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Forecasting of Solar Power and Planning using Soft Computing

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Abstract—This thesis deals with the forecasting of solar power, it's planning and control using integrated soft computing approaches. The work is divided and conducted into three main parts. In the first part solar data is accumulated using DAQ from the panels deployed. Different variables which affect solar power generation are monitored and the data is collected. These variables include solar power, temperature, current, wind velocity, atmospheric pressure, and clouds. Solar power forecasting is performed by modelling two algorithms named Flexible Neural Network (FNN) and Genetic Algorithm –Fuzzy –Flexible Neural Network (GA-F-FNN) for different time horizons i.e., for 30 sec, 1 min, 10 min, and 15 min. using the above mentioned data. It is found that amongst these two algorithms GA-F-FNN showed better results as compared to FNN. Different factors affecting these two algorithms are also studied and monitored and finally forecasting of solar power is recorded. Also the effect of different factors like time horizons, static and rotating panel types, movement and percentage of clouds hindering solar panels, noise, normalization ranges etc. are studied during solar power forecasting.

Keywords— GN, FNN.

I. INTRODUCTION

The increasing population and urbanization is resulting in depletion of natural resources. The energy demand required by the world will be projected to double the existing demand by 2050 and will be triple till the end of the century. So, it becomes important to have development in the current energy networks so as to fulfil the needs and demands of the users in a more efficient and sustained way possible. It is highly challenging to find out the adequate clean and natural (renewable) energy sources. There lies a strong link of worldwide economy, quality of life and stability with that to clean energy supplies. The hunt of energy sources is the first and foremost challenge of the society in order to fulfil the world's growing energy demand. There is a requirement of most coordinated worldwide efforts to find out the solutions to the prevalent problem by using most recent technologies. Solar forecasting is an efficient and one of the advanced methods to face above challenges. Atmospheric conditions, information about Sun direction, the process of scattering and also the characteristics of solar panels or the solar energy plant which transforms energy of the Sun into solar power are major factors which also effect solar power forecasting. The resulting output power or the solar power relies on the radiations received from the sun and on the solar panel characteristics. A huge population of PV power production plants are set up now-a-days. The accurate forecast knowledge is important for an efficient uses like managing the electricity grid, planning and control of different loads. It is also equally important for trading of solar energy. The motivation behind various solar forecasting research activities is because of the accuracy of solar forecasting methods and the improvisation of the energy quality that is sent to electricity grid. Also, extra expenses are minimized by applying solar power forecasting techniques which may occur due to atmospheric parameters.

Solar forecasting on various time horizons shown in Figure 1.1 helps in improving many parameters related to PV systems like storage management, control systems, grid regulation, power scheduling etc. In case of unavailability of solar power generation, grid operators need transportation of energy to get optimized and allow the remaining energy to get allocated from rest of the available resources. Solar forecasting is useful in scheduling of maintenance of plant in order to arrest production losses under extreme conditions.

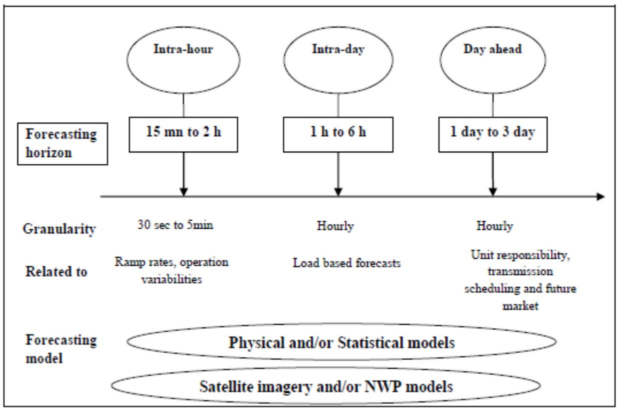


Figure 1.1: Solar forecasting time scale and their granularities

The forecasting methods are differentiated according to its uses and the time scale needed for the particular application. The time horizons from some seconds' upto some hours come under very short term timescale. For these types of time horizons and applications a time series model which uses on-site measurements are adequate. Ground based sky images are perfect models for obtaining intra-hour forecasts with high spatial and temporal resolutions. In order to obtain good performance for temporal ranges of half an hour upto 6-7 hours the best forecasting model is using satellite based images having cloud motion vectors. For grid integration based applications where PV power is integrated into grid, time scale required for forecast can vary up to two days ahead or even more than that. Numerical Weather Prediction (NWP) models are used for these types of forecasts. In [KOS 11] Kostylev and Pavlovski described different solar forecasting time scales and their corresponding granularities.

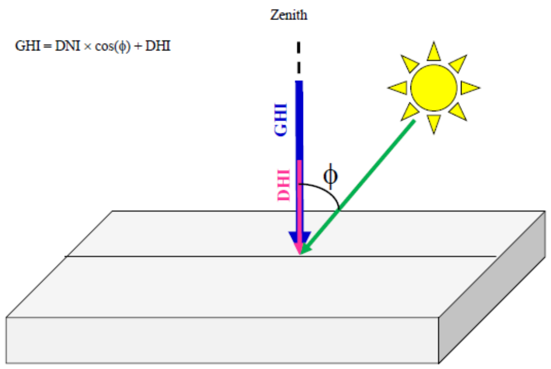


Figure 1.2: Relationship between GHI, DNI and DHI

1.2 Motivation

Solar based electricity generation has reached new heights of popularity in the past few years. The deployment of photovoltaic cells especially has increased immensely due to some major factors such as government policies, concern about green house gas emissions, depletion of non-renewable resources, lower equipment costs, affordable PV panels etc. Reliable and efficient integration of solar energy is not an easy task and goes through several issues. Main issue is to manage variability and uncertainty of solar power.

Maintenance of grid stability and quality of power is also a tedious task. Grid management poses significant technical difficulties due to variable generations from renewable energies like solar and wind plants. It is important to have good and accurate forecast so as to guard the future projections of higher share of renewable energies.

Solar energy availability largely depends on factors like solar radiation, weather conditions and therefore, has characterization of strong variability. Due to this reason power generation from renewable sources does not easily matches the electricity demand with that of conventional plants.

To ensure good, dependable and secured amalgamation of PV system to grid, it is very important for us to be prepared before hand for any unexpected variations in the PV output that occurs due to solar power's random and changeable behaviour. This fluctuating behavior results into deep repercussion on companies/organization's formation at all levels of electricity supply system. Therefore, the accuracy in forecasting is necessary. Solar forecasting can be evaluated for different time horizons. When the horizon is from one hour time period to several hours ahead it is known as short term forecasting. Similarly, midterm forecast ranges from several hours to a week ahead and when the horizon is beyond one week to several years ahead it is termed as long term forecasting.

It is important to understand the difference between the variability and uncertainty during planning and operation of a power plant. The change in the power output due to intermittency in solar power is variability, whereas uncertainty is the inability to predict in advance the timing and the magnitude of these changes. With the help of forecasting, we aim to reduce the uncertainty of the solar output so that the power operator can able to accommodate its variability.

II. LITERATURE REVIEW

According to Diagne [DIA 12] there are three types in which forecasting methods can be defined: Physical, Statistical and Hybrid methods Figure 2.1 describes the types of solar power forecasting methods. Physical method uses physical data for evaluation such as temperature, pressure, and cloud cover. This technique depends on numerical weather prediction (NWP) or atmosphere. When the model is trained using historical/past data then it is known as statistical model. Statistical model is considered as mathematical model. Hybrid models are a combination of physical and statistical approaches.

In the review paper by [INM 13], the forecasting techniques as per their applicable time horizons and spatial resolution on account of recent technologies and data are correlated to the forecasting methods, this is described in Table 2.1. There are five classes of forecasting techniques that can be categorized as follows:

1) Wireless sensor network based forecasting (high spatial proximity);

2) Total sky imagers based forecasting;

3) Satellite imaging based forecasting;

4) NWP based forecasting and

5) Stochastic and AI method based forecasting [INM 13].

2.1 Physical Methods

The numerical weather prediction is derived by the physics of the atmosphere. Assimilation process is used to predict future states of the weather depending upon the current observations of weather. In assimilation process current weather states as input are processed to produce outputs like temperature, wind, irradiance etc. The numerical weather prediction method is best for one day to multi day's ahead horizon and is helpful in applications like scheduling of solar power plants.

Table 2.1: Different Solar Power Forecasting Methods and their time horizon and spatial resolution

Forecasting Technique	Time Horizon	Spatial Resolution
Stochastic & AI Method	1 sec – 1 month	1 m – 2 km
Wireless Sensor Network	20 sec - 3 min	1 m – 1 km
Total Sky Imagers	3 min – 30 min	1 m – 2 km
Satellite Imaging	30 min – 6 hours	1 km – 10 km
Numerical Weather Prediction	4 hours – 36 hours	5 km – 20 km

Clouds which plays major role in hindering solar irradiance at the ground can also be predicted with NWP. Once the future weather states are forecasted error is calculated and corrected using statistical post-processing. NWP is a complex process and can be better understood by these three steps below:

Numerical Weather Prediction models may be grouped into global models and regional models. In the global model, the simulation of the climatic conditions is done on a global or worldwide scale. The regional (Mesoscale) model simulates the behaviour of the atmosphere for an area such as a continent or a country [JKL 13].

For the horizons longer than five hours the most reliable, accurate and efficient forecasting method is NWP method [MAT 13]. Model difference never affects the nRMSE of different NWP models, instead it is the difference in location which varies nRMSE of different NWP models from 15% to 45%. The locations having lot of clouds with high instability in their movement and low spatial resolutions tends to face a high forecasting error irrespective of the type of NWP model used.

2.2. Statistical Methods

Whenever, we talk about forecasting on the basis of historical data of solar irradiance statistical method comes into picture along with learning methods. Some examples of statistical methods include seasonality analysis, box-Jenkins or ARIMA, exponential smoothing, multiple regressions etc. Artificial Intelligence methods include examples of fuzzy systems, genetic algorithms, neural networks, support vector machines, machine learning etc. Table 2.3 lists the literature of statistical methods used.

To conclude, it is to be noted that apart from NWP and image based technique, time series models, empirical methods and artificial intelligence methods are also mostly applied in irradiance forecasting. The advantage of these models is that they are of much use for the locations where there are no irradiance measurement equipments or where there is limited access of forecast meteorological information from local meteorological centres. In general, for cloudy days non-linear models are considered as good models for forecasting and for sunny days linear models are considered as good [VOY 10]. In order to achieve accurate forecasting a model is framed for forecasting purpose.

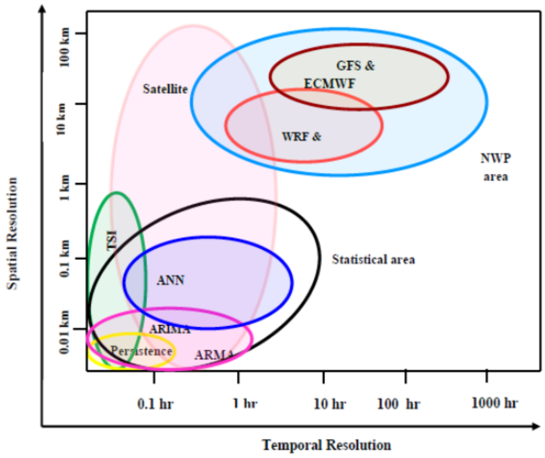


Figure 2.2: Spatial and Temporal Resolution Based Classification

The persistence models are considered as one of the easiest way of forecasting. The idea behind persistence models is that they assume that they assume that the predicted value is same as the previous value. They are also called by the name naïve predictor as this method helps in giving the clue in order to make comparison with other methods. This method is effective when there is very less change in the weather patterns.

The disadvantage of persistence model is it shows a high error result for forecasting more than one hour. A study was conducted in [HUA 12] to forecast the solar power output in a laboratory level microgrid using two methods, the ARMA and the persistence method. The study shows that for more than one hour forecast, the persistence forecast error was reduced by 17.62% when using ARMA model. So, persistence model is good in a very short term forecast. Conditional forecast model is designed to treat stationary series, which is weakly stationary for atleast during the use of statistical time series analysis. Non-stationary series are dealt with various methods to bring them in a suitable form.

The amount of solar radiation received on the horizontal surface over a particular time period for a particular area is called solar insolation. It is solar zenith angle dependent. Two transmissivity measures are given in literature: clearness index (k) and clear-sky index (k*).

Comparatively easier implementation and understanding make linear model more attractive. It may also be pointed out that non-linear patterns are also shown by many practical time series. It is evident in the literature that various non-linear models have also been forwarded for consideration by considering suitability of non-linear models for predicting volatility changes in financial and economic time series [RPA 01]. Considering these facts, various nonlinear models have been proposed in literature. Some of them are the famous Autoregressive Conditional Heteroskedasticity (ARCH) [HPA 99, RPA 01] model and its variations like Generalized ARCH (GARCH) [HPA 99, RPA 01], Exponential Generalized ARCH (EGARCH) [HPA 99] etc., the Threshold Autoregressive (TAR) [GPZ 03, HTO 83] model, the Non-linear Autoregressive (NAR) [GPZ 07] model, the Nonlinear Moving Average (NMA) [RPA 01] model, etc.

Prof. Lotfi Zadeh introduced the term Soft Computing to find out the tolerance for imprecision, uncertainty and partial facts to get tractability, robustness, low solution cost and better rapport with reality. The aim is to emulate the human mind as closely as possible. Neural networks, genetic algorithms and fuzzy logics are collectively important partners for soft computing.

Soft computing is nothing but hybridization of more than one method. There can be many permutations and combinations in soft computing. These soft computing methods are capable of exploiting all the advantages of single method but would not inherit features that are less desirable in a single method. These soft computing methods have to have great learning capability, less prone to individual problems etc.

Constituents of soft computing are complementary to each other, not competitive. They have their own advantages to provide solutions. Soft computing techniques viz neural networks, fuzzy systems and genetic algorithms are evolved from the biological computational strategies and in natural way to solve the problems in general. A simple and modified model of human nervous system can be represented as neural networks, which has ability to mimic certain situations and learn from the previous experiences. Fuzzy logic or fuzzy systems are used to find a solution dealing with uncertainty and vagueness in a system by formulating fuzzy rules. Fuzzy logic gives us a transformation among membership and non-membership of the variables for a given problem. Genetic algorithm, which is evolved by natural process inspiration and are adaptive search and optimization algorithms.

III. PROBLEM FORMULATION

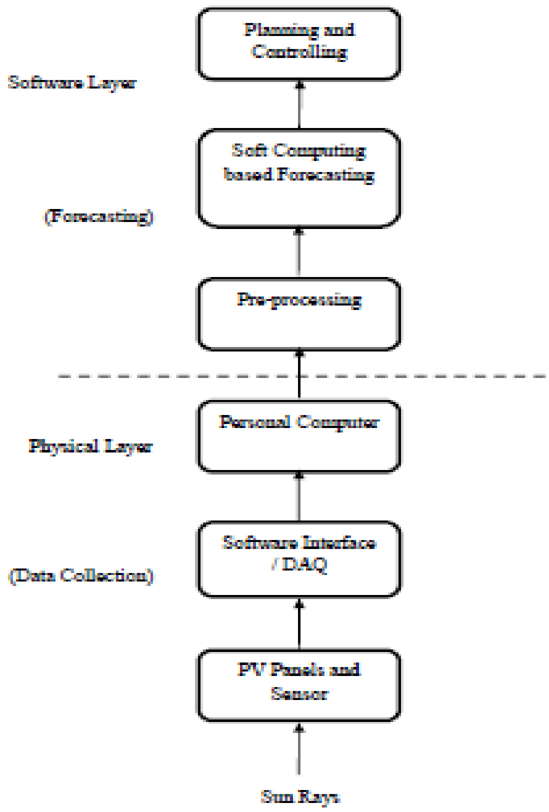
Solar Power Forecasting , planning and controlling of load using different soft computing techniques like Neural networks, Genetic algorithm, Quantum computing, Fuzzy computing etc. and their comparison.

IV. PROPOSED METHODOLOGY

The steps discussed here are briefing about the flow in which the work is being compiled.

- Thorough literature review is done so as to understand the concepts of solar power, different solar power forecasting techniques and evaluation metrics for solar power forecasting.
- A hardware setup is developed with the required sensors to acquire local weather parameters data for forecasting like solar irradiance, temperature, humidity, pressure, wind velocity and clouds All this data is collected online on a computer with the help of DAQ interfacing.
- The data collected is for static solar panels and rotating solar panels at the time intervals of 30 seconds, 1 minute, 10 minutes and 15 minutes.
- A model is developed using soft computing techniques which takes weather parameters as inputs and forecast solar power for different time horizons.
- Monitoring of different effects is seen and observed based on the model formed and best parameters are spotted.
- The forecasting accuracy is validated with the help of metric evaluation like MSE, RMSE etc.
- Once the forecasting is done planning and control of loads is performed by prioritizing the appliances according to the user. Figure 1.4 describes the methodology of the work done.

V. SIMULATION RESULTS



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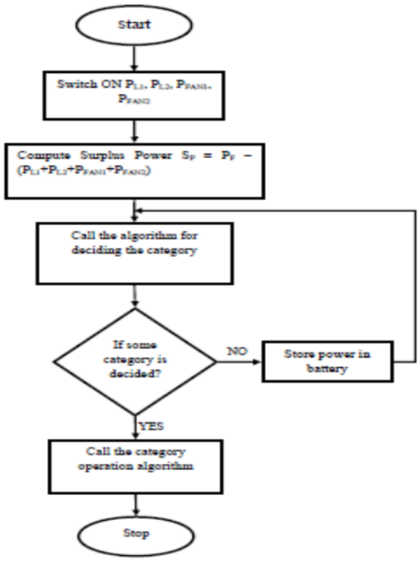

Figure 4.5: Scheduling Flow Chart

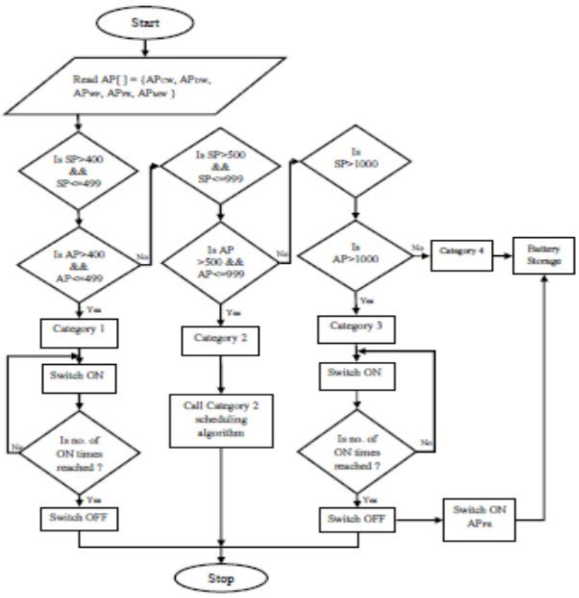

Figure 4.6: Category deciding flow chart

The Figure 4.8 and 4.9 below are the simulation results of the algorithm described above. The graph depicts the ON/OFF cycles of appliances i.e., the appliances operates by deciding the category to which it belong. The number of rounds mentioned is the data forecasted for every 15 min of time period. This simulation is being carried out using Matlab. As mentioned above in flowcharts it is clearly observed that once every appliance has finished its task the remaining data is being consumed by fridge which is an essential appliance and needs to be operated frequently so as to maintain the temperature. The Figure 4.8 and 4.9 depicts the same cycle where it is clearly observed that fridge is running and consuming the data left after all the appliances have finished their task and need not be operated further. Two data sets are simulated and two varied situations are depicted with their ON/OFF cycle graphs.

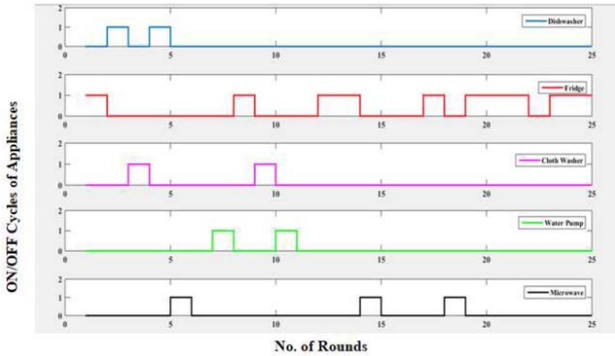

Figure 4.8: Appliance Scheduling Case 1

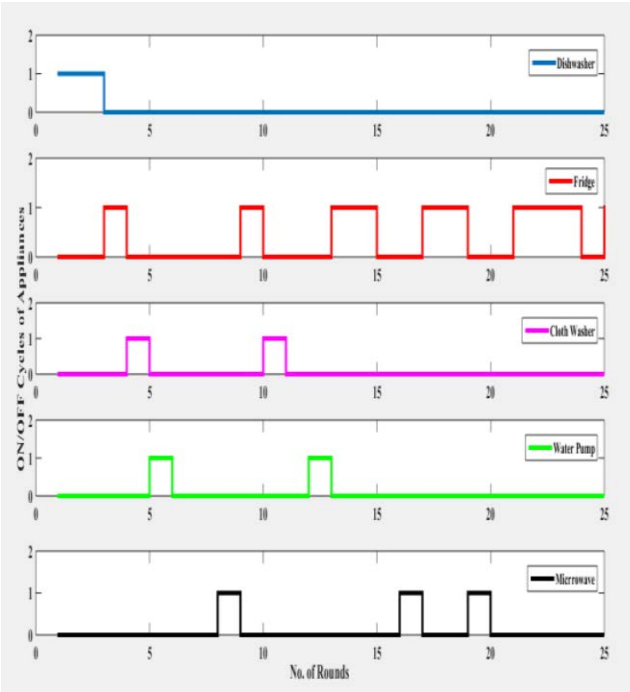

Figure 4.9: Appliance Scheduling Case 2

4.5 Fuzzy Decision Based Home Appliance Management (FDBHAM)

The short-term real time forecasted solar power of one day from PV system configuration considering real temperature, pressure, irradiance, wind velocity, cloud percentage etc. is used to feed the house loads. This is performed on a PV array of 2.25kW, and battery bank of 12kWh. The home energy requires satisfaction, which will be feeded by the locally PV generated energy mainly depending on the energy requirements of the residence, PV energy generated and the battery's charge status as shown in Figure 4.10 below. In order to get the best results between forecasted power produced and its use in the residence, a fuzzy decision based home appliance management model is developed.

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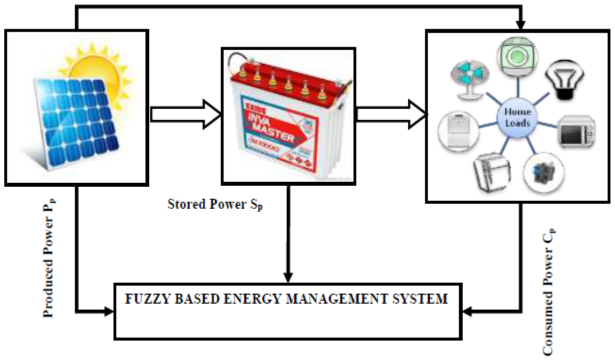

Figure 4.10: Fuzzy Based Energy Management System

4.5.21. Introduction to proposed method

Fuzzy logic is obtained from fuzzy set theory which basically operates based on reasoning whereas the classical set theory provides precise output. The variables used for computing the output are called fuzzy variables. The input data is first fuzzified using statically defined membership functions which generate a truth value between 0 to 1.The fuzzy logic define the connections between various inputs in natural language through a set of fuzzy rules with the output. The system continuously estimates the given inputs and delivers outputs of the system based on the rules. The Figure 4.11 below shows the fuzzy inference system.

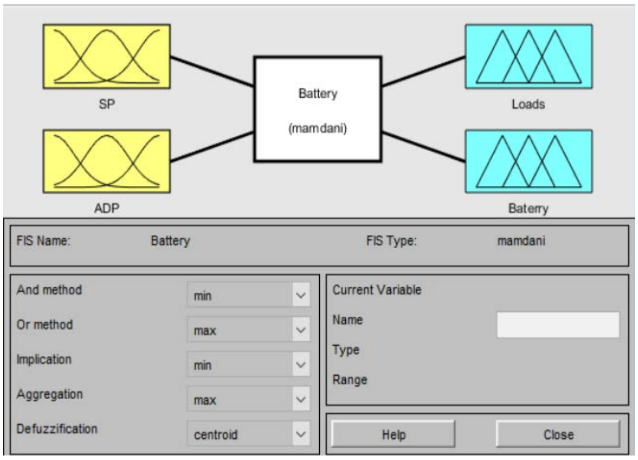

Figure 4.12: Fuzzy Logic Controller

Table 4.2: Membership Functions

	Term Sets	Membership functions	Limits
Surplus Power	Not Sufficient	Triangular	{-33.3; 0.132; 30.8}
	Low	Triangular	{8.47; 33.73; 60.2}
	Medium	Triangular	{30.56; 61.5; 88.5}
	Sufficient	Triangular	{59.92; 100; 133}
Additional Power	Low	Triangular	{-0.4; 0; 0.4}
	Medium	Triangular	{0.1; 0.5; 0.9}
	High	Triangular	{0.6; 1; 1.4}
Load	Battery Charging	Triangular	{-1.33; 0; 1.33}
	P1	Triangular	{0.1; 1.33; 2.667}
	P1P2	Triangular	{1.33; 2.667; 4}
	P1P2P3	Triangular	{2.667; 4; 5.332}
Battery	Tickle Charging	Triangular	{-0.4; 0; 0.4}
	Medium Charging	Triangular	{0.1; 0.5; 0.9}
	High Charging	Triangular	{0.6; 1; 1.4}

The working of energy management is based mostly on two inputs Surplus Power (SP) and Additional Power (ADP). It is important here to understand these two terms SP and ADP, surplus power here is the power left from the forecasted solar power produced from PV panels after switching ON the very essential loads i.e., two lights and two fans. On the other hand additional power is the power left after switching ON the appliances of different categories. Depending on these input parameters, the fuzzy home appliance management takes the decisionas to which loads will be switched ON and whether the battery will charge or not. The predefined priorities are taken into account for the same:

The priority 1(P1) is for category C1 defined above i.e., this is for the appliances that cannot be disconnected in case of C1 it is refrigerator.

− The priority 2 (P2) is for the category C2 defined above i.e., this is for the appliances that can be shifted in case of C2 it is cloth washer, water pump, microwave, dishwasher.

− The priority 3 (P3) is for the category C3 defined above i.e., this is for the appliances which are not essential and will not affect much if remains unused. In case of category C3 it is vacuum cleaner.

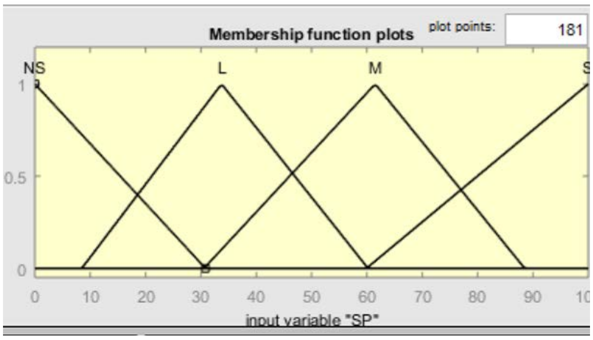

Figure 4.13: Input Membership Function “SP”

Figure 4.14:

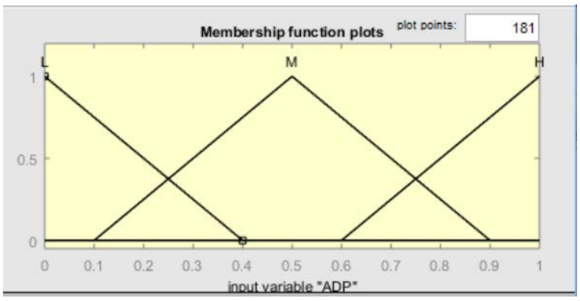

Figure 4.14: Input Membership Function “ADP”

The above Figure 4.13 describes the fuzzy range of the input variable “Surplus Power”. The range of the variable is divided into four main categories i.e., Not Sufficient (NS), Low (L), Medium (M) and Sufficient (S). Similarly, the Figure 4.14 describes the another fuzzy input variable “Additional Power” divided into three main categories Low (L), Medium (M) and High (H).

After defining the fuzzy variables and the membership functions, it is important to define the If-Then logic rules to proceed with the inference process. For understanding the membership functions, the rules are defined as below in Table 4.3 and linguistically mentioned for better understanding. The rules mentioned below are then defined and simulated using fuzzy logic controller which is shown in Figure 4.15.

VI. CONCLUSION & FUTURE WORK

6.1 Conclusion

As per this chapter the forecasted solar power from the previous chapter is utilized in appliance planning and controlling. The two methods are used for planning and controlling of household appliances. The two methods are Power Decision Based Home Appliance Management (PDBHAM) and Fuzzy Decision Based Home Appliance Management (FDBHAM). Amongst these two methods Fuzzy Decision Based Home Appliance Management (FDBHAM) is more efficient than Power Decision Based Home Appliance Management (PDBHAM) because of the fact that battery is involved in fuzzy based management system for utilizing the excess power. Also, the fuzzy decision rules manages and controls the appliances much more efficiently than power based management because in power based management the power is being utilized directly as per the generation and appliance falling under that generation group. The only case in which the battery is used when no appliance match the power requirements as per generated solar power, in such situation the power is stored in battery.

6.2 Future Work

As it is said that research is a never ending process, there is always a scope for future work. In case of this work the following future aspects can be seen for improvements.

1. This work can be further improved by selecting suitable error functions for Solar Power Forecasting.

2. Other tools like Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony optimization etc. can be used for solar power forecasting and health monitoring of solar panels, generation, batteries etc.

3. More detailed model of Solar Power Forecasting using different types of clouds, cloud heights, cloud densities etc. can be done.

4. Multiple site crossover and multi site mutation can happen in forecasting for better results.

5. For better planning hybrid systems can be applied in planning and controlling model.

6. Using Soft computing techniques we can apply smart protection on solar generation.

7. Economic study of solar generation, planning and control can be done.

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