to predict the power ramp rates of a wind farm of 100 turbines for a time horizon of 10-60 min. In the study, the power changes are predicted at 10 min intervals and five data mining algorithms are used to build the model. These are multilayer perceptron algorithm (MLP), the support vector machine (SVM) regression, the random forest, the classification and regression (C&R) tree and pace regression algorithm. According to the results of the study, the SVM regression algorithm outperforms the rest of the four algorithms. In [19] a least-squares SVM (LS_SVM) approach is applied for wind speed prediction. In the paper it is presented a systematic study on fine tuning of LS_SVM model parameters for one-step ahead wind speed forecasting. In the study they applied three different SVM kernels that are linear, Gaussian and polynomial kernels. Training sample size, SVM order, kernel parameters and regularization parameter are used as the SVM parameters. According to the obtained results LS-SVM performance is closely related to the dynamic characteristics of wind speed, performance of the model is closely related to the parameters comparable results are obtained for the three of the kernels under optimal combination of parameters after fine tuning and finally when the training sample size or SVM order is small the linear kernel gives the worse performance. In [50] they integrated data mining and evolutionary computations to monitor wind farm power output. In the study five different data mining algorithms are compared. These algorithms are multi layer perceptron (MLP), REP tree, M5P tree, bagging tree and the k-nearest neighbor (k-NN) algorithm. According to the results the best prediction results are obtained from the k-NN model combined with the principal component analysis approach. In order to obtain good performance from this model, the conditions of the wind farm has to be normal otherwise its performance is poor. In [51] they used learning systems algorithms to analyze time series models for predicting the power of a wind farm for 10-min and hour-long intervals. As in [50] the model is built using the same five data mining algorithms. The results showed that SVM regression algorithm gives the best predictions of wind power and wind speed at 10-min intervals up to 1 h into the future. The MLP gives the best predictions over hour-long intervals up to 4h ahead. As it is reported in the study wind speed predictions are poor.

4. Solar Energy Applications

In the literature in various fields of renewable energy systems it can be found many modeling and prediction applications of ANN. In [52] two different application of ANN can be seen. The two of these applications are for to determine the collector optical efficiency which is a very important parameter as it is used to determine the overall effectiveness of solar concentrating collectors. In the first application to determine the collector optical efficiency ANN is used for the estimation of collector intercept factor and in the second one it is used to estimate the radiation profile on the receiver of collector.

In [48] an extended version of the study given in [52] can be found. In [48] ANN is also used for solar water heating systems besides the modelling of a solar steam generator. According to the results ANN can be successfully used in the estimation of the system energy extraction and the stored water temperature rise [53].

In [10] a study is performed that gives an overview using Artificial Intelligence (AI) techniques for sizing photovoltaic (PV) systems. The Artificial techniques included in the paper are Artificial Neural Networks (ANN), fuzzy logic, genetic algorithm, wavelet and the hybrid systems that are fuzzy neural networks, genetic algorithms and neural networks, wavelet and neural networks, genetic algorithms and fuzzy logic. In the paper included applications of AI techniques are as follows: Neural networks for sizing stand-alone PV systems; genetic algorithms for sizing hybrid PV system; genetic algorithms for sizing grid-connected PV-system; genetic algorithms for sizing hydrogen PV system; neural networks, neuro-fuzzy and genetic algorithm for sizing stand-alone PV systems and neuro-fuzzy and wavelet for sizing PV systems. According to the overview in [10] the use of AI techniques for sizing PV systems has the advantage that it provides good optimization, especially in isolated areas, where the weather data are not always available. In [54] they argue the solar forecasting methodologies and also the solar resource and power output of solar plants applications. As learning system algorithms, they examine the ANN and k-NN algorithms. In [55] they performed a prediction model for solar power generation from weather forecasts using linear least squares and SVM using multiple kernel functions. According to the results they showed that SVM-based models are 27% more accurate than existing forecast-based models.

5. Solar Energy Applications

The Learning Systems (LS) are computer programs which learn from sample data and develop a prediction model makes prediction for new cases. The performance and accordingly the application of Learning Systems have been raised in the last years. This paper reviews some of the present applications of Learning Systems in energy system modelling and prediction especially in renewable energy systems such as wind and solar. As the learning systems linear regression, ANN and SVM are considered. It is aimed with this study to create a vision for researchers by gathering the present applications and outline their merits and limits and the prediction of their future performance on specific applications.

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