VSB TECHNICAL UNIVERSITY OF OSTRAVA | FACULTY OF ELECTRICAL ENGINEERING AND COMPUTER SCIENCE

Control System for Electrical Power Grids with Renewables using Artificial Intelligence Methods

Ibrahim Salem Jahan

PhD Thesis
Supervisor prof. Stanislav Misak, Study Program: Electrical Engineering
Ostrava, 2021

Abstract

Modern electrical and electronic devices are very sensitive to the power supply and require steady and stable electric power. Factories may also need electric power within a specific standard range of voltage, frequency, and current to avoid defects in the production. For these reasons electric power utilities must produce an electric power of a specific standard of power quality parameters [EN50160]. Nowadays, renewable energy sources, such as wind energy and solar energy are used to generate electric power as free and clean power sources as well to reduce fuel consumption and environmental pollution as much as possible. Renewable energy, e.g. wind speed or solar irradiance, are not stable or not constant energies over the time. Therefore smart control systems (SCSs) are needed for operate the power system in optimal way which help for producing a power with good quality from renewable sources. The forecasting and prediction models play a main role in these issues and contribute as the important part of the smart control system (SCS). The main task of the SCS is to keep the generated power equal to the consumed power as well as to consider standard levels of power quality parameters as much as possible.

Some of previous studies have focused on forecasting power quality parameters, power load, wind speed and solar irradiance using machine learning models as neural networks, support vector machines, fuzzy sets, and neuro fuzzy.

This thesis proposes designing forecasting systems using machine learning techniques in order to be use in control and operate an electrical power system.

In this study, design and tested forecasting systems related to the power and renewable energies. These systems include wind speed forecasting, power load forecasting and power quality parameters forecasting.

The main part of this thesis is focus in power quality parameters forecasting in short-term, these parameters are: power frequency, magnitude of the supply voltage, total harmonic distortion of voltage (THD_u), total harmonic distortion of current (THD_i), and short term flicker severity (P_{st}) according to the definition in [EN50160]. The output of the forecasting models of power quality parameters can be used in shifting the load to run in switch time which will help for correct and optimize the quality of the power.

Keywords

Smart power grid, power quality parameters, power load, renewable energies, weather data, decision tree, neural networks, linear regression, support vector machine, forecasting system

Acknowledgments

I wish to thank all those who helped me with my work, especially doc. Ing. Stanislav Mišák, Ph.D. for his advice and ideas during my studies and prof. RNDr. Václav Snášel, CSc.

Contents

1 Introduction **1**
1.1 Problem Definition and Motivation . . . 1
1.2 Goal of This Work . . . 1

2 Renewable Energies and Power Quality **4**
2.1 Introduction . . . 4
2.2 Off-Grid System . . . 4
2.3 Power Quality . . . 5
2.3.1 Introduction . . . 5
2.3.2 Power Quality Parameters . . . 6

3 Formal Methods **8**
3.1 Introduction . . . 8
3.2 Clustering . . . 8
3.2.1 K-means Clustering . . . 8
3.2.2 K-medoids Clustering . . . 9
3.3 Linear Regression (LR) . . . 9
3.4 Support Vector Machines (SVM) . . . 10
3.5 Artificial Neural Networks (ANN) . . . 10
3.6 Decision Tree (DT) . . . 11

4 Related Works **13**
4.1 Introduction . . . 13
4.2 Wind and Solar Power Forecasting . . . 13
4.3 Power Load Forecasting . . . 15
4.4 Reconfiguration Power System and Power Quality Parameters Forecasting . . . 21

5 The Proposed Methods **24**
5.1 Wind Speed Forecasting using Regression Models . . . 25
5.1.1 Data set . . . 25
5.1.2 Experiment Setup . . . 25
5.1.3 Experiment Results . . . 27
5.2 Intelligent System for Power Load Forecasting in Off-grid Platform 29
5.2.1 Data Set . . . 29
5.2.2 Experiments Setup . . . 29
5.2.3 Results and Discussion . . . 30

5.3 Smart Control System based on Power Quality Parameter Short-term Forecasting . . . 32
5.3.1 Data Set . . . 32
5.3.2 Experiments Setup . . . 33
5.3.3 Results . . . 33
5.4 Power Quality Parameters Analysis in Smart Grid Platform . . . 34
5.4.1 Experiments . . . 34
5.4.2 Data Set . . . 34
5.4.3 Discussion . . . 34

6 Discussion and Conclusion **39**
6.1 Results Comparison . . . 39
6.2 Discussion . . . 40
6.3 Conclusion . . . 42
6.4 Future Work . . . 42

List of Figures

1.1 Main Parts of The Smart Control System 2
1.2 Power Grid Balance 2
1.3 Power Quality Correction 3
1.4 The Basic Principle of Smart Control System 3

2.1 Simple Power Grid Diagram 5

3.1 Simple Linear Regression Model 10
3.2 Hard Margin Support Vector Regression 11
3.3 Example of ANN Structure 11

5.1 The Centre for Solar Energy Research and Studies 25
5.2 The Experiment Diagram of WS Forecasting 26
5.3 Comparison of AWS with FWS 28
5.4 Scheme Off-grid System 29
5.5 Power Load Forecasting Diagram 30
5.6 Comparison of Actual and Forecasted Power Load 32
5.7 Diagram of The Proposed Model: PQPs Forecasting using DT . 33
5.8 Diagram of the Comparison Model for PQPs Forecasting 35
5.9 Comparison of Actual and Forecasted Power Frequency using DT 37
5.10 Comparison of Actual and Forecasted Voltage using DT 37
5.11 Comparison of Actual and Forecasted THD_u using DT 38
5.12 Comparison of Actual and Forecasted THD_i using DT 38
5.13 Comparison of Actual and Forecasted (P_{st}) using DT 38

6.1 Results Comparison of Average Error per Day of ANN with DT 40

List of Tables

2.1 Power Quality Parameters 7

5.1 Wind Speed Prediction Results for 4 and 8 Hours Ahead 27
5.2 Wind Speed Prediction Results for 12 and 24 Hours Ahead . . . 27
5.3 Power Load Forecasting using K-means with DT & ANN 31
5.4 Power Load Forecasting using K-medoids with DT & ANN . . . 31
5.5 MAPE Error for Five PQPs Forecasting Models 33
5.6 Error of ANN for PQPs Forecasting 35
5.7 ANN MAPE Average of PQPs 35
5.8 Error of DT for PQPs Forecasting 36
5.9 DT MAPE Average of PQPs 36

6.1 Results Comparison of Wind Speed Forecasting 39
6.2 Results Comparison of Power Load Forecasting 40
6.3 Results Comparison of the PQPs Forecasting 40
6.4 Power Frequency and Supply Voltage Variations 41

List of Abbreviations

ANN	Artificial Neural Network
AWS	Actual Wind Speed
BNN	Backpropagation Neural Network
DN	Distribution Network
DSR	Distribution System Reconfiguration
FWS	Forecasted Wind Speed
LTLF	Long-Term Load Forecasting
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
MTLF	Medium-Term Load Forecasting
PH	Photovoltaic System
PQPs	Power Quality Parameters
PQP	Power Quality Parameter
P_{st}	Short Term Flicker Severity
RMS	Root Mean Squared
SCPS	Smart Control Power System
STLF	Short-Term Load Forecasting
SVM	Support Vector Machine
SVR	Support Vector Regression
THD	Total Harmonics Distortion
THD_i	Total Harmonics Distortion of Current
THD_u	Total Harmonics Distortion of Voltage
UV	Ultraviolet
V2G	Vehicle-to-grid
WS	Wind Speed
WT	Wavelet Transform

Chapter 1

Introduction

One of the important issues in our daily life is the electricity. All our devices that are used throughout needed to electric power to run. With of many different devices are used now as TVs, smart phones, wash machines, kettle, electric oven, lights, car passenger chargers, etc. Therefor the demand power became more consumed and more needed than before. In traditional power system to generating the demand power which are needed many of the fuel will consumed and addition increasing in the environment pollution and cost of the power generation. Nowadays for reducing the cost generation and air pollution, the renewable energies are used to generating the power. These sources are available free everywhere around the word, but these power sources are unstable. The challenge is to how producing a power with good quality from theses unstable source and became the focus of lots the researchers around the world.

1.1 Problem Definition and Motivation

At this times the electricity become one of the basic life requirements which needed to supply hold houses, factories, lighting of cities, etc. In traditional power plants use fuel to run the power generators which causes various pollutions. While in the modern power plants use renewable energies for generating the electricity, whether separately (off-grid system) or connected with external power grid (on-grid system), moreover generating electrical power as needed. It means power system should use renewable energies sources as much as possible, generating power as demand power. Therefor the power grid should operate by intelligence system. The challenge is to design an intelligence system which control power grid that producing a power and keeping the generated power at required limits of the power quality parameters as much as possible.
To build smart control model two main parts should consider: the main and difficult part is forecasting model and the second part optimization model. This thesis focuses on the first part, as can be seen in Figure 1.1

1.2 Goal of This Work

The main goal of this thesis is to design forecasting systems which contribute as a main part of the SCSs. The SCSs are needed when operate and control

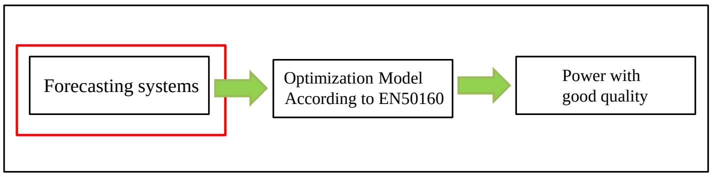

Figure 1.1: The thesis focuses on the main part which marked by red color

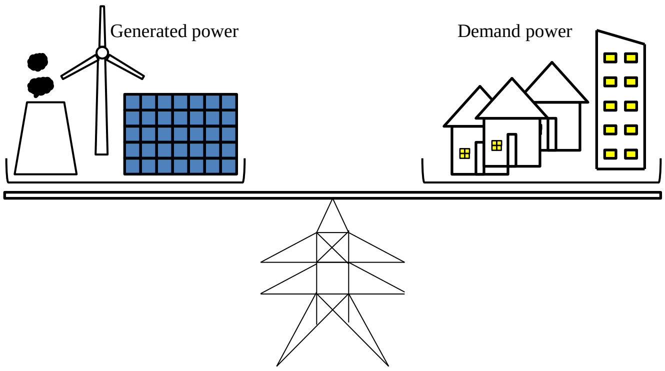

Figure 1.2: Power Grid Balance [1]. The balancing between the generated and consumed power, this is one of the main tasks of the distribution power system for producing power with good quality

power system especially with renewables.

Since power quality parameters are forecasted as power frequency, voltage THD, and flicker, then can shift the load to run in the switch time, this task will keep for producing a power with good quality. The important one of power quality parameters is the power frequency. For example- when the frequency power exceed the nominal value 50Hz [EN 50160] in this case, at same time can increase the equivalent load value that will cause the frequency to decrease to the nominal value. As can be seen in Figure 1.3 and Figure 1.4, that illustrated a simple example how to correcting the quality of the power.

The forecasted values of the power quality parameters will be used to find an optimal reconfiguration of the distribution power system. The reconfiguration of the distribution power system includes: moving household appliances to suitable runtime, changes in the power distribution switches, and turning on and off renewable electric power unit. These tasks will contribute to balancing between the generated power and demand power as much as possible.

In this thesis, for the purpose of design a forecasting system a different forecasting models using ANN, DT, SVM, LR have been already designed, tested, and published.

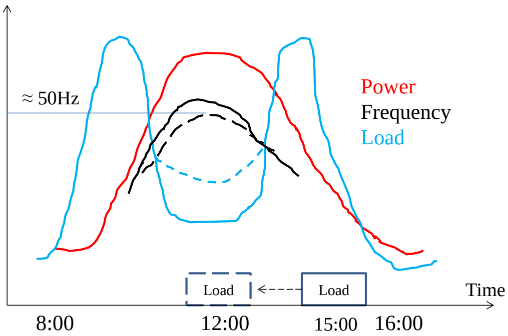

Figure 1.3: Power quality correction. Simple example shows how to correct the power frequency

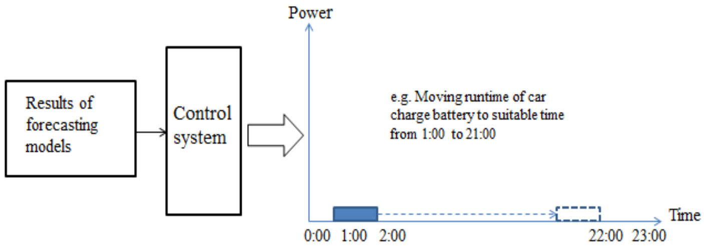

Figure 1.4: Moving home appliances to suitable runtime, which keeps the electric power at standard levels of power quality parameters as much as possible. For example moving runtime of car charge battery to suitable time from 1:00 to 21:00

This study presents sex chapters: in this chapter, we introduce the objective of this study, and define the problem. In the second chapter, we provide an introduction of the renewable energies and power quality parameters. In the third chapter explains the formal methods which used in this thesis such as ANN, TD, SVM, and LR. In the fourth chapter, we listed previous studies includes forecasting models, and reconfiguration the power systems. In the fifth chapter, we proposed methods that include designing forecasting models. In the sixth chapter, we lead a discussion and conclude this Ph.D. thesis.

Chapter 2

Renewable Energies and Power Quality

2.1 Introduction

Many types of renewable energies are naturally are available, such as tidal, water, wind, solar power. This study focused on solar and wind power. At present, renewable energies: as solar and wind power are used for generating electrical power as alternative free and clean power sources. Can build a power system from a wind turbine or solar panel, or from both together. It can in a small scale at consumer's homes, or in a large industrial scale according to the desired purpose. Using renewable energies as alternative power source helps to reduce the cost of energy generation and to reduce environmental pollution.

2.2 Off-Grid System

An off-grid system works independent on the external power grid. An off-grid system is designed and used to generate electrical power as an alternative, clean and free power source. It can also help customers when they are distant from the external power grid, and it is expensive to connect them to that distant external grid [2]. In general, Off-Grid Power System consists of the following main parts- at least one renewable energy generator, such as a power photovoltaic device or wind turbine, battery storage, converter, control unit, and is connected to the load, such as home appliances. An off-grid may also have an optional diesel generator to provide power on demand and charge the battery, or in case the weather conditions are unfavourable for a long time [2], [3]. Figure 2.1 illustrates an example of Off-Grid Power System built at VŠB-Technical University of Ostrava. It consists of the following components- two photovoltaic systems on the roof and tracker, battery system, control charger, inverter, weather station, and load home appliances. This system was used to supply the home appliances, such as LCD TV, lights, kettle, etc. At the same time, meteorological data and power load data were recorded to be used in this study.

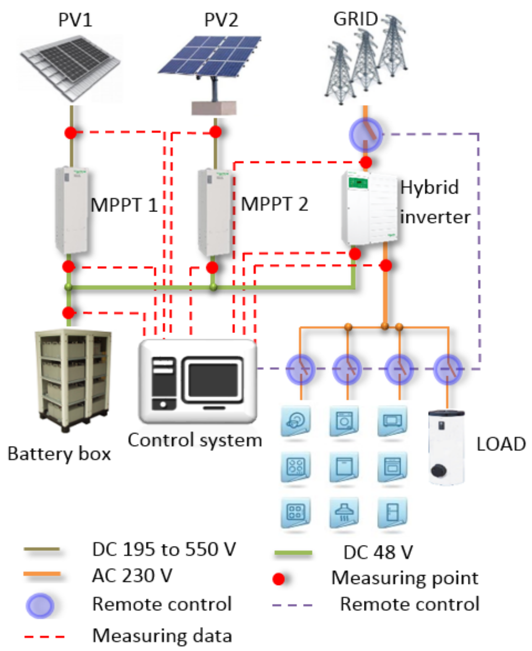

Figure 2.1: An example of off-grid power system built at VSB-Technical University of Ostrava. The system in normal operation works as off-grid system. In case the weather conditions are insufficient to generate the demand power and the battery is low, the system connects to the external grid which will works as on-grid system

2.3 Power Quality

2.3.1 Introduction

In general, the electrical and electronic devices are designed to run with specific range of power supply which defines the RMS limits of lower and upper for frequency and voltage. The power quality is purely defined as an interaction the electrical power with electrical appliances, or the ability of source power system to provide a constant and regular power flow as a regular power supply. It means any problem which can occur in the frequency, current, or in voltage, which cause failure in consumer devices [2]. For example, when the power grid is connected with consumers and electrical devices work without electrical damage, we can call the PQ good. Otherwise when electrical devices get damaged the PQ is low [2] [4]. Modern electrical and electronic devices are very sensitive and require a constant voltage and frequency. For example, suppose we a have light bulb 200 watt needed 220 volt to generate desired light. If the voltage of power supply goes down about 200 volt the light bulb still works but with low light efficiency. If the voltage increases about 240 volt the bulb produce more light than designed value causing overheating and stress of the bulb. So every change in voltage of power supply either by increase or decrease than designed value changes bulb efficiency. The voltage must be stable at designed value so to keep the bulb at desired efficiency and designed life. The low power quality causing result in lost production, damaged in electrical devices, and early defuse of electrical and components devices. PQ is an important matter for electricity users either in industries or in household appliances.

2.3.2 Power Quality Parameters

Power quality is estimated using power quality parameters according to a specific standard range. There are a number of such parameters- Harmonics, Power frequency variations, Voltage and Current unbalance, Transients, Flicker, Voltage Sag or Voltage Dip. But the important parameters are used in the most cases are magnitude of the supply voltage variations, power frequency, harmonics [EN 50160] which are in the centre of attention in this study.

- Harmonics

  Harmonics in the power system are frequencies of current or voltage which results of multiples fundamental frequency of the power with a integer.

  The waveform is not affected when the load linear, but in non-linear load the current consumption in a nonlinear manner which cause a change in the current waveform away from the sinusoidal form, for this reason changing in voltage waveform can occur accordingly.

  Total Harmonics Distortion (THD)

  THD is term uses to determine the distortion in a waveform signal which caused by harmonics. For example, if the fundamental waveform was about 50Hz, then the second, third, and fourth harmonic components will be equal to 100Hz, 150Hz, 200Hz, and so on.

  THD for voltage and current can describe by following equations:

  $$THD_u(\%) = \frac{\sqrt{V_2^2 + V_3^2 + \ldots + V_i^2}}{V_1} \times 100 \tag{2.1}$$

  $$THD_i(\%) = \frac{\sqrt{I_2^2 + I_3^2 + \ldots + I_i^2}}{I_1} \times 100 \tag{2.2}$$

  Where V_i, I_i are individual Harmonic of order i, V_1, I_1 are fundamental Harmonic (first harmonic) which has standard value of range from 50 to 60Hz.

- Voltage Drop (Variations).

  Voltage Variations: is changing whether increase or decrease in the voltage of the power system from designed nominal value for short time.

  Sag is decrease in RMS voltage from nominal value by 10 to 90% for short time (from half cycle to one minute).

  Swell- is increase in RMS voltage than nominal value by 10 to 80% for short time (from half cycle to one minute).

- Frequency.

  Frequency Variations: The Frequency Variations it means changing in the fundamental frequency of the power system from standard value (50 Hz) [EN50160]. Or by other meaning changing in the power frequency either less or more than nominal standard value of the frequency power supply, which causes the irregularity of the work of the customer devices efficiently, and perhaps the failure of these devices.

- Flickers.

  Voltage Flickers. is fast and random change in the voltage power which causes a rapid change in the light levels which can be detect and visible by human eyes. It means a change in the amplitude of the voltage power which can be seen and recognized in the surroundings. The flickers in power system can be measured and estimated by two main parameters-perception short term (P_{st}) and perception long term (P_{lt}), or short term flicker index, and long term flicker index respectively [5].

  In (P_{st}) the flicker severity estimated for short time interval about minutes, while in (P_{lt}) it estimated for long time interval about hours [EN 50160].

$$P_{st} = \sqrt{0.0314P_{0.1} + 0.0525P_1 + 0.06574P_3 + 0.028P_{10} + 0.08P_{50}} \tag{2.3}$$

$$P_{lt} = \sqrt[3]{\frac{1}{12}\sum P_{st}^3} \tag{2.4}$$

Table 2.1: Power Quality Parameters

Type	Standard Level	Cause	Possibility problems occur
Voltage variations	230 ±10 V	78.00%	76.50%
Frequency	49.5 - 50.1 Hz	———	78.00%
THD	For voltage 2%	85.52%	84.76%
Flickers	$P_{lt} \leq 1$	98.00%	90.00%

Chapter 3

Formal Methods

3.1 Introduction

This chapter contains a brief mathematical description about the mathematical techniques used in my experiments and my publications to design my proposed approach includes- Linear Regression, support vector regression (SVR), Artificial Neural Networks, and Decision Tree (DT).

3.2 Clustering

The main idea of clustering is grouping the original data set into groups or clusters. In this study, samples are clustered into several groups, followed by the extraction of new features space by measuring the distance between the samples and each group centre. New features space is fed into the next-stage forecasting models. In this study, K-means and K-medoids clustering were used and compared.

3.2.1 K-means Clustering

K-means [6] is one of the basic unsupervised learning methods for data analysis by grouping the data samples. The main idea is to measure the distance between the centre points and data points, and to assign every data sample to one cluster of minimum distance. In K-means, the following equation for Euclidean Distance is used [7].

$$d = \sqrt{\sum_{i=1}^{n} (c_i - x_i)^2} \tag{3.1}$$

where n is the number of the features in each sample.
K-means may be understood as follows:

- Choose a random number of samples considered as centroids.
- Calculate the distance between a sample and each centroid.
- Allocate each sample to a unique cluster that is closer in distance.

- Update the centroids via making the average of each assigned sample.
- Repeat the steps from step No. 2 till no sample changes.

3.2.2 K-medoids Clustering

K-medoids Clustering [6] is a modified version of K-means algorithm. K-means and K-medoids divide the data set in different groups.

K-medoids work in the following steps:

- Select a number of samples which represent the medoids.
- Compute the distance between all the samples and centres of medoids.
- Assign the rest of the samples to a closer cluster.
- Random choose nonmedoids sample o_{new}
- Determine the cost (T) of swapping o_{old} with o_{new}, $T =$ new total cost $-$ old total cost. Then change o_{old} with o_{new} if the swap reduced the total cost.
- Repeat the steps from step No. 2 to 4 till no sample changes [7].

3.3 Linear Regression (LR)

Linear regression (LR) [8] is an approach for modelling the relationship between a scalar dependent variable y and one or more explanatory variables (or independent variables) denoted X. The case of one explanatory variable is called simple linear regression. For more than one explanatory variable, the process is called multiple linear regression. LR can be used to fit a curve between patterns of data, or to predicted one value variable from input variables. The relationships are modelled using linear predictor functions whose unknown model parameters are estimated from the data. Such models are called linear models [9]. The general form LR is

$$Y' = BX + A \tag{3.2}$$

In Equation (3.2) Y' denoted predicted value or dependent variable, X is independent variable, B is line slop, and A is intercept of Y axel. The values B and A are calculated in training phase from training data set. Afterward we can use the obtained equation to predict new value Y'.

For multiple LR the process will find a curve which represents all data samples as possible as following equation

$$Y' = A + B_1X_1 + B_2X_2 + \ldots + B_nX_n + \epsilon. \tag{3.3}$$

Where $X_1, \ldots, X_n$ are independent variables (features) of the dataset.

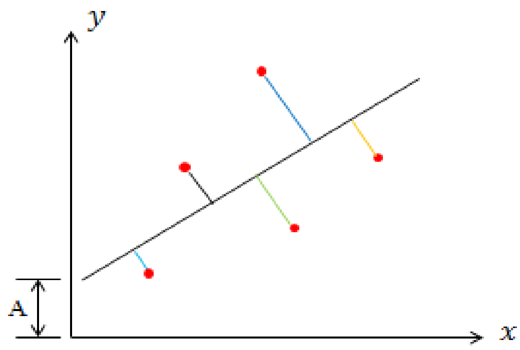

Figure 3.1: Simple linear regression model with actual data set and intercept of Y axel (A)

3.4 Support Vector Machines (SVM)

Support Vector Machine (SVM) for classification simply finds the best line which tries to separate data samples which belong to Two classes. In SVM for regression, the algorithm attempts to fit the best line of data samples which minimizing the error of cost function. This process can be done using an optimization method which deals data points of the training set that near to the line with the minimum error of cost function. These data samples which near to the line called support vectors.

We assume a data set with samples $(x_1, x_2, \ldots, x_m)$ and corresponding output values $(y_1, y_2, \ldots, y_m)$, where $x_i \in \mathbb{R}^n$, $y_i \in \mathbb{R}$. The basic concept of SVR is find a function $f(x) = wx + b$,

which estimate the values of output y. The best hard SVR model can be found by minimizing amount of $\frac{1}{2}w^2$ subject to

$$Y' - \langle wx_i - b \rangle \leqslant \epsilon. \tag{3.4}$$

$$\langle wx_i - b \rangle - Y' \leqslant \epsilon. \tag{3.5}$$

where $i = 1, 2, \ldots, m$, is the number of samples. As can be seen in Figure 3.2, there are hard and soft regression SVM whether linear or nonlinear, more details about that can found in [10].

3.5 Artificial Neural Networks (ANN)

Artificial neural network is a computation process which tries to mimic biological nervous systems that can learn from examples. NN constructed of a large number of neuron which connected in way to solve a specific problem such as pattern recognition, classification, forecasting, and so on. These neurons organized in three layers- input layer, hidden layer, and output layer. The neurons connected

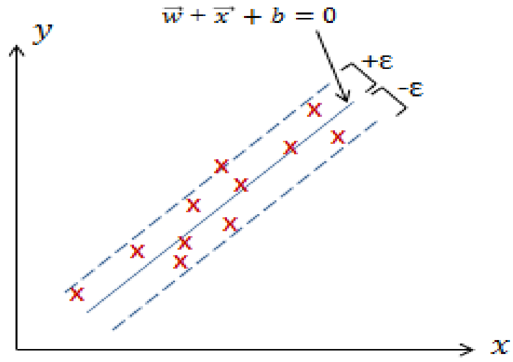

Figure 3.2: Hard Margin Support Vector Regression

of each other via weights, in learning phase the network tries to modify these weights to minimize the error between target output and network output till the network learned all of training examples. More details about ANN can be found in [11]. Figure 3.3 illustrates using NN for forecasting wind speed in our experiment. In our experiments we utilized Feedforward neural network (FfNet) and Function fitting neural network (FitNet) from Matlab Neural Network Toolbox.

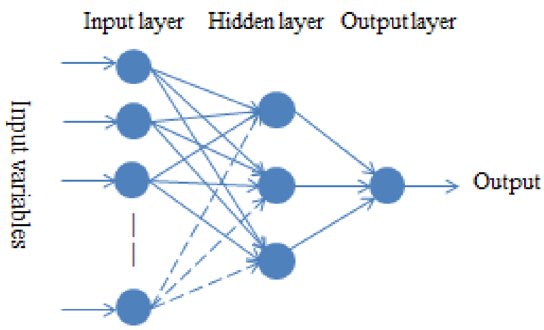

Figure 3.3: Example of ANN structure

3.6 Decision Tree (DT)

Decision Tree (DT) is supervisor learning, and the powerful technique has been used successfully in many applications for classification and regression purposes. The basic working principle of the decision tree is the same, whether for classification or regression purpose. In classification tree, the target output is classes (as yes, no, and so on) but in Regression Tree the target output is value numbers (as wind speed, price, and so on), more details about classification tree can found in [12].

In regression tree, each of features is handled as the independent variable later used to fit regression modes with the residue of the independent features. Data samples are splits for all independent features. In each split node computing the error between target and forecast output, then calculating the sum of squared error (SSE), the point with the minimum value of SSE is selected as a root node. By the same way, the process is repeatedly continued. In regression tree, the standard deviation is used instead of information gain which is used in classification tree to make decisions. More information about regression trees can be found in [13].

In this study, we used Microsoft Excel and MATLAB to design and run the experiments. Microsoft Excel used for cleaning and preparing the data set. MATLAB used for designing and creating the proposed forecasting models.

Chapter 4

Related Works

4.1 Introduction

There are many studies which focus on the designing and construct of smart control systems to control and operate power systems using different models. This section includes some previous studies related to the main part of this thesis is designing of forecasting systems in renewable energies, in the power load and in power quality parameters. As well includes other studies related to optimization of power flow or reconfiguration of power grids. All these tasks aim at the same goal of supplying users with power of good quality.

4.2 Wind and Solar Power Forecasting

There are many studies which used and designed different models to forecast wind speed and solar energy: in [14] proposed a method based on genetic programming with Fuzzy Logic, the proposed method was applied on solar data collected from the Czech Republic for the purpose of forecast output power from photovoltaic. The study mentioned that, the simulation result was reassured. A model to predict wind energy based on two stages: in the first stage they used wavelet decomposition with adaptive wavelet neural network (AWNN) to forecast speed of wind, in the second stage a feed forward neural network (FFNN) was used to convert the predicted wind speed into predicted wind power. The results of predicted wind power, confirmed the efficiency of the proposed method [15]. In [16] proposed and applied support vector machines (SVM) for forecasting power output of photovoltaic (PV) based weather conditions. The results confirmed the ability of the proposed model for the estimation of output of PV. Used statistical feature parameters with a neural network to forecast short time solar irradiance based temperature and irradiance data. Their model has been tested on different weather conditions, when compared the predicted value with measured value. The results proved the efficiency of the proposed model [17]. Applied Fuzzy sets with neural a network for solar irradiance prediction for various sky and temperature conditions. The irradiance predicted result of their proposed method was more accurate than other compared methods [18]. In [19] applied weighted support vector machine (WSVM) to predict short time photovoltaic power output. The simulation results of their model show the accuracy of the model and also better than ANN. In [20] proposed a technique for wind speed prediction, the planned method combined of wavelet transform (WT), with support vector machine (SVM) and Genetic Algorithm (GA), WT used to decompose the signal speed, GA used to evaluate and adjust the weights of SVM, SVM to predict wind speed. Their method was compared with others and was accurate for wind speed prediction. A combined wavelet transform (WT) with RBFNN neural network to predict photovoltaic power based on irradiance and temperature data designed in [21]. The experiments results proved the accuracy and efficiency of the proposed model. Forecasting energy productions of photovoltaic for times of 15 minute, 1 hour and 24 hours ahead using AAN and support vector regression (SVR) and compared their results have been proposed in [22]. The proposed approach was evaluated using statistical errors. The simulation results showed that, the proposed model exceed other classical methods. A proposed of Physical Hybrid Artificial Neural Network (PHANN) for ahead predicting of output of photovoltaic system was investigated in [23]. The results of the proposed approach were compared with standard ANN which proved the accuracy of proposed method than standard ANN. Least Square (LS) Support Vector Machine (SVM) has been used for solar prediction based on atmospheric data: humidity, wind speed, and sky cover. The simulation results showed that, the proposed model was better than others such as Autoregressive (AR) model and Radial Basis Function Neural Network (RBFNN) model. This proposed model was suggested in [24]. Wind speed forecasting using support vector machines was applied in [25]. The forecasting result of the proposed model outperformed back propagation algorithm and has minimal value of mean absolute error and mean square error. The combination of statistical model with neural network to predict hourly wind speed is planned in [26]. The simulation results proved that, the performance of the planned system was better than other present predicting methods. In [27] designed a forecasting of the output of photovoltaic using neural network trained with extreme learning machine algorithm. The experimental results showed that the proposed system can forecast photovoltaic power with high efficiency. Forecasting monthly mean of global solar radiation using Support Vector Machine (SVM) with Firefly Algorithm has been applied in [28]. The input features used are maximum temperature, minimum temperature, and sunshine duration. The result of proposed model was compared with other existing systems which proved the efficiency of their method. In [29] combining of empirical mode decomposition with elman neural network to predict wind speed. The forecasting results of the proposed approach was better when compared with other models, also the study conclude that the proposed system is appropriate for wind speed forecasting. Merging Wavelet decomposition and neural network to build an accurate hybrid model to predict short term wind speed was designed in the article [30]. Wavelet decomposing used to decompose Wind speed, and ANN optimized by crisscross optimization algorithm used to predict wind speed. The proposed system archived minimal mean absolute percentage error when compared with other hybrid methods. In [31] designed hybrid system to forecast wind speed, this model was constructed of improved empirical mode decomposition and Genetic Algorithm-BP neural network. The proposed model was tested and evaluated using a dataset collected from China. The simulation results demonstrate that the designed system was better than standard GA-BP neural network. Wind speed prediction using wavelet transform combined with neural network have been proposed in [32].

The proposed system was trained using: wind direction, temperature, pressure, humidity, and wind speed. The result proved the efficiency of the model for wind speed forecasting and takes less computation time when compared with backpropagation ANN. Combined neural network with wavelet transform for solar prediction have been designed and applied in [33]. The forecasted values of solar radiation were higher when compared with traditional ANN. In this article [34] designing forecasting photovoltaic power using wavelet transforms (WT) and neural network. The proposed method used WT to decompose and reconstruct power of PV which used as target output of ANN, where the meteorological data where used as input variables of NN, the results proved the activity of the designed system and needed less computation time when compared with other traditional methods. In [35] designed a model for short term wind power forecasting based on adaptive neuro fuzzy inference system (ANFIS) in China. The designed system was composed of two ANFIS stages: the first one for forecasting wind speed using meteorological data, while in the second one forecasted wind speed was used to predict wind power. Experiment results proved that the system was out-performed by other three existing models also with low time computation. Forecasting of short-term power generation from solar PV has been studied in [36], the designed system used wavelet transform (WT) for filtering and Fuzzy ARTMAP Network for power generation prediction, which was optimized using Firefly algorithm. The obtained results showed a higher efficiency of the planned mode than other of the tested models. The use of historical meteorological data for building a system for solar power generation forecasting using a least absolute shrinkage and selection operator (LASSO) was introduced in [37]. The results proved the activity of the system with little training data samples compared with two other existing approaches. Developed two models [38]: a fuzzy logic and ANFIS systems for predicting the solar irradiation, and the systems were tested and validated. The results confirmed the validity of the designed systems. In 2020, a hybrid model of a gated recurrent unit (GRU) neural network with an attention mechanism have been used for solar irradiance forecasting, designed in [39]. The planned model tested for all year seasons, and outcome of the system was compared with other traditional models. In [40] used direct explainable neural network: which consisting of one input layer, two linear layers and one nonlinear layer, for predicting solar irradiance. The model has been investigated using a data set of Lyon in France. The simulation results confirmed the performance of the planned system. A designed two systems: an ANN and a recurrent neural network (RNN) for solar radiation forecasting, and compared their results to each other investigated in [41]. The experimental results, shows the RNN model was improving the forecasting accuracy by 47% improvement in Normalized Mean Bias Error (NMBE), and 26% improvement in root mean squared error (RMSE), and the forecasting results was improved when using moving window algorithm.

4.3 Power Load Forecasting

Among the many published papers using and combining various types of techniques with the purpose to design models for electrical load forecasting. The load forecasting models seek to determine relations between the power load and many factors affecting it, such as air temperature, humidity, types of days, previous load, etc. In 2009, a back propagation neural network with rough sets for power demand forecasting proposed in [42]. The system was compared with standard BP and in general the performance of BP with rough sets was better than standard BP. In [43] applied the Feed Forward Neural Network (FFN) and Recurrent Neural Network (RNN) with deep learning for short period power load forecasting, using a dataset collected from New England for the period from 2007 to 2012. The model was tested for two cases: the first case time domain features were used, while in the second case both features from time and frequency domains were used. The evaluated system using MAPE, RMSE and MAE errors, which rendered lower rates in the second case than in the first one, and the accuracy of the model were improved in the second case. An applied ANN with wavelet decomposition was designed in [44]; the experiment results showed the efficiency performance of the proposed system, which exceeded ANN. Electrical load forecasting using advanced wavelets with neural networks was proposed in the article [45]. The proposed system consists of four steps: load data decomposed into high and low frequencies using wavelet transform, feature chosen based mutual information, training NN for each component and testing the trained model. The model was evaluated for two data sets from Australia and Spain. The mean absolute percentage errors were 0.268% and 1.716% for the Australian and Spanish data sets respectively. In addition, the articles conclude that the system out-performed the other existing models. Using a dynamic Neural network to forecast the electricity load was studied in [46]. The proposed system was designed and tested using a dataset of the French Transmission System Operator. The simulation results proved the validation of the designed method. In the article [47] proposed the idea for using loads of identical days as the input variable of the combination from wavelet transform with a neural network to predict future values of the load. Designed an intelligent model for demand power forecasting, k-means for cluster data wavelet transform to decompose the data and finally ANN to forecast the final value of the power load carried out in [48]. In [49] used a Hybrid Monte Carlo technique for training a Bayesian neural network (BNN) for the purpose of designing a power load forecasting model. The designed system was compared with BNN trained using a La-place algorithm and ANN trained using a Backpropagation technique using MAPE and RMSE criteria. The experiments result proved the validity of the designed method for load forecasting. Combining the K-means clustering with ANN for load forecasting was studied in [50]. The experiments used k-means and k-medoids for clustering the original data into groups then measuring the distance between each sample and each cluster as new features which were fed into ANN. The results of ANN proved better than a decision tree when comparing the results using the MAPE criterion. The idea of using a bagged neural network (BNN) for load forecasting is proposed in [51]. The concept of BNN is dividing the data set into random parts, then training the neural network for each part, the average of the outputs representing the output of the model. The outcome of the proposed idea reduced the forecasting error when compared with standard ANN and other existing approaches. The concept of BPNN for power load forecasting designed in [52]. The idea was to optimize the network weights using a genetic algorithm faster than standard BPNN. The results showed that the proposed optimization algorithm improved the learning speed and the accuracy of the learning process. An extreme learning machine (ELM), regularized ELM (RELM) and ANN for electrical load forecasting, and comparing their performance was investigated in [53]. The outcome of the experiments confirmed that the RELM learned much faster than ANN and the forecasting accuracy of RELM was better than standard ELM. A hybrid model for short load forecasting was studied in this article [54]. The model has been constructed from improved empirical mode decomposition, an autoregressive integrated moving average (ARIMA) and wavelet neural network optimized by the fruit fly optimization algorithm. The MAPE of the models forecasting results was improved and is about 0.82% higher than other compared systems. In the USA, designed a one day-ahead system for power load forecasting. The designed system constructed in three stages: pre-processing, in this stage removing unwanted samples, the forecasting stage using ANN, and the optimization stage for minimizing the forecasting errors. The forecasting accuracy of the system improved in comparison with other models [55]. In [56] introduced a hybrid system for electricity forecasting. The model is constructed as follows: empirical mode decomposition, minimal redundancy maximal relevance, neural network for regression with the fruit fly optimization algorithm. The simulation results of the model proved the validity of the system in STLF. In Spain, a short-term load forecasting model was designed using three stages: SOM maps used for pattern recognition, k-means for clustering the patterns, and ANN to predict the power load. The methodology has been trained and tested using a data set from the Iberdrola company. The system has a small error when compared with others [57]. Short-term weekday power load forecasting was proposed in [58]. The paper compared ANN with different learning algorithms. The best results were obtained when using a Generalized Neural Network with wavelet transform that was trained using an adaptive genetic algorithm and fuzzy system. In Canada, El-Hendawi and Wang designed a method for short-term demand power forecasting. The method combined the full wavelet packet transform with neural networks. The designed system decreases the forecasting error by 20% when compared with standard neural networks [59].

SVM is a powerful tool for classification and regression purposes. SVM was applied and used by several researchers in the area of power load forecasting, whether alone or combined with other techniques to improve the forecasting accuracy. In [60] designed a prediction system to predict demand power using a wavelet transform with least squares SVM (LSSVM) with the optimization factors of LSSVM using a cuckoo search; the results of designed system were compared with other various methods of SVM, which proved the efficiency of the introduced model. An annual power load forecasting system of based SVM, which was optimized by particle swarm optimization was introduced in [61]. The proposed approach was trained and tested using data of the city of Beijing city for the years from 1978 till 2010. The simulation results proved the validity of the model for load prediction, where the MSE error was about 2.53%. In [62] designed an intelligent system for short-term load forecasting using wavelet least square SVM (W-LSSVM) combined with the DWT and inconsistency rate model (DWT-IR) for feature selection. The system was evaluated using RMSE and MAPE, which was about 0.019 and 1.83% respectively. It proved the activity of the model and out-performed other existing methods when the results were compared. Another study in [63] have designed a power load prediction method, which combined an ant colony optimization (ACO) with a support vector machine (SVM), ACO used for feature selection and SVM for load regression.

The proposed system was suitable for short-term load forecasting and surpassed other existing methods. The use of the large-scale linear programming support vector regression (LP-SVR) for STLF was studied in [64]. The studied model was compared against bagged regression tree, Feed Forward ANN and Large-Scale Support Vector Regression (LSSVR). The MAPE error of the LP-SVR approach was about 1.58% lower than from the other compared models. In [65] applied and tested a tree model of SVM for short-term power demand forecasting. Standard SVM, SVM optimized using Genetic Algorithm (SVRGA), and SVM optimized using a Particle Swarm Optimization Algorithm (SVRPSO). The outcome accuracy of the proposed mode when estimated for SVM, SVRGA and SVRPSO was about 97.67%, 97.82% and 97.89% respectively. The article concluded that the three models were highly active for STLF, but SVRPSO, and SVRGA consumed more time than standard SVM. A data set from Hubei SVM for short-term power load prediction was studied in [66]. The performance of the proposed approach was compared with traditional models: BPNN and the time series method. The MAPE error for SVM was about 1.91%, for BPNN it was 4.06% and for the time series it was about 4.47%. The capacity of SVM in STLF was better than others according to the simulation results. A combination of singular spectrum analysis (SSA), a support vector machine (SVM) and Cuckoo search (CS), was applied for power forecasting. Results of the proposed approach were compared with other studies, which confirmed the capability of the hybrid model in load forecasting [67]. A hybrid intelligent system was designed for STLF in [68]. The previous temperature and the wavelet coefficients of the previous load are used as input variables where the GramSchmidt (GS) was used for feature selection and SVR was used to predict the consumed power. The system was applied for both weekdays and weekend days. The hybrid system produced the best prediction accuracy when compared with others. In [69] designed a daily peak power load forecasting system. The load was decomposed using the complete ensemble empirical mode decomposition with adaptive noise, and modified grey wolf optimization and support vector machine used to forecast the final result of the load. The performance of the model was compared with various SVMs and ANN. The simulation results confirmed the ability and reliability of the designed system. The empirical mode decomposition (EMD) method and the support vector machine with the particle swarm optimization (PSO) algorithm were designed in [70]. The experiment was carried out in three forecasting parts, followed by a summation of the results of these parts as the final forecasting result. The experiment outcome demonstrated that the proposed example was effective when compared with other existing formations of SVM.

There are a huge number of studies which used various kinds of decision trees to estimate the demand power. Using a random forest decision tree for demand power forecasting was designed in [71]. The proposed method was tested on a dataset from Poland. The performance of the system was highly accurate when compared with the results of other current methods. The REPTree Decision Tree for power load forecasting is applied and tested in [72]. The designed system was compared with standard and other decision trees which proved the validity of the proposed system for predicting the power load. In [73] designed a decision tree to estimate future demand power for short-term periods. The input features were weather data and power load, while the current load was used as the output of the system. The outcome of the experiments showed the validation of DT for power load forecasting. The use of generalized minimum redundancy and maximum relevance (G-mRMR) for feature selection and random forest for short-term demand power forecasting is studied in [74]. Results showed that the G-mRMR can capture important features for STLF, plus the forecasting results were better than other tested existing patterns. In Tunisia, one day ahead of one-hour step for short-term power demand prediction using a random forest technique was studied in [75]. The article concluded that the designed system was fast and did not need any improvement in the approach. In 2018, [76] designed two stages to predict daily power load: a moving average method and random forest, and the predicted result was evaluated using time-series cross-validation. The results of the proposed model outperformed others when comparing the results, which proves the validity of the proposed model. In Spain four models of regression trees (bagging, random forest, conditional forest and boosting) have been designed and tested for power load prediction using the data set of a campus university in Cartagena [77]. The temperature, calendar information and types of days are used as predictors to improve the performance of the model. The designed system has been tested for special and regular days. In southern China, used the days average humidity, average temperature, humidity average of the first three days, temperature average of first three days and historical load at same moment of the first days. The used factors were input variables to predict the load using a Gradient Boosting Decision Tree. The forecasting accuracy was evaluated and compared with other current systems. The compared result proved the validity of the designed method for load prediction [78].

Linear regression for STLF and its various types have been used and studied by many researchers. In [79] have constructed a system for power load prediction as follows: a whale optimization algorithm to detect and choose the appropriate level of the wavelet decomposition, discrete wavelet transform to decompose data into detail and approximation signals and a multiple linear regression technique to predict the final result of the load. The proposed scheme was tested for weekdays and holiday days for all seasons and produced a low forecasting error when compared with different models. Another study in [80] designed multiple linear regression for load forecasting. The experiments were made for both the dry and rainy seasons. The MAPE error between the actual and forecasted values was about 3.52% and 4.34% for the dry and rainy days respectively. An article applied multiple linear regression on a big data set to find the relation between weather conditions and demand power. Multi-core parallel processing is used to deal with big data. The MAPE error of the system was about 3.99% and the implementation time was faster than the other existing models like ANN [81]. Improving the accuracy of the STLF based combining clustering K-nearest neighbour (K-NN) and K-means with multivariate linear regression was studied in [82]. The used input variables are: Max and Min temperature and the previous power load. The MAPE of the combined model was about 3.345%, i.e., better than multi-linear regression.

There are many studies which used and designed fuzzy models for power load forecasting. The main and basic idea is converting the input crisp values into fuzzy values or membership degree (fuzzification), such as air temperature, wind speed and so on. The same procedure is used for the target output (power load). Next, the fuzzy inputs pass the inference engine which include several fuzzy rules (if - then) to make decisions. The last stage is defuzzification to convert the output of the inference engine from a fuzzy to crisp value, which will represent the forecasted power load. Fuzzy sets and their different configurations have been used successfully by several researchers for load forecasting fields. For example, the use of fuzzy logic and an adaptive neuro fuzzy inference system (ANFIS) for short-term load forecasting has been applied in [83]. The system has been tested and compared with other systems where the MAPE error was about 2.1% and 1.85% for fuzzy logic and ANFIS respectively, which confirmed the validity of the proposed model. Short period load forecasting using fuzzy control in Jordan has been designed in [84]. They used the previous day load, previous week load, previous day temperature, forecasted temperature, weather and index day, which is classified as a weekend or workday. The results confirmed the validity of the system for demand power forecasting. A new type of reduction (TR) based on an artificial neural network (ANN) of an interval type two fuzzy logic system (IT2FLS) for power load prediction was proposed in[85]. The paper compared the result of the planned system with 5 conventional TR. The numerical results show that the performance of the designed model outperformed IT2FLS with traditional TR. An article [86] applied IT2FLS for short-term load forecasting. The input variables used are: lagged power demands, meteorology data and calendar information, where the genetic algorithm was used for training the system. The simulation results proved the validity of the IT2FLS for STLF problem, which out-performed the type 1 fuzzy system and ANN. Power demand prediction using a fuzzy logic system was applied in [87], where the temperature, similar previous day load and time are used as input variables. The forecasted and the real load were compared, where the error ranged between about $+2.69\%$ and -1.88%. An extreme learning machine (ELM) algorithm for training IT2FLS of the purpose of designing a power load forecasting model was designed in [88]. The data set used in this experiment is taken from the Australian National Electricity Market and Ontario Electricity Market. The performance of the proposed system was compared with the performance of ANN, ANFIS and IT2FS, which was trained using a KF algorithm. The Empirical results showed and confirmed that the designed model works better for load forecasting and it out-performed the other compared systems. Another study in Indonesia used IT2FLS to design a model for load forecasting. The system tested using the data sets of 2005 and 2006, where the MAPE error was about 1.0335% and 1.5683% for the years 2005 and 2006 respectively. This study also concluded that IT2FLS can solve load forecasting problems better than standard fuzzy logic [89]. Analysing demand power prediction using a fuzzy logic system was introduced in [90]. The input variables used are temperature, humidity and wind speed while the power load was used as the target output. The model was tested for different numbers of days: holidays and working days. In 2016, a study designed a model for demand power forecasting based on fuzzy sets. The model used three parameters as inputs: temperature, time and previous day load. The MAPE of the model was about 6.17%, as well observed that the most significant weather parameters affecting the power load was the temperature [91]. A fuzzy model for hourly load forecasting for different days has been designed [92]. Time and day type (workday, weekend or holiday) were used as input variables. The results of the suggested model were satisfactory.

They also concluded that the model could not deal with any sudden changes in the load. In Iran, an article used a data set measured from Iran and a locally applied linear model tree for training the Takagi-Sugeno-Kang neuro fuzzy model. The model has been used to analyse short-term power load forecasting. The local linear model tree helps to set up the parameters and build a flexible neuro fuzzy [93].

4.4 Reconfiguration Power System and Power Quality Parameters Forecasting

There are many studies focusing on Reconfiguration Power System using different techniques. In the following listing some methods were designed for the reconfiguration of distribution power system which will keep generated power equal to consumed power as well keep the generated power at required power quality parameters. For example, in [94] designed a multi agent system (MAS) for the reconfiguration and restoration of distribution power system. The designed model was built using an artificial immune system. The proposed system was tested and the experimental results proved the ability and efficiency of the proposed method for reconfiguration power system. Another study has designed a model for the reconfiguration of power system using a genetic algorithm (GA). The simulation results of the proposed system showed that the GA can deal with reconfiguration of distribution system, and it can be used to set a switch process program. And the results were promising to reduce the power loss as well increase the reliability of the power system [95]. Reinforcement Learning (RL) technique has been applied in [96] for control power distribution grid (DG). RL algorithm was used for choose the best branch which will flow the power, this will help in minimizing the power loss. The system was able to control and set DG better than other approaches when comparing the performance. In [97] applied and proposed MAS for restoration power distribution system after an electrical defect. The system was tested under three different cases, which confirmed that the MAS are suitable for resetting power distribution system after electrical default. Refined genetic algorithm designed in [98], which applied for optimal switches setup of the power distribution grid. In [99] used a Binary particle swarm optimization (BPSO) algorithm to find a better configuration of the switches in the distribution power grid, in each cycle of learning the algorithm the reliability and the power loss are calculated. The model was successful when evaluated and tested using 32 bus and 123 bus distribution system. An article has applied Dynamic Fuzzy C-means (DFCM) clustering with 3-layers artificial neural network (ANN) for optimal reconfiguration power distribution system. The proposed approach implemented on IEEE 33 and IEEE 69 bus. The simulation results proved that the designed system took short computation time, simple design, and higher accuracy when compared with other traditional models [100]. Another article applied a multi agent model for restoration power distribution system after an electrical failure. The experiment extracted that the designed system can set the switches of the distribution system using local information, and it can be applied for complex and wide-range power networks [101]. In [102] designed a multi agent model for the reconfiguration of the topology of the power distribution network. The model was tested under two systems- 11-Bus and 16-Bus. The results demonstrated the validity of the system, which gave a good quality reconfiguration of the distribution network. Teaching learning based optimization algorithm was applied to determine the best reconfiguration of the distribution generation (DG), which will help in improving the voltage profile, voltage stability, and minimizing the power loss. The type was evaluated using two radial distribution system 33 bus and 6 bus, the effectiveness of the system was good when comparing the results for the same tested system [103]. In [104] designed a model for the reconfiguration of redial distribution system in fuzzy framework using a genetic algorithm. The designed model tested for 70 and 136 bus distribution power system. The experiment results compared with results of other methods which proved the validity of the system. Automatic reconfiguration of shipboard power distribution system using Q-learning was applied in [105]. The results demonstrated the validity of the designed system to find an optimal configuration of power system. Distribution system Reconfiguration using a mathematical mode with consideration some factors as load balancing, switching cost, and line loss minimization. The system was tested under three distribution system- 32, 70, 135 bus [106]. In [107] designed a system for optimal reconfiguration power system using whale optimization algorithm. The mode is estimated under different number of test bus and as well the results of the proposed system out-perform the results of other models when comparing the results. A study investigated three methods to find the optimal reconfiguration of renewable power distribution system- the harmony search (HS), bat-inspired (BA) , and cuckoo search (CS) techniques. The performance of three models was tested using radial distribution network with 33 node. The BA and the HS achieved better results than CS [108]. For reducing the electrical power losses, in [109] designed a model for reach optimal solution for reconfiguration power system using improved binary particle swarm optimization (IBPSO) algorithm. The proposed system was tested using 16, and 33 bus. The validity of the designed system was proved when compared the results of other models. In [110] applied catfish particle swarm optimization (PSO) to solve the feeder power network. The system was tested for 33 and 16 bus power network. The article as well concluded that the proposed mode is suitable method for distribution grid restoration. Applying Fuzzy multi-objective technique for the purpose of minimizing the active loss power and increase the power system reliability has been designed in [111]. Constructed system was tested for 70 notes distribution generation. The results showed that the system reduced the loss active power by 37.92%. For reducing loss power active and balancing load, in [112] introduced a method for optimal reconfiguration of the power distribution grid based on ant colony algorithm. The designed model was applied for two types of bus distribution system. Outcome confirmed the efficiency of the approach in finding optimal reconfiguration of power system. In [113] applied Modified plant growth simulation algorithm for reconfiguration distribution system which aimed to minimize the real power loss. The designed system has been applied and tested for radial distribution system with 33 bus. The outcome of this study confirmed the efficiency of this algorithm as well it can be applies in real time .

Many studies focused on power quality parameters forecasting in short-tem as power frequency and magnitude of the supply voltage such as following articles. There are a study used Arterial neural networks (ANN) for forecasting power frequency. The input variables fed to ANN to predicting power frequency. The planned model produced low forecasting MAPE error when compared with other traditional models [114]. Another study used Artificial Intelligence with Backpropagation Learning tool for forecasting power quality parameters (PQPs), and the model used as supporting off-grid system to produce power with good quality [115]. In [116] used optimized random forest to forecasting PQPs: frequency, voltage, THD, and flicker as supporting tool in off-grid platform. The forecasted results exceed 90% for 15 min time step. In China, an article applied to use cluster analysis, feature selection, and support vector machine for forecasting PQPs as harmonic distortion and voltage deviation. The article concludes that the relative error of results is improved significantly [117]. In [118] designed a model for forecasting voltage deviation. The model was constructed of PCA for dimension reduction, affinity propagation for grouping the input variables into groups, and back propagation neural network for predicting the voltage deviation. The MAPE where used to evaluate the results and was about 3.06%, the results of the proposed system was improved when compared with others.

Chapter 5

The Proposed Methods

In this chapter, I introduce the proposed methods. We have made some experiments on weather and power data for purpose of creating and testing forecasting models. Our goal is to find an efficient model for power quality parameters forecasting in short term as a main part of SCSs, which still remains challenging on global level.

The basic idea of the experiments is to find a relation between the input variables as weather condition and with one of power quality parameters (power frequency, magnitude of the supply voltage, THD_u, THD_i, and short term flicker severity). These experiments, and their results have been published in conference papers and scientific journals. They include:

- Jahan, I. S., Prilepok, M., Misak, S., Snasel, V. "Wind Speed Forecasting by regression Models." *Proceedings of the Dateso 2016 Workshop.*
- Jahan, I. S., Prilepok, M., Misak, S., Snasel, V. "Intelligent System for Power Load Forecasting in Off-grid Platform." *2018 19th International scientific Conference on Electric Power Engineering (EPE).*
- Jahan, Ibrahim S., Stanislav Misak, Vaclav Snasel. "Smart Control System based on Power Quality Parameter Short-term Forecasting." In 2020 21st International Scientific Conference on Electric Power Engineering (EPE), pp. 1-5. IEEE, 2020.
- Jahan, Ibrahim S., Vaclav Snasel, Stanislav Misak. "Intelligent Systems for Power Load Forecasting: A Study Review." Energies 13, no. 22 (2020): 6105.
- Jahan Ibrahim Salem, Stanislav Misak, Vaclav Snasel. "Power Quality parameters analysis in smart Grid platform." (2021). In the process review.

5.1 Wind Speed Forecasting using Regression Models

5.1.1 Data set

The dataset which we used was taken from the Centre for Solar Energy Research and Studies Tripoli- Libya (www.csers.ly/en) as can be seen in Figure 5.1. The captured data has been recorded for the whole month November 2015 every one minute. From the recorded data we choose the following values wind direction and speed, air temperature, air humidity, global radiation, and air pressure [119].

In our experiments we used following attributes to learn and test selected models. In time t we utilized wind direction Wd_t, air temperature Tt_t, relative humidity Rh_t, air pressure P_t, and global irradiation Gr_t. To these five current vales we added two measurements back for the past $t-1$, and $t-2$, for wind

speed Ws_{t-1}, and Ws_{t-2}, wind direction Wd_{t-1} and Wd_{t-2}, air pressure P_{t-1} and P_{t-2} , and global irradiation Gr_{t-1} and Gr_{t-2} .

The training and testing vector consist of following elements: $(Wd_t, Tt_t, Rh_t, Ws_{t-1}, Wd_{t-1}, Ws_{t-2}, Wd_{t-2}, Pt, P_{t-1}, P_{t-2}, Gr_t, Gr_{t-1}, Gr_{t-2})$. For training we used in the input the current measured wind speed Ws_t.

Figure 5.1: The Centre for Solar Energy Research and Studies: Tripoli-Libya (www.csers.ly/en). Data set used in the wind speed forecasting experiments taken from this Centre

5.1.2 Experiment Setup

This experiment has been done to forecasting wind speed based weather conditions using few selected models. The aim is to compare the selected four models. The experiment was run many times with different settings of selected method. We preformed five settings with LR model, one with SVM, two for NN and one for decision tree. All models used same data. The data description can be found in section 5.1.1. The model performance was evaluated using mean squared error (MSE), and mean absolute percentage error (MAPE)

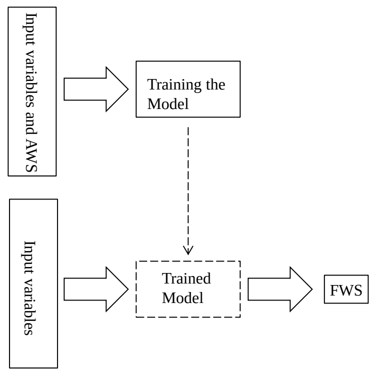

Figure 5.2: The experiment diagram of wind speed forecasting

$$\text{MSE} = \frac{1}{n}\sum_{i-1}^{n}(F_i - A_i)^2 \tag{5.1}$$

$$\text{MAPE} = \frac{100}{n}\sum_{i-1}^{n}\left(\frac{A_i - F_i}{A_i}\right) \tag{5.2}$$

Where A_i is the actual value: actual wind speed, F_i is forecast value: forecasting wind speed, n is the number of evaluated forecast values. MSE measures the average of the squares of the errors or deviations, the difference between the estimator and what is estimated. MAPE expresses accuracy as a percentage.

The experiment diagram is depicted in Figure 5.2. The diagram shows the scheme of forecasting wind speed model. The training the model is in the upper part of the figure. The model uses input variables and actual wind speed (AWS) described in Data set Section. The forecasting model is depicted in the bottom part of the figure. It uses the same input variables excluding AWS, and the output predicts forecasting wind speed (FWS). For each model we find the best combination of settings of models were implemented in Matlab toolboxes. In the linear regression model we evaluated the following model specification: constant model contains only a constant (intercept) term, linear model contains an intercept and linear terms for each predictor, interactions model contains an intercept, linear terms, and all products of pairs of distinct predictors (no squared terms), pure quadratic model contains an intercept, linear terms, and squared terms, and quadratic model contains an intercept, linear terms, interactions, and squared terms. The SVM and DT were used with standard configuration. For ANN FitNet, fitting neural network with a hidden layer, and FfNet, Feedforward neural network, we used one input layer, three hidden layers with 10, 4, and 2 neurons and the out layer.

All obtained results for all nine models and four prediction periods are summed up in Table 5.1 and Table 5.2. The prediction performance was evaluated using MSE and MAPE. We forecasted the wind speed for four following time 4, 8 12 and 24 hours. These time periods can be considered all middle and long terms prediction intervals.

Table 5.1: Wind Speed Prediction Results for 4 and 8 Hours Ahead

Model	4 hours prediction		8 houre prediction	
	MSE	MAPE	MSE	MAPE
LR Constant	3.1626	37.6082	3.1756	38.0709
LR Linear	0.3282	10.7470	0.3009	10.0924
LR interactions	**0.3135**	**10.0655**	**0.2920**	**9.5814**
LR purequadratic	0.3222	10.9760	0.2988	10.4888
LR quadratic	0.3195	10.5295	0.3089	10.5441
SVM	0.5662	16.7659	0.5326	15.9842
FitNet	0.4393	11.9273	0.4234	12.0511
FfNet	0.4324	11.9273	0.4308	13.2712
DT	0.5823	15.4267	0.5907	15.5128

Table 5.2: Wind Speed Prediction Results for 12 and 24 Hours Ahead

Model	12 hours prediction		24 houre prediction	
	MSE	MAPE	MSE	MAPE
LR Constant	4.2618	41.0187	3.6625	46.2635
LR Linear	0.4284	11.1261	0.4135	15.2689
LR interactions	**0.4020**	**10.8391**	**0.3928**	**14.1704**
LR purequadratic	0.4137	11.3224	0.4017	15.4776
LR quadratic	0.4183	11.6243	0.3957	14.3196
SVM	1.5502	20.6647	2.2201	36.5536
FitNet	0.9252	16.9117	4.2796	40.6134
FfNet	0.8438	16.1433	0.4620	15.9578
DT	0.7649	15.9241	0.6913	18.5174

5.1.3 Experiment Results

All obtained result for all nine models and four prediction periods all summed up in Table 5.1 and Table 5.2. The prediction performance was evaluated using MSE and MAPE error. We forecasted the wind speed for four following time 4, 8 12 and 24 hours. These time periods can be considered all middle and long terms prediction intervals [119]. The best results were obtained in all prediction intervals for LR with interactions model. These model has the lowest MSE and MAPE values. We got the best prediction for 8 hour period. The other models except LR constant had very similar results. For 4 hour prediction interval the MSE value varied between 0.2988 (LR pure quadratic 8 hours) and 4.2796 (FitNet 24 hours). The MAPE varied between 10.4888 (LR pure quadratic 8 hours) and 40.6134 (FitNet 24 hours). In general we can say, that for this data and selected model and they settings the best prediction period was 8 hours. The worst prediction performed LR constant model. But this was expected. The constant model is not suitable to fit or predict time series data with lots of changes well. The Figure 5.3 shows a comparison between AWS and FWS for the best linear regression and SVM model [119].

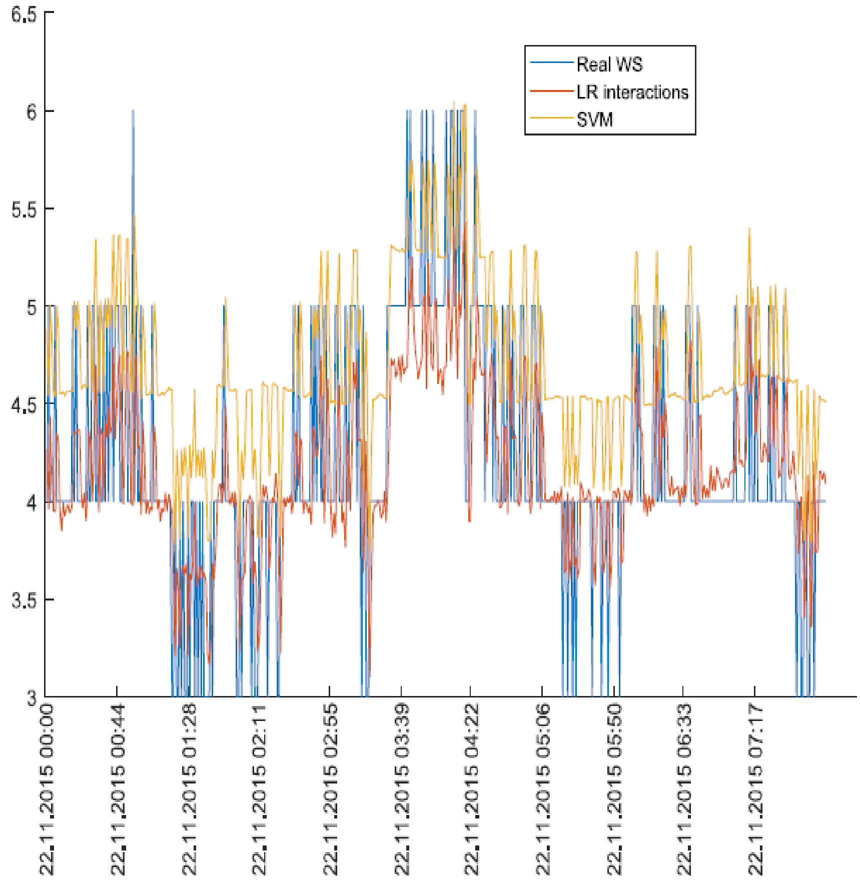

Figure 5.3: Wind speed results comparison: actual wind speed with forecasted wind speed by LR and SVM

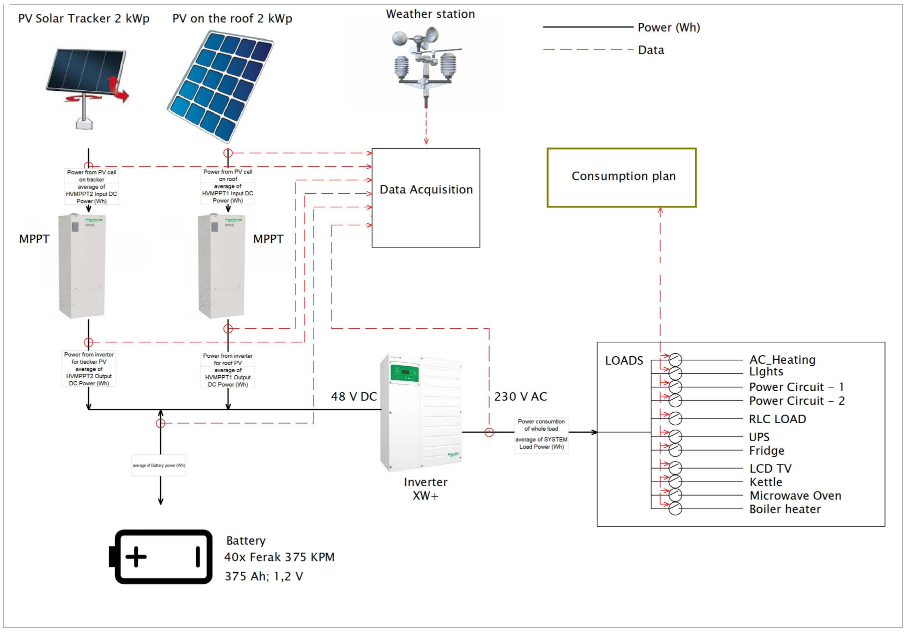

Figure 5.4: Diagram of the off-grid platform constructed at VŠB-Technical University of Ostrava used for the experiment

5.2 Intelligent System for Power Load Forecasting in Off-grid Platform

5.2.1 Data Set

The data set used in this article was taken from the off-grid platform constructed at the Faculty of Electrical Engineering and Computer Science at VŠB-Technical University of Ostrava, the Czech Republic. This data set includes several variables related to meteorology and power data. In our experiment, we used index day, normalized temperature, normalized humidity, wind speed, normalized pressure, and one, two, three steps back of power load. These are used as input variables, while the power load is used as the output. The data set used to train our model was from 23/05/2017 to 18/06/2017. In the testing phase, one-day ahead (19/06/2017) was used to test the model and predict the power load [50].

5.2.2 Experiments Setup

The experiments were carried out in three steps as follows. In the first step, the weather data were clustered into groups using K-means and K-medoids. In the second step, the distances between the samples and each cluster centre were measured using Squared Euclidean Distance. These distances represented the new features of the data set. In the third step, the new features were fed into the regression model with the smoothed actual power load for training the model. We applied the smoothing because the measured data come from one

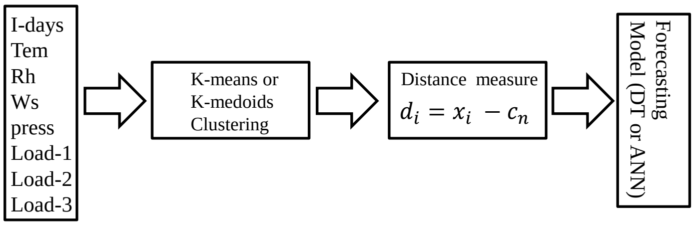

Figure 5.5: Diagram of the training phase for the proposed model. The used variables are: index of days, normalized temperature, normalized humidity, wind speed, normalized pressure, and one, two, three steps back of the power load, with actual load as target output. The same procedure is used in the testing phase, where only the input variables were fed into the model to produce the power load

household and contain rapid peaks which are generated by switching on and off devices with high load. The input power load was smoothed using a moving average technique. In the testing phase, only the distances are fed into the regression model to predict the load in the future time. The features used in this experiment are: index day - any working day = 1, weekend = 0, normalized temperature, normalized humidity, wind speed, normalized pressure, and one, two, three steps back of the power load, as can be seen in Figure 5.5. The experiments were carried out using four models: K-means with DT, K-means with ANN, K-medoids with DT, and K-medoids with ANN [50].

5.2.3 Results and Discussion

The results of the four models are compared using the mean absolute percentage error (MAPE). The results of MAPE values of K-means (with DT or ANN) and K-medoids (with DT or ANN) are listed in Table 5.3, Table 5.4, respectively [50].

The experiment was repeated with different numbers of clusters- 5, 10, 15, . . . , 50. The best results of K-medoids was achieved with 10 clusters combined with ANN, which was about 8.08%, as can be seen in Figure 5.6.

It shows the difference between the actual load and the output of the proposed model. In this study the numerical results of both DT and ANN in Table 5.3 and in Table 5.4, show that the ANN performance outperformed DT in load forecasting.

Table 5.3: K-means with DT & ANN for one Day Ahead

Number of Clusters	DT MAPE	ANN MAPE
5	163.00%	270.89%
10	46.74%	36.73%
15	263.77%	30.80%
20	185.47%	40.87%
25	261.72%	47.26%
30	221.17%	52.29%
35	464.30%	49.50%
40	142.56%	32.94%
45	745.15%	39.04%
50	458.09%	28.76%

Table 5.4: K-medoids with DT & ANN for one Day Ahead

Number of Clusters	DT MAPE	ANN MAPE
5	440.61%	47.95%
10	494.28%	8.08%
15	153.21%	29.23%
20	257.29%	27.38%
25	437.33%	30.31%
30	60.54%	31.00%
35	454.92%	39.50%
40	481.29%	38.20%
45	503.35%	36.60%
50	446.19%	29.04%

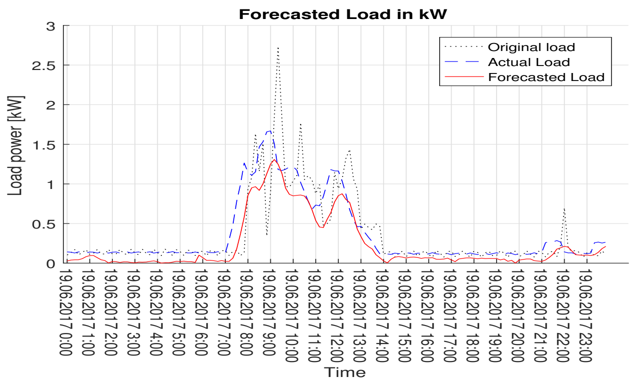

Figure 5.6: Power Load forecasting for 24 hours using K-medoids Clustering with Artificial neural network (where the original load is power load before smoothing, blue one is actual smoothed power load and red one is forecasted load)

5.3 Smart Control System based on Power Quality Parameter Short-term Forecasting

The proposed model has been constructed as five separate forecasting models. As can be seen in Figure 5.7, these models are- voltage, power frequency, total harmonic distortion of voltage (THD_u), total harmonic distortion of current (THD_i), and short term flicker severity (P_{st}) forecasting models. The forecasted values of PQPs can be used to schedule and find the appropriate time for the running of home appliances. This procedure will help towards improving the flow of good-quality power as efficient as possible. The experiments used a regression tree model to predict the target output (PQPs). The five models were designed using the same procedure: the input variables which are fed directly to a regression tree with target output of one of the power quality parameters [120].

5.3.1 Data Set

The data set of June and July 2019 are used in this experiments. They were obtained from the off-grid platform constructed at the Faculty of Electrical Engineering and Computer Science at VŠB-Technical University of Ostrava, the Czech Republic. This data set includes several variables related to power data, such as: magnitude of the supply voltage, power frequency, THD_u, THD_i, short term flicker severity (P_{st}), and status (on = 1, off= 0) of running load (as AC heating, fridge, light, TV). In addition, the data set includes weather conditions (as wind speed, air temperature, air pressure, UV steps, . . . , ect) at the same time step. The data set was available every one minutes as time step.

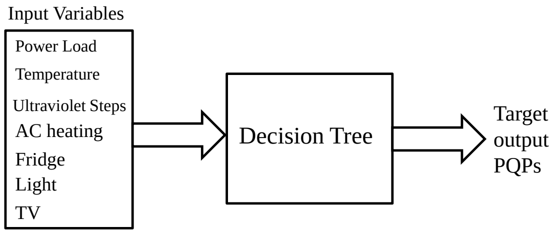

Figure 5.7: Diagram of The Proposed Model: PQPs Forecasting using DT. Input variables are: power load, temperature, UV steps, and home appliances status (1, or 0) with one of PQPs as a targot output

5.3.2 Experiments Setup

The used input variables are- power load, temperature, ultraviolet step (from 0 till 10 steps where each step represent intensity of the Ultraviolet), and status of home appliances (AC heating, fridge, light, and TV), as well PQPs as target outputs. The data set used in training the model is from 14 June till 5 July 2019, while we forecasted one day ahead, the day of 6 July was used to predict every one hour[120].

5.3.3 Results

The more significant power quality parameters are power frequency, magnitude of the supply voltage, THD_u, THD_i, and flicker (P_{st}).

The experiments were run many times for every model with different types of input variables, and the best forecasted results were selected, see Table 5.5.

The results of five forecasting models have been evaluated using mean absolute percentage (MAPE), and root mean square error (RMSE). As can be seen in Table 5.5 which depict the MAPE of all forecasted PQPs [120].

Table 5.5: MAPE Error for Five PQPs Forecasting Models

PQP Type	MAPE
Power frequency	5.4701×10^{-07}
Voltage	2.3×10^{-04}
THD_u	0.0253
THD_i	0.0176
Flicker (P_{st})	1.2279

The model was forecasted PQPs for one day ahead, in every one hour, it means 24 points were forecasted. The MAPE and RMSE errors were for power frequency 5.4701×10^{-07}%, 1.7487×10^{-05}, for voltage 0.0002%, 0.0189, for THD_u 0.0253%, 0.0267, for THD_i 0.0176%, 0.2416, and flicker (P_{st}) 1.227%, 0.529, respectively. The experiments noted that: the forecasted voltage was affected by power load and step of ultraviolet, the power frequency was very sensitive to power load and air temperature, THD_i was more affected by power load and type of home appliances, THD_u was slightly influenced by power load and slightly by the step of ultraviolet, and flicker (P_{st}) was slightly affected by power load and step of ultraviolet [120].

5.4 Power Quality Parameters Analysis in Smart Grid Platform

5.4.1 Experiments

In this study two models for PQPs forecasting have been designed, tested and compared: ANN and DT. The planned system tested for short-term period for each one day separately (one day ahead), and for two days together 7th-8th (two days ahead).

One day ahead forecasting:

The experiments are tested for 6 days separately: 7, 8, 9, 10, 11, 12 of July 2019. The forecasting was every one hour for one day ahead, it means 24 points was forecasted per one day. In each day, the error was calculated for each PQP type. The same experiment procedure was implemented for six tested days.

Then the error average was taken for both: per day and for each PQP type. Finally, the total error averages for both models (ANN and DT) were compared.

The input variables are fed with one of power quality parameters as a target output to construct the model. Since the training phase done, in testing phase the constructed model use to forecast the PQPs, as can be seen in Figure 5.8 which illustrate the planned system [121].

5.4.2 Data Set

The data set of June and July 2019 are used in this study. They were obtained from the off-grid platform constructed at our school VŠB-Technical University of Ostrava, the Czech Republic. The data set from 14.06.2019 till 05.07.2019 used for training the models, and six days from 7th, till 12th were used for testing the models. The input variables which used are: power load, air temperature, ultraviolet steps, and status of home appliances (AC heating, fridge, lights system, and TV) either on=1, or off=0. Were the output variables are: power frequency, magnitude of the supply voltage, total harmonic distortion of voltage (THD_u), total harmonic distortion of current (THD_i), and short term flicker severity (P_{st}) [121].

5.4.3 Discussion

The experiments runs for ANN and DT as can be seen in Table 5.6, and in Table 5.8, which illustrate the forecasting results of the ANN and DT respectively.

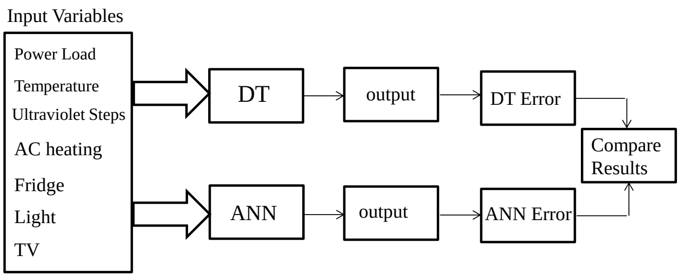

Figure 5.8: Diagram of the planned comparison model for PQPs forecasting using ANN and DT. Input variables are: power load, temperature, UV steps, and home appliances status with one of PQPs as a targot output

Table 5.6: MAPE error achived by ANN when using 100 epochs and 10 hidden neurons. The experiments carried out for two periods: for one day ahead (for each day separately from 7th till 12th day) and for two days ahead (7th and 8th days together)

PQP Type	Days						
	07.07.19	08.07.19	09.07.19	10.07.19	11.07.19	12.07.19	7-8.07.19
Frequency	6.5×10^{-6}	5.0×10^{-6}	6.2×10^{-6}	9.3×10^{-6}	2.2×10^{-5}	2.0×10^{-5}	5.8×10^{-6}
Voltage	0.0048	0.003	0.0025	0.0033	0.0145	0.0122	0.0038
THD_u	0.0943	0.0433	0.048	0.0884	0.256	0.1946	0.0455
THD_i	0.1050	0.0968	0.1364	0.1428	0.1134	0.1146	0.0746
Flicker(P_{st})	1.920	3.495	3.796	3.155	0.6681	0.876	2.526
Average	0.420	0.726	0.795	0.677	0.194	**0.237**	0.526

Table 5.7: Error average of PQPs for six tested days achieved by ANN

PQP Type	MAPE
Frequency	1.16×10^{-5}
Voltage	0.0066
THD_u	0.11
THD_I	0.117
Flicker (P_{st})	2.27
Average	0.50

Table 5.8: MAPE error achived by DT. The experiments carried out for two periods: for one day ahead (for each day separately from 7th till 12th day) and for two days ahead (7th and 8th days together)

PQP Type	Days						
	07.07.19	08.07.19	09.07.19	10.07.19	11.07.19	12.07.19	7-8.07.19
Frequency	2.2×10^{-5}	9.3×10^{-7}	1.9×10^{-5}	1.3×10^{-5}	1.4×10^{-5}	1×10^{-5}	1.1×10^{-5}
Voltage	0.003	2.1×10^{-4}	0.0059	1.8×10^{-4}	0.0052	0.002	0.0016
THD_u	0.062	0.0281	0.0627	0.0259	0.1171	0.0581	0.045
THD_i	0.0193	0.0181	0.0654	0.0441	0.0541	0.0771	0.0187
Flicker(P_{st})	1.0160	1.8698	0.9631	1.1081	0.7353	1.6010	1.44
Average	0.2201	0.3832	0.2194	0.2357	**0.1823**	0.3476	0.314

Table 5.9: Error average of PQPs for six tested days achieved by DT

PQP Type	MAPE
Frequency	1.34×10^{-5}
Voltage	0.00274
THD_u	0.0575
THD_I	0.045
Flicker (P_{st})	1.18
Average	0.25

ANN results: the experiment runs for 50 and 100 epochs, in each one used different number of the hidden neuron 10, 20, 30, the best results achieved when used 100 epochs with 10 hidden neuron.

The MAPE error for each PQP in all days as following: the error between actual and forecasted power frequency it was varied between 5×10^{-6} and 2×10^{-5}, the lowest error of magnitude supply voltage forecasting is 0.0025, and the biggest was 0.014, for (THD_u) was between 0,0433 and 0.256, (THD_i) from 0.096 till 0.142, and for (P_{st}) it was 0.668 and 3.7 as can be seen in Table 5.6, and the average error per day for all days was about 0.508, the average error per PQP was about 0.50 as can be seen in Table 5.7 [121].

DT results: the MAPE error for each PQP in all days as following: the power frequency forecasting error it was varied between 9.35×10^{-7} and 2.26×10^{-5}, for magnitude supply voltage was in between 1.80×10^{-4} and 0.0059, for (THD_u) it was from 0.0259 to 0.117, with regard (THD_i) it was from 0.0181 to 0.077, and for (P_{st}) was varied between 0.735 and 1.86 as can be seen in Table 5.8, and the average error per day for all days was around 0.264, the average error per PQP was about 0.25 as can be seen in Table 5.9. In figures from Figure 5.9 till Figure 5.13, comparison of acual and forecasted value using DT for frequency, voltage, (THD_u), (THD_i) , and (P_{st}) respectively [121].

Two days ahead forecasting:

As well the experiments are tested for the period more than one day. Two days together (7th and 8th) used to forecast PQPs every one hour it means 48 points forecasted as can be seen the forecasting error in the last column in Table 5.6, and in Table 5.8, which shows the forecasting results of the ANN

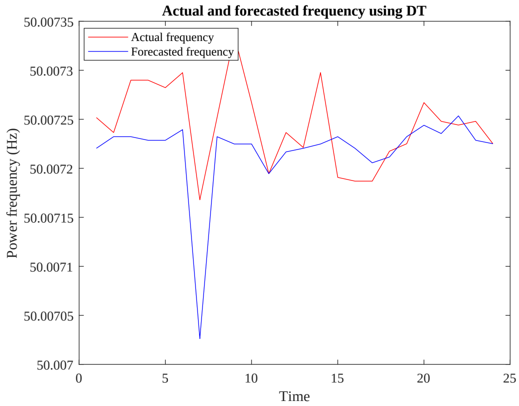

Figure 5.9: Comparison of actual and forecasted power frequency using DT

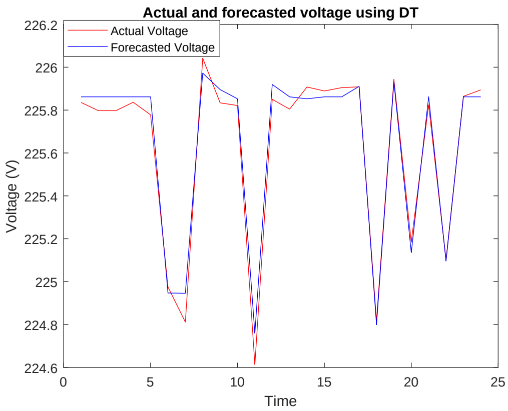

Figure 5.10: Comparison of actual and forecasted voltage using DT

and DT respectively. The experiments carried out with the same procedure and data set of one day ahead experiments.
In this study when comparing the results of ANN with DT, the performance of DT better than ANN, and the results confirmed the validity of performance of DT in PQPs forecasting for the both tested periods one day ahead (24 hours) and two days ahead (48 hours).

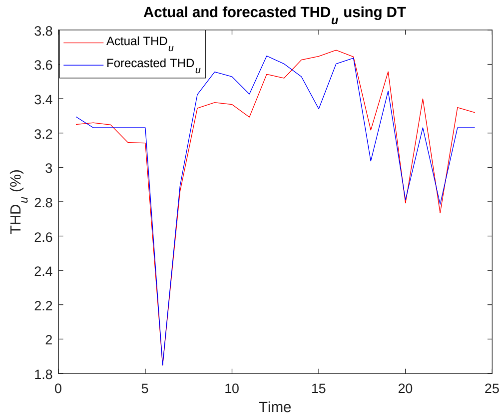

Figure 5.11: Comparison of actual and forecasted THD_u using DT

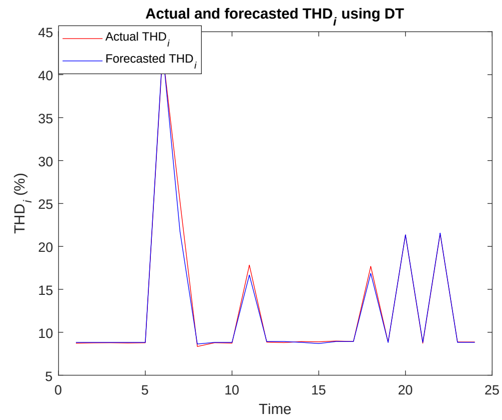

Figure 5.12: Comparison of actual and forecasted THD_i using DT

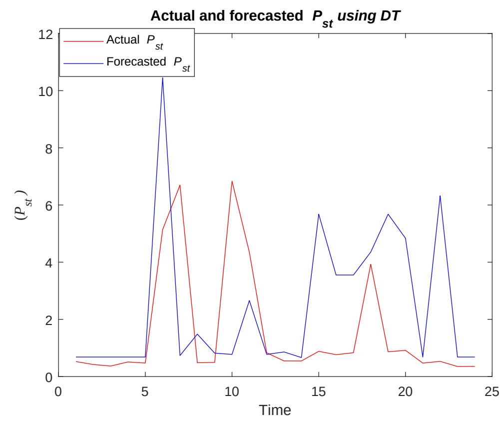

Figure 5.13: Comparison of actual and forecasted (P_{st}) using DT

Chapter 6

Discussion and Conclusion

6.1 Results Comparison

In this section, we compare the forecasting results of our experiments. In the first experiments we designed and comparing 4 types of forecasting models: ANN, DR, SVM, and LR for forecasting wind speed using dataset from the Centre for Solar Energy Research and Studies Libya [119]. The best forecasting result was achieved by LR interactions was 9.5814% for the period 8 hours forecasting ahead, 10.0655 for 4 hours, 10.8391 for 12 hours, and 14.1704 for one day ahead. Then ANN ranks second achieved results for 4 hours was 11.9273, and for 8 hours 13.2712, and for one day was about 15.9578. Just for 8 hours period DT was achieved best result than ANN it was 13.2712. In the last, worst results achieved by SVM. As can be seen in Table 6.1 that depict the lowest MAPE error of forecasting used models.

Table 6.1: Results comparison of the wind speed forecasting models

Model Type	Forecasting period			
	4 hours	8 hours	12 hours	24 hours
ANN	11.9273	13.2712	16.1433	15.9578
DT	15.4267	15.5128	15.9241	18.5174
SVM	16.7659	15.9842	20.6647	36.5536
LR	**10.0655**	**9.5814**	**10.8391**	**14.1704**

In the second experiments [50], compiling K-means with ANN, DT, and K-medoids with ANN, DT, for power load forecasting in short-term for one day ahead for every one hour from 00:00 till 23:00 clock, it means 24 points forecasted. The experiments have been carried out for different number of clusters from 10 till 50 clusters. For ANN the lowest error 8.08% achieved when compiling K-medoids with ANN with 10 numbers of clusters. For DT the lowest error 46.74% achieved when compiling K-means with DT with 10 numbers of clusters. In this experiments the performance of ANN was better than DT, as can be seen in Table 6.2.

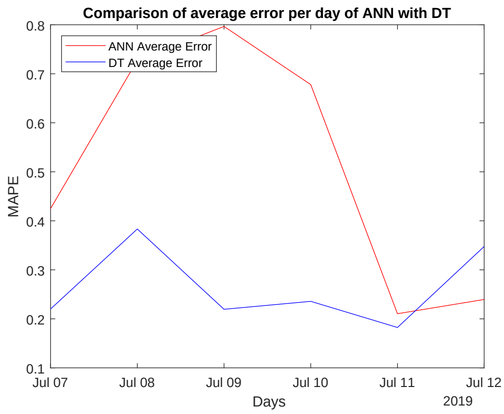

Figure 6.1: Results comparison of average error per day of ANN with DT

Table 6.2: Comparison of the forecasting results of the power load

Model Type	Number of clusters	MAPE
K-medoids with ANN	**10**	**8.08%**
K-means with DR	10	46.74%

In the fourth experiments: two models ANN and DT have been tested for PQPs forecasting using dataset from off-grid system in VSB- Technical university of Ostrava. The experiments carried out for both ANN, DT and compared their results. As can be seen in Figure 6.1, that shows the comparison of MAPE error of ANN and DT. The curve shows the average errors for all 6 tested days (7th - 12th July 2019). Reults of DT overcome the results of ANN for all days just in last days 12th July, which proved the performance of DT model in this study [121].

Table 6.3: Comparison of the PQPs forecasting results

Model Type	MAPE	Forecasting period
ANN	0.508	24H
DR	**0.2647**	**24H**

6.2 Discussion

Till now, for designing and applying forecasting model especially in the real time seems very hard due to nature of the nonlinearity of the forecasted values.

In this study three data sets have been used, the first data set was collected from Libya, and second and third data sets was collected from off-grid system in Ostrava, we tested four models ANN, DT, LR, SVM for forecasting purpose. For power quality parameters we used ANN, and TD which gives good results with small computation time.

Generally in power quality field, the important power quality parameters are-power frequency and magnitude of the supply voltage as in following limitations of [EN 50160] as can be seen in Table 6.4.

- For power frequency - LV: mean value of fundamental measured over 10 second, ±1% (49.5 – 50.5 Hz) for 99.5% of week, -6% till +4% (47 – 52 Hz) for 100% of week [EN 50160] .
- For voltage magnitude variations- LV: ±10% for 99.5% of week, mean 10 minutes rms values [EN 50160].

In our experiments- the forecasted values of power frequency was about in the range between 50.00701 till 50.00725 Hz, for voltage it was in range about from 224.75 till 225.97 volt. These forecasted values depends on several factors such as used data set.

These important power quality parameters are reflect the power quality and they use for correcting the quality of the generated power. As can be seen in simple example in Figure 1.3, which illustrate how to correcting the frequency power to nominal value (50 Hz) [EN 50160].

This study noted that:
The forecasting results of PQPs using DT better than ANN, that may be due to data set included on logical values which represented the working status of home appliances: either on = 1, or off=0.
The forecasted power frequency was sensitive to the power load and air temperature. Forecasted voltage was affected by power load and step of ultraviolet.

Table 6.4: Power frequency and supply voltage variations [EN 50160]

Parameter	Supply voltage characteristics according to EN 50160
Power Frequency	LV: mean value of fundamental measured over 10 s $\mp$ 1 % (49.5 - 50.5 Hz) for 99.5% week - 6% / + 4% (47 - 52 Hz) for 100% of week
Voltage magnitude variations	LV: $\mp$ 10 % for 95% of week mean 10 minutes rms value

6.3 Conclusion

Accurate smart control power systems (SCS) are important for the operation and control of power systems as they ensure the supply of accurate and reliable electricity to users, which aim to balance the consumed power and generated power as well as to maintain power quality parameters at standard levels. Despite a number of previous studies focused on the design of various smart control power system models, the challenge remains to design and apply efficient techniques in real time. Nowadays, most common of renewable energies are solar and wind power used to generating the electricity as an alternative power sources, and they available around all the world as a clean and free power sources. These power sources are fluctuate randomly dependence to weather conditions. A power control system are needed to control in following the power to users with good quality, and the forecasting systems are consider as an important part of power control system. Since, the PQPs are forecasted successfully, then the forecasted values can be used for scheduling the load. This thesis focuses on designing short-term forecasting systems of renewables power sources, which represent the goal of this study. For that in proposed methods in chapter five four forecasting systems have been designed and tested includes: Wind Speed Forecasting by regression Models, in this article nine models are designed and tested using data set from Libya. And second article Intelligent System for Power Load Forecasting in Off-grid Platform, in this article two models are implemented- ANN and TD using data set from off-grid system in the school. In the third article Smart Control System based on Power Quality Parameter Short-term Forecasting, DT was investigated using data set from off-grid system in the school. In the fourth article which still in the progress: Power Quality Parameters Analysis in Smart Grid Platform, two models ANN and DT have been investigated for short-term PQPs forecasting and compared their performance. The best forecasting performance was achieved by DT. We noticed from the experiments that- the voltage was affected by power load and step of the ultraviolet, the power frequency was sensitive to power load and air temperature, total harmonics distortion of current was more affected by power load and type of home appliances, total harmonics distortion of Voltage was slightly influenced by power load and slightly by the step of the ultraviolet, and short term flicker severity was slightly affected by power load and step of ultraviolet.

6.4 Future Work

In the future work, we will try to designing PQPs forecasting system, using data set from another off-grid system with more power load consumption: it means implementation with Vehicle-to-grid (V2G). Since PQPs forecasted then these forecasted values of PQPs will use to scheduling the load to run in switch time. This procedure will keep the balancing between generated energy with consumed energy.

Bibliography

[1] Jahan, Ibrahim Salem, Vaclav Snasel, and Stanislav Misak. "Intelligent Systems for Power Load Forecasting: A Study Review." *Energies* 13, no. 22 (2020): 6105.

[2] Misak, Stanislav, and Lukas Prokop. "Off-grid power systems." In *2010 9th International conference on environment and electrical engineering*, pp. 14-17. IEEE, 2010.

[3] Misak, Stanislav, Jindrich Stuchly, Jakub Vramba, Tomas Vantuch, and David Seidl. "A novel approach to adaptive active relay protection system in single phase AC coupling Off-Grid systems." *Electric power systems research* 131 (2016): 159–167.

[4] Misak, Stanislav, Lukas Prokop, and Petr Bilik. "Power quality analysis in off-grid power system." In *2014 ELEKTRO*, pp. 337–342. IEEE, 2014.

[5] Gosbell VJ. "Voltage Fluctuations in the Electric Supply System." *emph University of Wollongong.* 2003 Aug.

[6] MacKay, David. "An example inference task: clustering. Information theory, inference and learning algorithms." *PLoS One* 6, no. 8 (2003): 284–292.

[7] T. Hastie, R. Tibshirani, and J. Friedman. "The Elements of Statistical Learning." Springer- Verlaf New York, 2009.

[8] D. A. Freedman. *Statistical Models: Theory and Practice.* University of California, Berkeley, 2009.

[9] Seal, Hilary L. "Studies in the History of Probability and Statistics. XV The historical development of the Gauss linear model." Biometrika 54, no. 1-2 (1967): 1-24.

[10] Smola, Alex J., and Bernhard Schlkopf. "A tutorial on support vector regression." Statistics and computing 14, no. 3 (2004): 199-222.

[11] Zurada, Jacek M. Introduction to artificial neural systems. Vol. 8. St. Paul: West, 1992.

[12] Tan, Pang-Ning, Michael Steinbach, and Vipin Kumar. "Introduction to data mining: Pearson addison wesley." Boston (2005).

[13] Hastie, Trevor, Robert Tibshirani, and Jerome Friedman. *The elements of statistical learning: data mining, inference, and prediction.* Springer Science & Business Media, 2009.

[14] Prokop, L., S. Misak, V. Snasel, P. Kromer, and J. Platos. "Photovoltaic power plant power output prediction using fuzzy rules." Przegld Elektrotechniczny 89, no. 11 (2013): 77-80.

[15] Bhaskar, Kanna, and Sri Niwas Singh. "AWNN-assisted wind power forecasting using feed-forward neural network." *IEEE transactions on sustainable energy* 3, no. 2 (2012): 306-315.

[16] Shi, Jie, Wei-Jen Lee, Yongqian Liu, Yongping Yang, and Peng Wang. "Forecasting power output of photovoltaic systems based on weather classification and support vector machines." *IEEE Transactions on Industry Applications* 48, no. 3 (2012): 1064-1069.

[17] Wang, Fei, Zengqiang Mi, Shi Su, and Hongshan Zhao. "Short-term solar irradiance forecasting model based on artificial neural network using statistical feature parameters." *Energies* 5, no. 5 (2012): 1355-1370.

[18] Chen, S. X., H. B. Gooi, and M. Q. Wang. "Solar radiation forecast based on fuzzy logic and neural networks." *Renewable Energy* 60 (2013): 195-201.

[19] Xu, Ruidong, Hao Chen, and Xiaoyan Sun. "Short-term photovoltaic power forecasting with weighted support vector machine." In 2012 *IEEE International Conference on Automation and Logistics*, pp. 248-253. IEEE, 2012.

[20] Liu, Da, Dongxiao Niu, Hui Wang, and Leilei Fan. "Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm." *Renewable Energy* 62 (2014): 592–597.

[21] Mandal, Paras, Surya Teja Swarroop Madhira, Julian Meng, and Ricardo L. Pineda. "Forecasting power output of solar photovoltaic system using wavelet transform and artificial intelligence techniques." *Procedia Computer Science* 12 (2012): 332–337.

[22] Li, Zhaoxuan, S. M. Rahman, Rolando Vega, and Bing Dong. "A hierarchical approach using machine learning methods in solar photovoltaic energy production forecasting." *Energies* 9, no. 1 (2016): 55.

[23] Dolara, Alberto, Francesco Grimaccia, Sonia Leva, Marco Mussetta, and Emanuele Ogliari. "A physical hybrid artificial neural network for short term forecasting of PV plant power output." *Energies* 8, no. 2 (2015): 1138-1153.

[24] Zeng, Jianwu, and Wei Qiao. "Short-term solar power prediction using a support vector machine." *Renewable Energy* 52 (2013): 118-127.

[25] Zhao, Pan, Junrong Xia, Yiping Dai, and Jiaxing He. "Wind speed prediction using support vector regression." In 2010 *5th IEEE Conference on Industrial Electronics and Applications*, pp. 882-886. IEEE, 2010.

[26] Azad, Hanieh Borhan, Saad Mekhilef, and Vellapa Gounder Ganapathy. "Long-term wind speed forecasting and general pattern recognition using neural networks." *IEEE Transactions on Sustainable Energy* 5, no. 2 (2014): 546-553.

[27] Teo, Tiong Teck, Thillainathan Logenthiran, and Wai Lok Woo. "Forecasting of photovoltaic power using extreme learning machine." In 2015 *IEEE Innovative Smart Grid Technologies-Asia* (ISGT ASIA), pp. 1-6. IEEE, 2015.

[28] Olatomiwa, Lanre, Saad Mekhilef, Shahaboddin Shamshirband, Kasra Mohammadi, Dalibor Petkovic, and Ch Sudheer. "A support vector machine-firefly algorithm-based model for global solar radiation prediction." *Solar Energy* 115 (2015): 632–644.

[29] Wang, Jujie, Wenyu Zhang, Yaning Li, Jianzhou Wang, and Zhangli Dang. "Forecasting wind speed using empirical mode decomposition and Elman neural network." *Applied Soft Computing* 23 (2014): 452–459.

[30] Meng, Anbo, Jiafei Ge, Hao Yin, and Sizhe Chen. "Wind speed forecasting based on wavelet packet decomposition and artificial neural networks trained by crisscross optimization algorithm." *AEnergy Conversion and Management* 114 (2016): 75-88.

[31] Wang, Shouxiang, Na Zhang, Lei Wu, and Yamin Wang. "Wind speed forecasting based on the hybrid ensemble empirical mode decomposition and GA-BP neural network method." *Renewable Energy* 94 (2016): 629–636.

[32] Ramesh, Babu, and P. Arulmozhivarman. "Improving forecast accuracy of wind speed using wavelet transform and neural networks." *Journal of Electrical Engineering and Technology* 8, no. 3 (2013): 559–564.

[33] Teixeira Junior, Luiz Albino, Rafael Morais de Souza, Moises Lima de Menezes, Keila Mara Cassiano, Jose Francisco Moreira Pessanha, and Reinaldo Castro Souza. "Artificial neural network and wavelet decomposition in the forecast of global horizontal solar radiation." *Pesquisa Operacional* 35, no. 1 (2015): 73–90.

[34] Zhu, Honglu, Xu Li, Qiao Sun, Ling Nie, Jianxi Yao, and Gang Zhao. "A power prediction method for photovoltaic power plant based on wavelet decomposition and artificial neural networks." *Energies* 9, no. 1 (2015): 1-15.

[35] Zheng, Dehua, Abinet Tesfaye Eseye, Jianhua Zhang, and Han Li. "Short-term wind power forecasting using a double-stage hierarchical ANFIS approach for energy management in microgrids." *Protection and Control of Modern Power Systems* 2, no. 1 (2017): 1-10.

[36] Haque, Ashraf U., M. Hashem Nehrir, and Paras Mandal. "Solar PV power generation forecast using a hybrid intelligent approach." In *2013 IEEE Power & Energy Society General Meeting*, pp. 1–5. IEEE, 2013.

[37] Tang, Ningkai, Shiwen Mao, Yu Wang, and Mark Nelms. "LASSO-based single index model for solar power generation forecasting." In *GLOBECOM 2017-2017 IEEE Global Communications Conference*, pp. 1–6. IEEE, 2017.

[38] Viswavandya, Meera, Bakdevi Sarangi, Sthitapragyan Mohanty, and Asit Mohanty. "Short Term Solar Energy Forecasting by Using Fuzzy Logic and ANFIS." In *Computational Intelligence in Data Mining*, pp. 751–765. Springer, Singapore, 2020.

[39] Yan, Ke, Hengle Shen, Lei Wang, Huiming Zhou, Meiling Xu, and Yuchang Mo. "Short-term solar irradiance forecasting based on a hybrid deep learning methodology." *Information* 11, no. 1 (2020): 32.

[40] Wang, Huaizhi, Ren Cai, Bin Zhou, Saddam Aziz, Bin Qin, Nikolai Voropai, Lingxiao Gan, and Evgeny Barakhtenko. "Solar irradiance forecasting based on direct explainable neural network." *Energy Conversion and Management* 226 (2020): 113487.

[41] Pang, Zhihong, Fuxin Niu, and Zheng ONeill. "Solar radiation prediction using recurrent neural network and artificial neural network: A case study with comparisons." *ERenewable Energy* 156 (2020): 279–289.

[42] Xiao, Zhi, Shi-Jie Ye, Bo Zhong, and Cai-Xin Sun. "BP neural network with rough set for short term load forecasting." *Expert Systems with Applications* 36, no. 1 (2009): 273-279.

[43] Din, Ghulam Mohi Ud, and Angelos K. Marnerides. "Short term power load forecasting using deep neural networks." In 2017 *International conference on computing, networking and communications* (ICNC), pp. 594-598. IEEE, 2017.

[44] Reddy, S. Surender, and Chan-Mook Jung. "Short-term load forecasting using artificial neural networks and wavelet transform." *Int J Appl Eng Res* 11, no. 19 (2016): 9831–9836.

[45] Rana, Mashud, and Irena Koprinska. "Forecasting electricity load with advanced wavelet neural networks." *Neurocomputing* 182 (2016): 118–132.

[46] Mordjaoui, Mourad, Salim Haddad, Ammar Medoued, and Abderrezak Laouafi. "Electric load forecasting by using dynamic neural network." *International journal of hydrogen energy* 42, no. 28 (2017): 17655–17663.

[47] Chen, Ying, Peter B. Luh, Che Guan, Yige Zhao, Laurent D. Michel, Matthew A. Coolbeth, Peter B. Friedland, and Stephen J. Rourke. "Short-term load forecasting: Similar day-based wavelet neural networks." *IIEEE Transactions on Power Systems* 25, no. 1 (2009): 322–330.

[48] Zheng, Huiting, Jiabin Yuan, and Long Chen. "Short-term load forecasting using EMD-LSTM neural networks with a Xgboost algorithm for feature importance evaluation." *Energies* 10, no. 8 (2017): 1168.

[49] Niu, Dong-xiao, Hui-feng Shi, and Desheng Dash Wu. "Short-term load forecasting using bayesian neural networks learned by Hybrid Monte Carlo algorithm." *Applied Soft Computing* 12, no. 6 (2012): 1822–1827.

[50] Jahan, Ibrahim S., Michal Prilepok, Stanislav Misak, and Vaclav Snasel. "Intelligent system for power load forecasting in off-grid platform." In 2018 19th *International Scientific Conference on Electric Power Engineering (EPE)*, pp. 1-5. IEEE, 2018.

[51] Khwaja, A. S., M. Naeem, A. Anpalagan, A. Venetsanopoulos, and B. Venkatesh. "Improved short-term load forecasting using bagged neural networks." *Electric Power Systems Research* 125 (2015): 109–115.

[52] Wang, Yongli, Dongxiao Niu, and Li Ji. "Short-term power load forecasting based on IVL-BP neural network technology." *Systems Engineering Procedia* 4 (2012): 168–174.

[53] Ekici, S. A. M. I. "Electric load forecasting using regularized extreme learning machines." *International Journal of Industrial Electronics and Electrical Engineering* 4, no. 6 (2016): 119–122.

[54] Zhang, Jinliang, Yi-Ming Wei, Dezhi Li, Zhongfu Tan, and Jianhua Zhou. "Short term electricity load forecasting using a hybrid model." *Energy* 158 (2018): 774–781.

[55] Ahmad, Ashfaq, Nadeem Javaid, Abdul Mateen, Muhammad Awais, and Zahoor Ali Khan. "Short-term load forecasting in smart grids: an intelligent modular approach." *Energies* 12, no. 1 (2019): 164.

[56] Liang, Yi, Dongxiao Niu, and Wei-Chiang Hong. "Short term load forecasting based on feature extraction and improved general regression neural network model." *Energy* 166 (2019): 653–663.

[57] Hernandez, Luis, Carlos Baladron, Javier M. Aguiar, Belen Carro, Antonio Sanchez-Esguevillas, and Jaime Lloret. "Artificial neural networks for short-term load forecasting in microgrids environment." *Energy* 75 (2014): 252–264.

[58] Chaturvedi, D. K., A. P. Sinha, and O. P. Malik. "Short term load forecast using fuzzy logic and wavelet transform integrated generalized neural network." *International Journal of Electrical Power & Energy Systems* 67 (2015): 230–237.

[59] El-Hendawi, Mohamed, and Zhanle Wang. "An ensemble method of full wavelet packet transform and neural network for short term electrical load forecasting." *Electric Power Systems Research* 182 (2020): 106265.

[60] Liang, Yi, Dongxiao Niu, Minquan Ye, and Wei-Chiang Hong. "Short-term load forecasting based on wavelet transform and least squares support vector machine optimized by improved cuckoo search." *Energies* 9, no. 10 (2016): 827.

[61] Ren, Guanghua, Shiping Wen, Zheng Yan, Rui Hu, Zhigang Zeng, and Yuting Cao. "Power load forecasting based on support vector machine and particle swarm optimization." In *2016 12th World Congress on Intelligent Control and Automation (WCICA)*, pp. 2003–2008. IEEE, 2016.

[62] Liu, Jin-peng, and Chang-ling Li. "The short-term power load forecasting based on sperm whale algorithm and wavelet least square support vector machine with DWT-IR for feature selection." *Sustainability* 9, no. 7 (2017): 1188.

[63] Niu, Dongxiao, Yongli Wang, and Desheng Dash Wu. "Power load forecasting using support vector machine and ant colony optimization." *Expert Systems with Applications* 37, no. 3 (2010): 2531–2539.

[64] Rivas-Perea, Pablo, Juan Cota-Ruiz, David Garcia Chaparro, Abel Quezada Carren, Francisco J. Enrquez Aguilera, and Jose-Gerardo Rosiles. "Forecasting the demand of short-term electric power load with large-scale LP-SVR." (2013).

[65] Sreekumar, S.; Verma, J.; Verma, J.; Sujil, A.; Kumar, R. Comparative analysis of intelligently tuned support vector regression models for short term load forecasting in smart grid framework. *Technol. Econ. Smart Grids Sustain. Energy* **2017**, *2*, 1.

[66] Ning, Ye, Yong Liu, and Yong Wang. "Short-term power load forecasting based on SVM." In *Proceedings of the World Automation Congress (WAC)*, Puerto Vallarta, Mexico, pp. 24–28. 2012.

[67] Zhang, Xiaobo, Jianzhou Wang, and Kequan Zhang. "Short-term electric load forecasting based on singular spectrum analysis and support vector machine optimized by Cuckoo search algorithm." *Electric Power Systems Research* 146 (2017): 270–285.

[68] Abdoos, Adel, Mohammad Hemmati, and Ali Akbar Abdoos. "Short term load forecasting using a hybrid intelligent method." *Knowledge-Based Systems* 76 (2015): 139–147.

[69] Dai, Shuyu, Dongxiao Niu, and Yan Li. "Daily peak load forecasting based on complete ensemble empirical mode decomposition with adaptive noise and support vector machine optimized by modified grey wolf optimization algorithm." *Energies* 11, no. 1 (2018): 163.

[70] Hong, Wei-Chiang, and Guo-Feng Fan. "Hybrid empirical mode decomposition with support vector regression model for short term load forecasting." *Energies* 12, no. 6 (2019): 1093.

[71] Dudek, Grzegorz. "Short-term load forecasting using random forests." In *Intelligent Systems'* 2014, pp. 821–828. Springer, Cham, 2015.

[72] Hambali, M.; Akinyemi, A.; Oladunjoye, J.; Yusuf, N. Electric Power Load Forecast Using Decision Tree Algorithms. *Comput. Inf. Syst. Dev. Inform. Allied Res. J.* 2016, *7*, 29–42.

[73] Li, Jian-qiang, Cheng-lin Niu, Ji-zhen Liu, and Jun-jie Gu. "The application of data mining in electric short-term load forecasting." In *2008 Fifth International Conference on Fuzzy Systems and Knowledge Discovery*, vol. 2, pp. 519–522. IEEE, 2008.

[74] Huang, Nantian, Zhiqiang Hu, Guowei Cai, and Dongfeng Yang. "Short term electrical load forecasting using mutual information based feature selection with generalized minimum-redundancy and maximum-relevance criteria." *Entropy* 18, no. 9 (2016): 330.

[75] Lahouar, Ali, and Jaleleddine Ben Hadj Slama. "Random forests model for one day ahead load forecasting." In *EIREC2015 The Sixth International Renewable Energy Congress*, pp. 1–6. IEEE, 2015.

[76] Moon, Jihoon, Kyu-Hyung Kim, Yongsung Kim, and Eenjun Hwang. "A short-term electric load forecasting scheme using 2-stage predictive analytics." In *2018 IEEE International Conference on Big Data and Smart Computing (BigComp)*, pp. 219–226. IEEE, 2018.

[77] Ruiz-Abellon, Maria Del Carmen, Antonio Gabaldon, and Antonio Guillamon. "Load forecasting for a campus university using ensemble methods based on regression trees." *Energies* 11, no. 8 (2018): 2038.

[78] Liu, Song, Yaming Cui, Yaze Ma, and Peng Liu. "Short-term load forecasting based on GBDT combinatorial optimization." In *2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2)*, pp. 1-5. IEEE, 2018.

[79] Aprillia, Happy, Hong-Tzer Yang, and Chao-Ming Huang. "Optimal decomposition and reconstruction of discrete wavelet transformation for short-term load forecasting."*Energies* 12, no. 24 (2019): 4654.

[80] Amral, N., C. S. Ozveren, and D. King. "Short term load forecasting using multiple linear regression." In *2007 42nd International universities power engineering conference*, pp. 1192–1198. IEEE, 2007.

[81] Saber, Ahmed Yousuf, and AKM Rezaul Alam. "Short term load forecasting using multiple linear regression for big data." In *2017 IEEE symposium series on computational intelligence (SSCI)*, pp. 1-6. IEEE, 2017.

[82] Sun, Xiaokui, Zhiyou Ouyang, and Dong Yue. "Short-term load forecasting based on multivariate linear regression." In *2017 IEEE Conference on Energy Internet and Energy System Integration (EI2)*, pp. 1-5. IEEE, 2017.

[83] Cevik, Hasan Huseyin, and Mehmet Cunka. "Short-term load forecasting using fuzzy logic and ANFIS." *Neural Computing and Applications* 26, no. 6 (2015): 1355-1367.

[84] Mamlook, Rustum, Omar Badran, and Emad Abdulhadi. "A fuzzy inference model for short-term load forecasting." *Energy Policy* 37, no. 4 (2009): 1239–1248.

[85] Khosravi, Abbas, and Saeid Nahavandi. "Load forecasting using interval type-2 fuzzy logic systems: Optimal type reduction." *IEEE Transactions on Industrial Informatics* 10, no. 2 (2014): 1055-1063.

[86] Khosravi, Abbas, Saeid Nahavandi, Doug Creighton, and Dipti Srinivasan. "Interval type-2 fuzzy logic systems for load forecasting: A comparative study." *IEEE Transactions on Power Systems* 27, no. 3 (2012): 1274–1282.

[87] Manoj, Patel Parth, and Ashish Pravinchandra Shah. "Fuzzy logic methodology for short term load forecasting." *International Journal of Research in Engineering and Technology* 3, no. 4 (2014): 322–328.

[88] Hassan, Saima, Abbas Khosravi, Jafreezal Jaafar, and Mojtaba Ahmadieh Khanesar. "A systematic design of interval type-2 fuzzy logic system using extreme learning machine for electricity load demand forecasting."*International Journal of Electrical Power & Energy Systems* 82 (2016): 1–10.

[89] Dharma, Agus, Imam Robandi, and Mauridhi Hery Purnomo. "Application of Interval Type-2 Fuzzy Logic System in Short Term Load Forecasting on Special Days."*IPTEK The Journal for Technology and Science* 22, no. 2 (2011).

[90] Gohil, P.; Gupta, M. "Short term load forecasting using fuzzy logic 1." *Int. J. Eng. Dev. Res.* 2014, *1*, 127–130.

[91] Danladi, A. D., M. I. Puwu, Y. Michael, and B. M. Garkida. "Use of Fuzzy Logic To Investigate Weather Parameter Impact on Electrical Load Based on Short Term Forecasting." *Nigerian Journal of Technology* 35, no. 3 (2016): 562–567.

[92] Ganguly, P.; Kalam, A.; Zayegh, A. "Short term load forecasting using fuzzy logic. " *In Proceedings of the International Conference on Research in Education and Science, Ephesus-Kusadasi*, Turkey, 18–21 May 2017; pp. 355–361.

[93] Malekizadeh, M., H. Karami, M. Karimi, A. Moshari, and M. J. Sanjari. "Short-term load forecast using ensemble neuro-fuzzy model." *Energy* 196 (2020): 117127.

[94] Belkacemi, Rabie, and Ali Feliachi. "Multi-agent design for power distribution system reconfiguration based on the artificial immune system algorithm." In *Proceedings of 2010 IEEE International Symposium on Circuits and Systems*, pp. 3461–3464. IEEE, 2010.

[95] Duan, Dong-Li, Xiao-Dong Ling, Xiao-Yue Wu, and Bin Zhong. "Reconfiguration of distribution network for loss reduction and reliability improvement based on an enhanced genetic algorithm." *International Journal of Electrical Power & Energy Systems* 64 (2015): 88–95.

[96] Vlachogiannis, John G., and Nikos Hatziargyriou. "Reinforcement learning (RL) to optimal reconfiguration of radial distribution system (RDS)." In*Hellenic Conference on Artificial Intelligence*, pp. 439–446. Springer, Berlin, Heidelberg, 2004.

[97] Solanki, Jignesh M., Sarika Khushalani, and Noel N. Schulz. "A multi-agent solution to distribution systems restoration." *IEEE Transactions on Power systems* 22, no. 3 (2007): 1026–1034.

[98] Zhu, Ji Zhong. "Optimal reconfiguration of electrical distribution network using the refined genetic algorithm." *Electric Power Systems Research* 62, no. 1 (2002): 37–42.

[99] Amanulla, B., Saikat Chakrabarti, and S. N. Singh. "Reconfiguration of power distribution systems considering reliability and power loss." *IEEE transactions on power delivery* 27, no. 2 (2012): 918–926.

[100] Fathabadi, Hassan. "Power distribution network reconfiguration for power loss minimization using novel dynamic fuzzy c-means (dFCM) clustering based ANN approach." *International Journal of Electrical Power & Energy Systems* 78 (2016): 96–107.

[101] Nagata, Takeshi, and Hiroshi Sasaki. "A multi-agent approach to power system restoration." *IEEE transactions on power systems* 17, no. 2 (2002): 457–462.

[102] de Oliveira Saraiva, Filipe, and Eduardo Nobuhiro Asada. "Multi-agent systems applied to topological reconfiguration of smart power distribution systems." In *2014 International Joint Conference on Neural Networks (IJCNN)*, pp. 2812–2819. IEEE, 2014.

[103] Mohanty, Banaja, and Sasmita Tripathy. "A teaching learning based optimization technique for optimal location and size of DG in distribution network." *journal of electrical systems and information technology* 3, no. 1 (2016): 33–44.

[104] Gupta, N., A. Swarnkar, K. R. Niazi, and R. C. Bansal. "Multi-objective reconfiguration of distribution systems using adaptive genetic algorithm in fuzzy framework." *IET generation, transmission & distribution* 4, no. 12 (2010): 1288–1298.

[105] Das, Sanjoy, Sayak Bose, Siddharth Pal, Noel N. Schulz, Caterina M. Scoglio, and Bala Natarajan. "Dynamic reconfiguration of shipboard power systems using reinforcement learning." *IEEE Transactions on Power Systems* 28, no. 2 (2012): 669–676.

[106] Hyder, Md Mashud, and Kaushik Mahata. "Reconfiguration of distribution system using a binary programming model." *AIMS Energy* 4, no. 3 (2016): 461–480.

[107] Reddy, P. Dinakara Prasad, VC Veera Reddy, and T. Gowri Manohar. "Whale optimization algorithm for optimal sizing of renewable resources for loss reduction in distribution systems." *Renewables: wind, water, and solar* 4, no. 1 (2017): 1-13.

[108] Candelo-Becerra, John E., Helman E. Hernandez-Riano, and Alcides R. Santander-Mercado. "Comparison of multiobjective harmony search, cuckoo search and bat-inspired algorithms for renewable distributed generation placement." *TecnoLogicas* 18, no. 35 (2015): 105–116.

[109] Sedighizadeh, Mostafa, Marzieh Dakhem, Mohammad Sarvi, and Hadi Hosseini Kordkheili. "Optimal reconfiguration and capacitor placement for power loss reduction of distribution system using improved binary particle swarm optimization." *International Journal of Energy and Environmental Engineering* 5, no. 1 (2014): 1–11

[110] Kumar, K. Sathish, and S. Naveen. "Power system reconfiguration and loss minimization for a distribution systems using Catfish PSO algorithm." *Frontiers in Energy* 8, no. 4 (2014): 434–442.

[111] Syahputra, Ramadoni, Imam Robandi, and Mochamad Ashari. "Reconfiguration of distribution network with DG using fuzzy multi-objective method." In *2012 International Conference on Innovation Management and Technology Research*, pp. 316–321. IEEE, 2012.

[112] Saffar, A., Rahmatollah Hooshmand, and Amin Khodabakhshian. "A new fuzzy optimal reconfiguration of distribution systems for loss reduction and load balancing using ant colony search-based algorithm." *Applied Soft Computing* 11, no. 5 (2011): 4021–4028.

[113] Rajaram, R., K. Sathish Kumar, and N. Rajasekar. "Power system reconfiguration in a radial distribution network for reducing losses and to improve voltage profile using modified plant growth simulation algorithm with Distributed Generation (DG)." *Energy Reports* 1 (2015): 116–122.

[114] Kaur, Simarjit, Sunil Agrawal, and Yajvender Pal Verma. "Power grid frequency prediction using ANN considering the stochasticity of wind power." In *2013 5th International Conference and Computational Intelligence and Communication Networks*, pp. 311–315. IEEE, 2013.

[115] Stuchly, Jindrich, Stanislav Misak, Tomas Vantuch, and Tomas Burianek. "A power quality forecasting model as an integrate part of active demand side management using Artificial Intelligence Technique-Multilayer Neural Network with Backpropagation Learning Algorithm." In *2015 IEEE 15th International Conference on Environment and Electrical Engineering (EEEIC)*, pp. 611–616. IEEE, 2015.

[116] Vantuch, Tomas, Stanislav Misak, Tomas Jezowicz, Tomas Burianek, and Vaclav Snasel. "The power quality forecasting model for off-grid system supported by multiobjective optimization."*IEEE Transactions on Industrial Electronics* 64, no. 12 (2017): 9507–9516.

[117] Song, Jie, Zhenzhen Xie, Jian Zhou, Xiu Yang, and Aiqiang Pan. "Power quality indexes prediction based on cluster analysis and support vector machine." *CIRED-Open Access Proceedings Journal 2017*, no. 1 (2017): 814–817.

[118] Yong, Zhang, Fang Chen, Wang Zhifang, and Yang Xiu. "Voltage Deviation Forecasting with Improved BP Neural Network." In *CProceedings of the 2018 International Conference on Mechatronic Systems and Robots*, pp. 37–41. 2018.

[119] Jahan, I. S., Prilepok, M., Misak, S., Snasel, V. "Wind Speed Forecasting by regression Models." *Proceedings of the Dateso Workshop*, 2016.

[120] Jahan, Ibrahim S., Stanislav Misak, and Vaclav Snasel. "Smart Control System based on Power Quality Parameter Short-term Forecasting." In *2020 21st International Scientific Conference on Electric Power Engineering (EPE)*, pp. 1–5. IEEE, 2020.

[121] Jahan Ibrahim Salem, Stanislav Misak, Vaclav Snasel. "Power Quality parameters analysis in smart Grid platform." (2021). In the process review.

My Publication

Articles published for this study

[A1] Jahan, I. S., Prilepok, M., Misak, S., Snasel, V. “Wind Speed Forecasting by regression Models.” *Proceedings of the Dateso 2016 Workshop*. Bibliography [119]

[A2] Jahan, I. S., Prilepok, M., Misak, S., Snasel, V. “Intelligent System for Power Load Forecasting in Off-grid Platform.” *2018 19th International scientific Conference on Electric Power Engineering (EPE)*. Bibliography [50].

[A3] Jahan, Ibrahim S., Stanislav Misak, Vaclav Snasel. ”Smart Control System based on Power Quality Parameter Short-term Forecasting.” In 2020 21st International Scientific Conference on Electric Power Engineering (EPE), pp. 1-5. IEEE, 2020. Bibliography [120].

[A4] Jahan, Ibrahim S., Vaclav Snasel, Stanislav Misak. ”Intelligent Systems for Power Load Forecasting: A Study Review.” Energies 13, no. 22 (2020): 6105. Bibliography [1]

[A5] Jahan Ibrahim Salem, Stanislav Misak, Vaclav Snasel. ”Power Quality parameters analysis in smart Grid platform.” (2021). Bibliography [121]. In the process review.

Other publication

[A6] Kasik, F., Jahan, I. S., Kurecka, A. “FPGA Based Digital Logic Emulator for Educational Purposes.”*International Conference on Software and Computer Applications, (IPCSIT’11) (Vol. 9)*. Singapore. 2011. pp. 23 – 27.

[A7] Jahan, I. S., Snasel, V. “ Non-negative Matrix factorization for EEG.” *Technological Advances in Electrical, Electronics and Computer Engineering (TAEECE), 2013 International Conference*. Konya. 2013. pp. 183 – 187. (Scopus), (WoS).

[A8] Jahan, I. S., Prilepok, M., Snasel, V., “EEG Data Similarity using Lempel-Ziv Complexity.” *The International Conference on Advanced Engineering - Theory ana Applications 2013 (AETA2013)*.Vitname. Ho Chi Minh. pp. 289 – 295.(Scopus), (WoS).

[A9] Prilepok, M., Jahan, I. S., Snasel, V. “ Electroencephalogram classification methods.” *Elektrotechniczny International Journal, Polish 2013*. pp. 51 – 54.

[A10] Prilepok, M., Platos, J., Snasel, V., Jahan, I. “Compression-based similarity in EEG signals.”*13th International Conference Intelligent System Design and Applications*. Malaysia, Selangor. 2013. (Scopus), (WoS).

[A11] Jahan, I., Prilepok, M., Snasel, V., Penhaker, M. “Similarity Analysis of EEG Data Based on Self Organizing Map Neural Network” *Advances in*

Electrical and Electronic Engineering (AEEE), Vol. 12, no. 5. 2014. (Scopus).

[A12] Prilepok, M., Jahan, I. S., Snasel, V. "Detection of Finger Flexion Based on Decision Tree." *Third International Afro-European Conference for Industrial Advancement.2016.*