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TECHNICAL DESIGN AND OPERATIONAL CONTROL OF A DECENTRALIZED MICROGRID IN RURAL AREA

Saiful Islam[1], Sanket Shrikant Patil[1], Goran Rafajlovski[1], Michael Hartmann[1], Reiner Creutzburg[1,2]

[1]SRH Berlin University of Applied Sciences, Berlin School of Technology, Ernst-Reuter-Platz 10, D-10587 Berlin, Germany

[2]Technische Hochschule Brandenburg, Department of Informatics and Media, IT- and Media Forensics Lab, Magdeburger Str. 50, D-14770 Brandenburg, Germany

Email (s): saiful.islam@srh.de, sanketshrikant.patil@stud.srh-campus-berlin.de, goran.rafajlovski@srh.de, michael.hartmann@srh.de, creutzburg@th-brandenburg.de, reiner.creutzburg@srh.de

Abstract

Microgrids incorporating Renewable Energy (RE) sources are being used nowadays to overcome the lack of electric power supply or grid instabilities in rural areas. Microgrids are decentralized and performant solutions to distribute electric power and to supply the consumers of a community with energy. They can be used to provide stable electrical energy to hospitals, companies and residential areas and therefore, they can contribute significantly to rural development. Based on renewable sources, they are climate neutral as well. Very often, in regular operation, a Microgrid is connected with an utility national or another distributed grid. In case of an utility grid fault occurrence, the Microgrid can still provide power since it incorporates renewable sources. However, since renewable sources like photovoltaics or wind power are volatile in supply, grid instabilities, voltage and frequency fluctuations and harmonic distortions in the Microgrid can occur. This paper focuses on developing a Microgrid (M.G.) model using MATLAB Simulink and analyzing its issues at different operational modes assuming a photovoltaic generator and a coupling to an utility grid as power sources. In order to analyze and predict the behavior of the Microgrid, deep learning methods based on Auto Regressive Moving Average (ARIMA) and Artificial Neural Networks (ANN) will be applied. It is shown that these methods allow to optimize the operation modes of the Microgrid. For instance, a balance between power supply and demand at different times could be reached and lead to economic efficiency and feasibility.

Key words: M.G., Simulink, Droop, PCC, Forecasting, ANN, Deep Learning, ARIMA.

Introduction

Currently, about 1.3 billion people out of the total world population of seven billion do not have access to modern energy supply. This affects 622 million people in Africa alone according to the International Energy Association (IEA). For instance, more than 60% of Nigeria's citizens do not have access to its national grid [1]. South Asia accounts for 42% of the global population without access to electricity. The current level of household electrification in the rural areas of the region is around 50%, leaving some 612 million people without electricity (IEA, 2010). There are also de-electrified villages; village that has been electrified earlier; however, it has become un-electrified at present as the distribution infrastructure has not been in working condition for a long time [2]. To overcome problems in the utility grid of rural areas, decentralized power supply systems based on microgrids of different power sources could be a solution. Apart from the power sources, the microgrid comprises all electrical consumer loads of a community and electrical devices like inverter and control units. Power sources could include different renewable energy sources like e.g. photovoltaics, wind or hydro power as well as bioenergy but also a coupling to the national utility grid. In case of the utility grid's failure, it can work as an off-grid system powered by the renewable energy sources. The electrical load types in the microgrid are the different appliances in the community, typically operated at 230V or 380 V. The function of the inverter is to match the electrical parameter in the utility gird side to the electrical load side. The control unit is responsible for monitoring and operating the system. Microgrids should, in theory, be continuously linked to the utility grid, allowing any surplus energy from the microgrid to be sent to the main grid and any energy shortfall in the microgrid to be met by the utility. Control methods must be implemented to achieve optimum efficiency and convergence between conventional grid and microgrid systems. Therefore, a microgrid is a decentralized network architecture with locally connected production, transmission, regulation, and utilization that can function independently or in conjunction with other microgrids or the main grid. So far, the most innovative approach focuses on a mechanism called "droop control," which had been established based on traditional power systems to enable the parallel connection of different voltage sources exchanging network loads [3].

A M.G. can operate in a variety of modes. The three primary operating modes are grid-connected mode, which refers to contact with the power grid; islanded mode, which refers to autonomous operation; and transient operating mode, which is the transfer mode when the main grid is disconnected or revived. The micro - grid ensures energy and power control flow in grid-connected mode by transporting energy from the power utility grid. At the typical connection point of common coupling (PCC), which is an electrical link point between the micro-grid and the grid, the power utility grid regulates the network voltage amplitude, frequency, and phase. A synchronization procedure of voltage amplitude, frequency, and phase, of distributed energy resources, are needed during the transient operating mode to ensure a smooth transition [3].

The inverter is converting the D.C. voltages to A.C. Power converters act as a controller, that have two central capabilities: grid forming mode and the grid following method. The function of a power converter is to process and regulate the flow of electric energy by providing voltages and currents that are optimally suitable for the consumer loads. Voltage and current are the two characteristics of sources. When a source's instantaneous impedance is zero, it is known to as a voltage source, and when it's infinite, it's alluded to as a current source. In terms of grid forming, the converter is used to control the system's frequency output; it tends the inverters to acquire the system frequency during load sharing. Power converters can also be operated as network (grid)-forming devices, acting as voltage sources, which is especially useful for managing power requirements in islanded operations. A grid following converter is being used to track the grid's voltage angle and adopt the output. In grid forming mode, the functionality of the converter is to control the frequency of the framework. In a grid forming converter, where it is a source of voltage and the waveform of voltage as a frequency of the framework, it follows the converter's output as a droop concept. It is a concept of power-sharing among the converters, which are operating in parallel. The phase locked loop (PLL) function is used to synchronize network (grid) forming converters to the grid. The voltage amplitude and frequency at the PCC are regulated by network (grid)-forming converters, which produce active and reactive power signals [3]- [4],[5]-[6].

To understand the complex behaviour of microgrids in different operation modes and configurations is fundamental for proper applications and implementations. Therefore, mathematical models have to be developed in order to simulate the microgrid in a given design and configuration. Researchers are trying to simulate and implement a mathematical model to make system reliable and maintain power quality. The technical feasibility analysis is an essential part of the Microgrid system, which has been focused on this research. It aims on design a system for a specific rural area. The Photovoltaic system design is done with the proposed data of the *PVSol* software. These data are used during the simulation with *MATLAB Simulink*. Assuming specific system parameters allows to predict the annual total energy production and to forecast power supply by employing methods of Artificial Intelligence. Finally, a first step towards a financial analysis is performed.

Problems associated with Microgrids

Microgrids could have problems such as harmonic distortion, voltage fluctuation, frequency variations, control between the loads and the generation of power. For instance, voltage variety and frequency drop during the off-grid mode of operation can occur by higher load requests. Because of uncertainty of renewable sources, variation in voltage and frequency could happen and is higher especially in the islanded mode than in the grid-connected one. It is known that harmonic distortion can occur by the inverter.

Electronic filters are utilized to solve this problem. These are connected between the inverters and the contact line to the Point of Common Coupling (PCC). If any problem occurs in the utility grid, the system automatically switches into the off-grid or islanded mode.

A smarter subsystem can be considered a reliable solution for these different issues and has become a topic of intensive research in recent years. The concept consists of various micro resources which operate together as a single controllable unit. The design and development of such subsystems require a model to analyze the M.G.'s performance [5]-[6]. It is essential to understand the reliability factors and the critical parameter such as active $(P = VI \cos(\theta))$ and reactive power $(Q = VI \sin(\theta))$ and the impact of the *power factor* $(\cos(\theta))$ in the system. According to the research's objective basic modeling and sizing has to be performed which form the prerequisite for analyzing the performance of a Microgrid. Inaccurately planned M.G. framework tends to an undesirable consonant current to the framework driving voltage problems and harmonic distortion problems [7].

In a Microgrid, as we discussed, a grid-forming converter with serial low-output impedance (voltage/frequency grid control) is an ideal AC voltage source. It can be used as a reference for the rest of grid-feeding (following) power converter connected to it. On the other hand, a Grid-feeding converter is an ideal current source with parallel high impedance (active and reactive power grid control). Reference current is provided as function of reference power P*- and Q*-current control based on PI controller in *d-q frame* of reference rotated with fundamental grid frequency. Current control is based on proportional resonant controller (PR) in stationary $\alpha{-}\beta$ *frame* of reference. [9] - [10].

Technical analysis and Control System

To overcome the problems as mentioned in the previous section, a grid connected system has been simulated and analyzed. It consists of one inverter operating as a current source connected in parallel with one local load. In the grid-connected operating mode, the utility grid is defining the voltage amplitude, frequency, and phase. The main advantage of current-controlled systems is its fast response and high stability. The main objective is to control the active and reactive power to the main grid. The model is shown in Fig. 1. On the left side, the photovoltaic generator is depicted at a solar light intensity of 1000 W7m^2 and a temperature of 25 degree Celsius corresponding to the standard test condition of photovoltaics. In the simulation we used 108 modules arranged as 9 parallel strings, each string contains 12 modules in series. Maximum power of each module is 300 W with 72 cells per module and open circuit voltage V_{oc} = 44.5 V and short circuit current I_{sc} = 8.93 A. Above the module, pulse width modulation generators are shown to trigger the three-phase inverter. The correct current output is measured. The

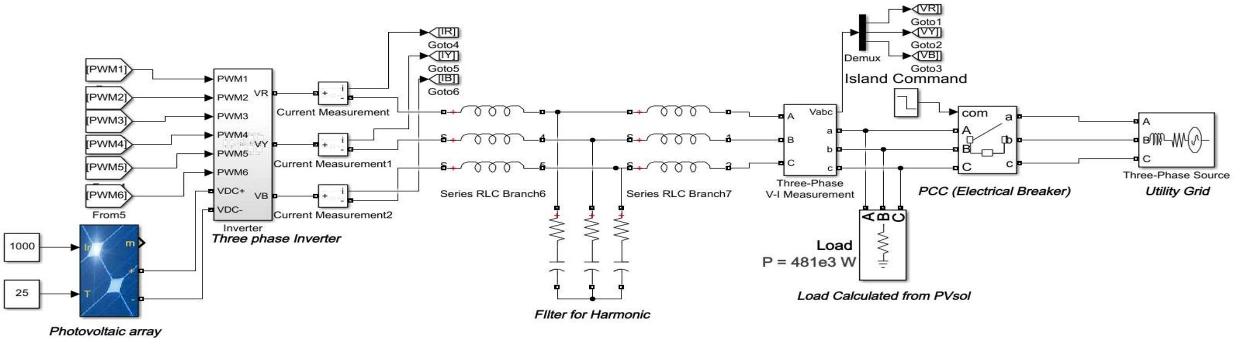


Fig. 1: The microgrid model using Simulink. PV data are taken from PVsol software

output current is filtered by a standard RLC filter to obtain a harmonic shape. The quality of the harmonic current is tested by an I-V three-phase measurement. At the point of common coupling, this output current is meeting the three-phase voltage source from the utility grid of 230 V and frequency 50 Hz. For the simulation we assumed a concrete load profile. In this paper we used 481 kW as an example.

Fig. 2 illustrates the procedure of the simulation. The upper part represents the basic structure of the model as was explained in Fig. 1 consisting of the DC source (PV generator), the three-phase inverter, the RLC filter and the three-phase utility grid. The lower part of Fig. 2 represents the voltage and current controller. We assume a grid-following mode; therefore Fig. 2 is specified as a current controller marked by the blue lines. Note that for a grid forming mode, the PI controller had to be connected to the voltage controller side marked by red lines. For the control mechanism, active and reactive power must be controlled. Therefore, the three-phase a-b-c voltage has to be converted to two-phases $\alpha\text{–}\beta$ -fame which is additionally transformed into a d-q frame (active-reactive frame). For this, the angle information is important and is explained in detail in Fig. 3. The a-b-c to *$\alpha\text{–}\beta$ to d-q-frame* is added to a PI controller and integrator which gives the phase information determining the active and reactive power components. The feedback phase locked loop (PLL) is used as an input for the d-q-frame which allows to control the phase angle. Fig. 4 shows the control mechanism of the angle [3]- [17- [15].

The diagram (Fig. 4) shows the line voltages transformation by a *PLL (Phase Locked Loop)*. A *phase-locked loop* is an important control mechanism in the three-phase inverter. When it needs to send an active current to the grid for that one should consider a grid side voltage. The current which has to be sent should in phase with the voltage. If one needs to send reactive power to the grid, then *PLL* needs to generate a signal which is 90 degree out of phase with actual voltage. A new angle θ (Fig. 4) is formed which is used to generate the active and reactive power. The *PLL* used a PI controller to refer v_{qref} value zero. This *d-q frame's* angular positioning *(in PLL)* is operated via a feedback controller that shifts the (reference voltage) v_{qref} portion to zero. The phase estimation is obtained by integrating grid frequency ω (Fig. 3) [10] [11]. In the (Fig. 4) we can see the current transformation using *$\alpha\text{–}\beta$ frame* to *d-q frame.*

Fig. 5 shows the output voltage from the inverter (cp. three-phase V-I voltage measurement in Fig. 1). It can be clearly seen that the signal shows no harmonic distortion and has equal voltage amplitudes in all three phases.

Fig. 6 demonstrates the d-q-active-reactive current control explained above. Here we assumed zero active power and reactive current for the current controller (cp. Fig. 3). It can be seen that after injecting reactive current, the current is phase shifted by *90 degree* with respect to the voltage but has no harmonic distortion.

The result of the overall simulation of the microgrid arrangement of Fig. 1 is shown in Fig. 7. The simulation starts with the parameter given above. The *FFT analysis* clearly shows that the harmonic distortion is less than 5%. Additionally, the phase shift is close to zero. Thus, the active power is maximized, and reactive power minimized due to the action of the PLL controller [3]- [8]-[9] [15]-[17].

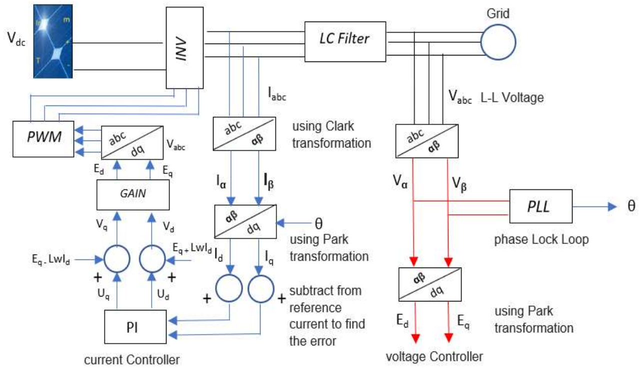


Fig. 2: Microgrid voltage and Current controller with d-q frame

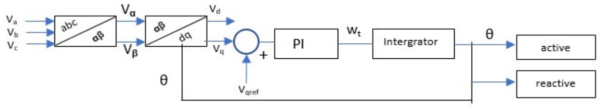
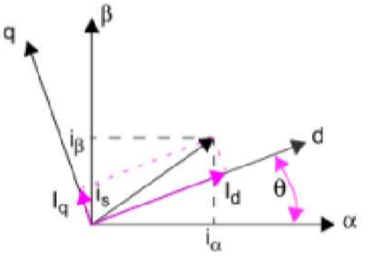


Fig. 3: PLL Microgrid controller with d-q frame



$(i_d = i_\alpha \cos\theta \quad + i_\beta \sin\theta)$
$(i_q = -i_\alpha \cos\theta + i_\beta \sin\theta)$

Fig. 4: Current control mechanism by PLL

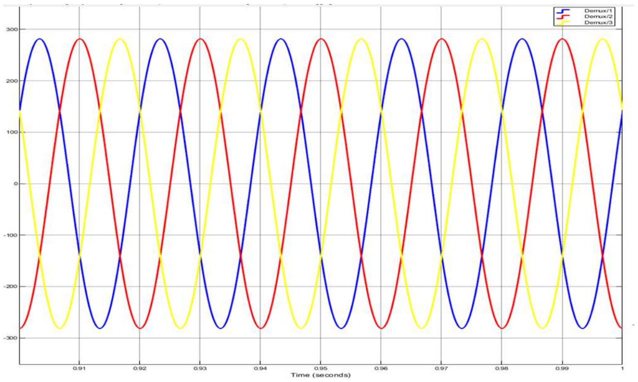


Fig. 5: 3- Φ voltage controller with d-q frame

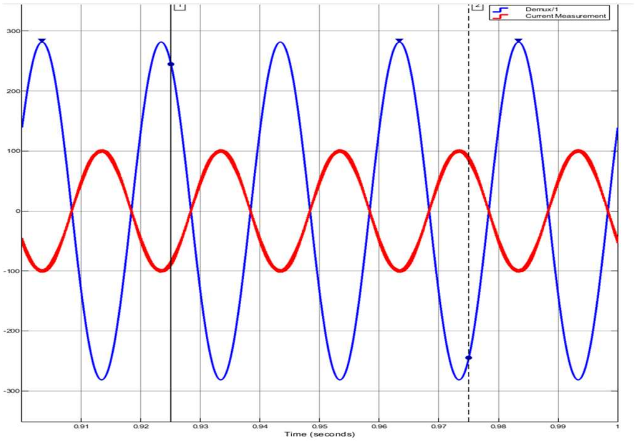


Fig. 6: Output of the voltage and Current in phase for the Microgrid system

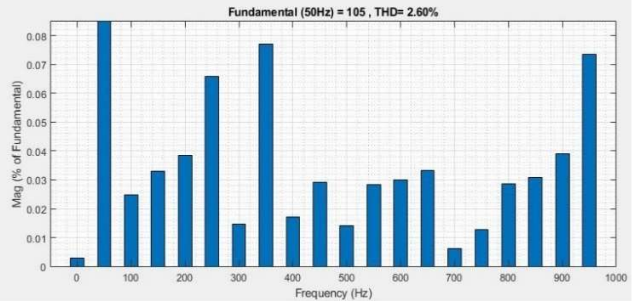


Fig. 7: THD (Total Harmonic Distortion) observation for the Microgrid system

Economic factors and feasibility analysis

A simple cash flow model (Fig. 8) has been also done to see the simple payback time in terms of cost calculation and the cash inflow and outflow of the system [12]. The Cash flow model included the capital cost of the whole system (45,360 €) at an interest rate of 1%. We assumed the total energy requirement for a small system of *11,559 kWh/day* with a demand of *481 kW* peak. The Return on Investment of the project is 29.11% and the first-year savings are *9,656.61€/year* compared to a system without PV according to the input's parameters. Here we assumed an energy price of the utility grid of *0.22 €/kWh*. The cash flow analysis is given in Fig. 8 and shows an amortization time of 5 years.

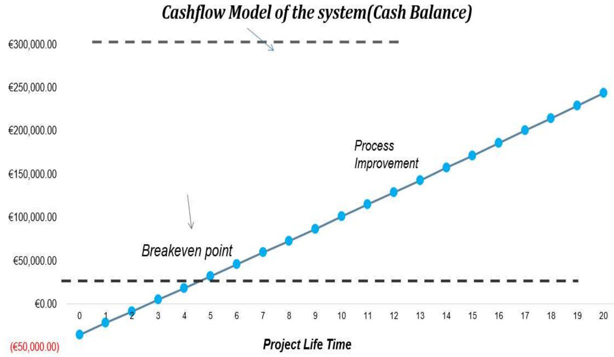


Fig. 8: A Cashflow model of including 481 kW demand and 30 kW_p system with utility grid (template: slideteam.net)

Deep Learning method for power prediction

The output power of a photovoltaic source in a Microgrid is an essential point. It could be added value in financial analysis because the renewable sources uncertainty is the issue if we compare it to the conventional energy providing systems. Furthermore, the forecast of supply of energy is relevant for the viability and efficiency of a microgrid. That means, if we could determine the future outcome of a system, it is possible to aim a balance between supply and demand. When there is a higher supply in the system, the demand could be higher and vice versa. If we can predict future uncertainty to some extend, it would be possible to control the supply and demand and overcome the problem of peak load and heavy excess energy. Therefore, in this section we present a method to predict the photovoltaic energy yield from data of the past. Three tools are involved to do so: Firstly, the PVSol software package is used in order to extract long-term statistical data of the solar irradiance of the past. Secondly, to separate seasonal influences in the data from long-term trends in the solar irradiance, the *Auto Regressive Moving Average* (ARIMA) is employed. Thirdly, ARIMA results are used as an input for an Artificial Neural Network (ANN) procedure which allows to forecast the energy output of the given Photovoltaic system in the microgrid.

We use a dataset implemented in the software package PVSol named Solar SGI resource dataset and considered the location *23°27.4'N, 91°10.3'E.* Based on these data, ARIMA is used to perform a time series analysis as follows: The data are either stationary or non-stationary where stationary means constant to time and variance will be in the same equal interval of time. In ARIMA, the test procedure for stationarity analysis is the Rolling statistics and Augmented Dickey Fuller (ADCF) test. The output for our example is given in the following table.

Results of Dickey-Fuller Test:	
Test Statistic	-2.764701
p-value	0.063496
#Lags Used	14.00000
Number of Observations Used	129.000
Critical Value (10%)	2.57886

Table 1: Output of the stationarity test (ADCF)

The test result can be interpreted as follows: If $P < 0.05$ the test is failed and the null hypothesis has to be rejected, that means the data are non-stationary. Therefore, it needs to convert the moving average value of the dataset into log scale to see the data output. Logscale we need to do for transforming the data to be stationary (Fig. 9) [14]. It is being obtained the $p\text{-}value = 0.016982$ which provides a better value than the value tested in Table-1.

The ARIMA model depends on the values of the lag order p, the degree of differencing d, and the order of moving average q. The lag order p describes the number of lag measurements used in the model. If p=5, for example, the previous five period series must be used in the autoregressive calculation. It can improve the series prediction. The number of times the actual findings are differed is known as the degree of differencing d. It helps to convert non-stationary data to stationary data. The size of the moving average distance is referred to as q, that is also known as the order of moving average. The moving average is the relationship between observation and process error. It can also determine the dataset's trend. It assists in predicting and deciding how much the data are dependent on previous values. It measures the observing model's error.

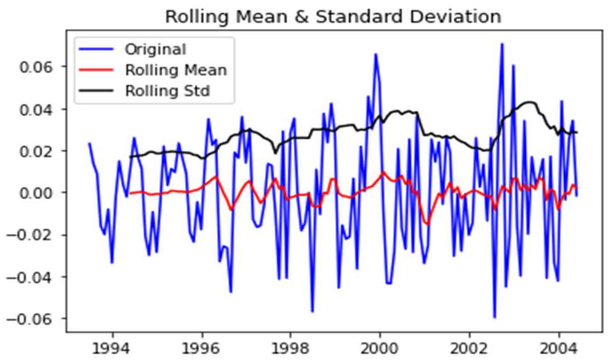


Fig. 9: Checking stationarity of the dataset after converting the data in logscale

From (Fig. 10), we can see the structure of a time series analysis within the ARIMA model that has been used. It has to be checked stationarity, i.e. statistical properties are constant with time with constant mean value & constant variance (there can be variations, but the variations shouldn't be irregular). The function could be used as a process named as *Akaike information criterion (AIC)* to evaluate the model. The AIC scores provides the value of the required parameter (p, d, q) of ARIMA model. The smallest value of AIC is a better fit for the model.

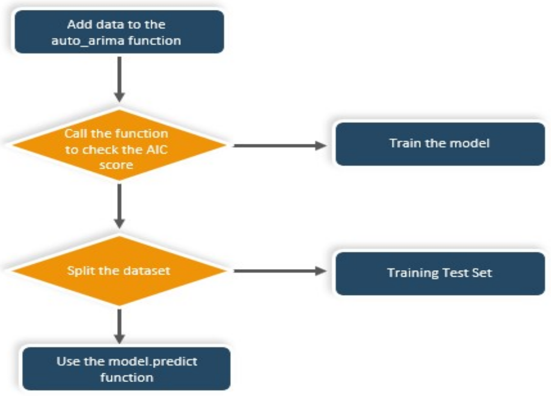


Fig. 10: Flowchart of the time series forecasting model

If we divided the dataset into training and test set (Fig. 10) the start variable will be the total length of the training dataset. The training set is a subset of the data that will demonstrate the model how to predict the dependent variable using the independent variables. The test set is a subset of the training set that is equivalent to it. It will assess the model to see if it is capable of correctly predicting the dependent variable using the independent variables. The dependent variable must have well-distributed values in both the training and test sets. If the dependent variable in the training set has the same value, the model will not develop any correlation between the independent and dependent variables. The end variable will be the combination of the length of the training set and test set including with the value we would like to observe. The accuracy of the model can be calculated by checking the mean squared error = mean (forecast error^2) where the forecast error = expected value − predicted value [12]- [14].

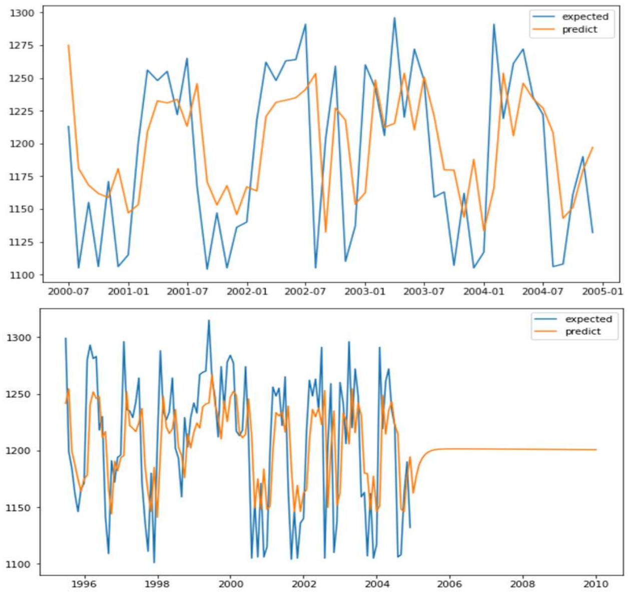


Fig. 11: Output of the expected and precited value of the solar irradiation (W/m^2)

In our example, the global irradiation average data per year *(1993-2004)* has been used to predict the future values. The predicted *(2005-2010)* value was nearest with the expected value (Fig. 11). At the top of the figure, the prediction and the expectation values based on the historical data are shown. At the bottom, the future prediction based on the previous data has been simulated.

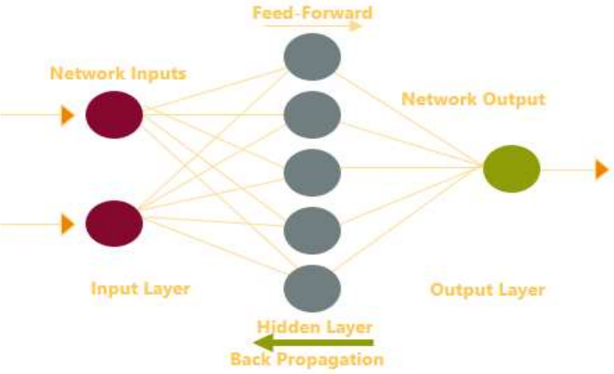


Fig. 12: A basic structure of an ANN model (template: slideteam.net)

Finally, the results of the ARIMA model for the uncertain irradiance prediction are used to find out the power production of the system employing an Artificial Neural Network (ANN) as the power output from a photovoltaic source depends on the solar irradiation. An ANN model comprises different layers (cp. Fig. 12) which are formed to calculate the power production (output layer) from the input by several iterations. In ANN, there are few parameters, such as the optimal weight base algorithm, which minimizes the loss function. Loss is a prediction error of the Neural Net. The method to calculate the error is called the Loss Function. The training stops when the error is near zero. Another parameter is the cost function which calculates how unmatched the predictions are. Reduction in the cost function reduces the error in the network. For updating the weights, the model needs several iterations, which are called epochs, and it reduces the loss error in the direction of prediction. The loss error back-propagated also in the network for comparing the real-time value concerning predicted values. Sequential training is utilized to instate the deep learning model as an arrangement of layers, where dense is used to add one layer of neurons (Fig. 12) in the neural organization. The cycle is incorporated with adding the information layer and the initially concealed layer, adding the second hidden layer, adding the output layer, compiling the ANN and fitting the ANN to the training set. By changing several concealed layers and normalizing information, we can improve the ANN model as well [13]. Apart from prediction of the future power production (kW), the model allows also to predict future instability in the grid or in a microgrid. This is valuable to identify possible problems and could reduce the cost of operation.

For our example, the following output were obtained

```
[[17.95 17.94]
[23.15 23.14]
[18.61 18.60]
[21.12 21.12]
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where column 1 and 2 are actual and predicted values, respectively. As can be seen, actual and predicted values are very close showing the accuracy and performance of the model.

Conclusion and Outlook

The main objective was to simulate a microgrid with a photovoltaic generator and coupling to a grid. To analyze the technical design, *MATLAB Simulink* was used as a simulation tool. The total renewable contribution from the whole system has been 30 kW_p. As mentioned above, the graphs have expressed the output phase equality of the grid voltage and the outcome of total THD, which is simulated by using the Simulink tool. More research has to be done in terms of converter application in the microgrid system. Also, if more than one renewable source is used, the question arises how phase of voltages can be stabilized and harmonic distortion can be avoided. A deep learning mechanism was used to forecast the energy supply of the system. The ability to predict the future energy output, excess energy, grid voltage and power factor could also play a vital role to analyze possible technical problems like grid instabilities and economic feasibility. To maintain the competitiveness of sustainable energy resources and new increasing demand, forecasting models could be employed to reduce time-based energy tariff expenses. In terms of renewable energy, future research can include more renewable sources and forecasting methods can be utilized to analyze the power output from photovoltaics, wind power systems, bioenergy, etc. In this research, the key elements have been discussed, and the processes were explained in terms of a microgrid system that can be established in the rural areas and provide more grid stability by making power control [16].

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Author Biography

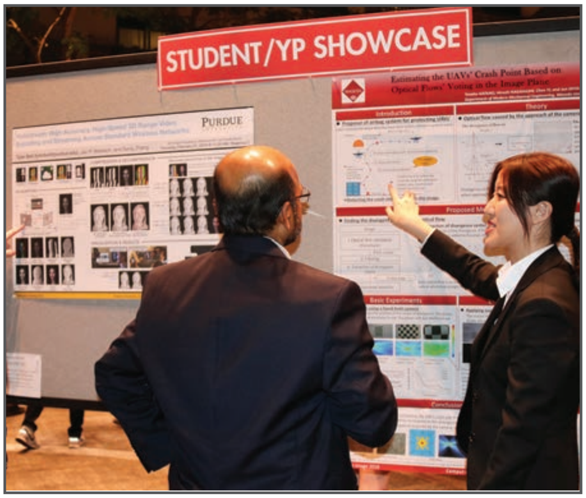
Prof. Dr. Goran Rafajlovski – Professor of Energy Engineering at the SRH University of Applied Sciences in Berlin. Senior Member of IEEE IAS. Current research focuses on improving the efficiency of the drive systems in decentralized RES-based supply and the investigation of grid integration of energy storage systems in microgrids with improved controllability and monitoring.

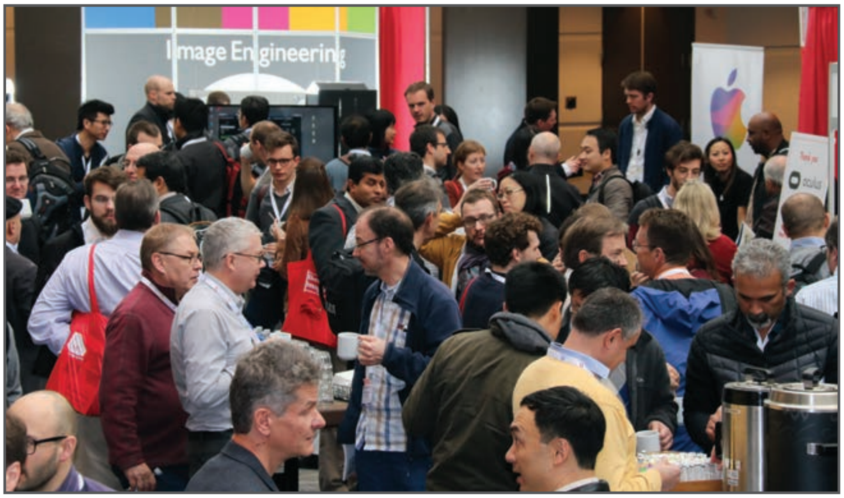
Prof. Dr. Michael Hartmann – Academic Director of SRH Berlin School of Technology; Head of the Study Programs: Engineering and International Business; Engineering and Sustainable Technology Management.

Prof. Dr. Reiner Creutzburg - Retired Professor for Applied Computer Science at the Technische Hochschule Brandenburg in Brandenburg, Germany. Since 2019 he is a Professor of IT Security at the SRH Berlin University of Applied Sciences, Berlin School of Technology. He is a member of the IEEE and SPIE and chairman of the Multimedia on Mobile Devices (MOBMU) Conference at the Electronic Imaging conferences since 2005.
In 2019, he was elected a member of the Leibniz Society of Sciences to Berlin e.V. His research interest is focused on Cybersecurity, Digital Forensics, Open-Source Intelligence (OSINT), Multimedia Signal Processing, eLearning, Parallel Memory Architectures, and Modern Digital Media and Imaging Applications.

B.Eng. Sanket Shrikant Patil – Master of Engineering student of mobility management at SRH University of Applied Sciences in Berlin, Bachelor of Electrical Engineering. Current research focuses on future mobility concepts, integration to the existing electric grid and with the help of AI; improve demand-supply scheduling with energy storage systems.

M. Eng. Md Saiful Islam – Research Associate at SRH Berlin University of Applied Sciences. Department of Berlin School of Technology. Researcher in the field of Renewable Energy and Electrical Engineering.





- AR is a fundamental and transformative interface and platform.
- 20+ years from my initial working demo to today's AR displays
- Optimistic that it won't take another 20 to reach ubiquitous consumer AR!