Planning Issues in Grid Connected Solar Power System: An Overview

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Abstract - A long term prediction of future load is helpful in better operation of power systems and its economical utilization. A number of algorithms have been suggested for solving this problem. In soft computing techniques neural networks and combined Fuzzy Logic, for long term load forecasting is proposed. The output load obtained is corrected using a correction factor from neural networks, which depends on the previous set of loads, number of customers etc. The data is taken for the three years and the results are obtained for the fourth year. It is further validated using the actual data from an electrical company.

Key Words: Fuzzy Logic, Grid Computing, Solar Power, Forecasting, Neural Network.

1. INTRODUCTION

For centuries humans have designed buildings and settlements to take advantage of light and heat from the sun. While many of these design techniques fell out of favor with the advent of fossil-fuel-produced heat and electricity, in recent years communities across the India and throughout the world have taken a renewed interest in both passive and active solar energy use. In many industrialized nations, rising fuel prices and concerns over energy security during the 1970s planted the first seeds of the modern market for solar energy production. However, these initial investments in solar technology remained quite modest until the first decade of the twenty-first century. Solar energy is a community resource and should, therefore, be treated as such. Five strategic points of intervention that planners, public officials, and other community stakeholders can use to foster opportunities for solar energy use and evaluate solar development opportunities.

A long term prediction of future load is helpful in better operation of power systems and its economical utilization. A number of algorithms have been suggested for solving this problem. In soft computing techniques neural networks and combined Fuzzy Logic, for long term load forecasting is proposed. The output load obtained is corrected using a correction factor from neural networks, which depends on the previous set of loads, number of customers etc. The data is taken for the three years and the results are obtained for the fourth year. It is further validated using the actual data from an electrical company.

2. Concentrating Solar PowerSystems

Concentrating solar power (CSP) systems use mirrors to focus light and heat a contained substance such as molten salts or water to create steam. These mirrors may be arranged as a trough focusing the light on a substance trav-elling through a tube, or as a dish focusing the light on a single point. The heat from that substance is harnessed to drive a mechanical engine, which subsequently drives an electric generator.

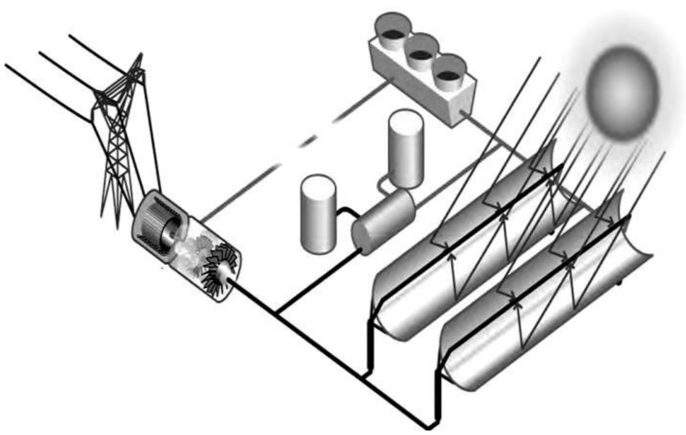

Fig.1 Parabolic trough concentrating solar power (CSP) collectors capture the sun's energy with large mirrors that reflect and focus the sunlight onto a linear receiver tube

Unlike PV systems, CSP systems are generally only commercially viable on a large scale, typically for large industrial facilities or as a wholesale electricity generator for utilities larger than 100 megawatts (MW) in capacity. In order to meet this large scale, CSP systems require a significant amount of land, normally five to 10 acres per MW. Furthermore, CSP systems, like all thermal power plants, use large amounts of water. Perhaps the primary benefit of CSP systems over PV systems in utility applications is that CSP systems can store energy more efficiently. While PV electricity production drops off substantially in the late afternoon and early evening, when electricity use is still high, the thermal energy collected by a CSP system can be stored for extended periods of time, allowing it to generate electricity as the sun sets.

3. Interconnection

Interconnection refers to the technical and procedural requirements necessary to safely, reliably, and efficiently connect an electricity-generating system (e.g., a PV system) to the electricity grid. In order for a PV system to net meter, rather than rely on batteries to store the electricity, the system must be interconnected. The interconnection process sets forth guidelines and criteria in order to allow electricity to flow from the PV system out into the grid. Traditionally, utilities (regardless of the type) owned generation facilities and thus had control over the how producers connected to their electricity grid systems. Interconnection procedures run counter to this established method by allowing a potentially large number of electricity-generating systems to interconnect at various points along a grid. Without established interconnection procedures, the cost of studying the potential impacts of connecting to the grid could overwhelm the cost of a PV system. Therefore, it is critical that utilities use well- established guidelines and best practices to facilitate the interconnection of PV systems in order to safely and efficiently allow and capture the benefits of PV generation.

4. Plan Making

The second strategic point of intervention for communities looking to promote solar energy use through planning is plan making. Communities adopt local plans in order to chart courses for more sustainable and livable futures. Planners and public officials then use these plans to inform decisions that affect the social, economic, and physical growth and change of their communities. Given the potential economic and environmental benefits of local solar de-velopment, it is no wonder that an increasing number of cities and countries are addressing solar energy use in their plans.

Solar in the comprehensiveplan

Comprehensive plans are named as such because they cover a broad range of topics of communitywide concern. All states either allow or require local governments to prepare comprehensive plans, and many states require local development regulations to be in conformance with an adopted comprehensive plan. While enabling laws vary from state to state, common topics for plan elements (i.e., chapters or major sections) include land use, transportation, housing, economic development, and community facilities. In recent years an increasing number of cities and counties have added elements addressing sustainability, natural resources, or energy to their comprehensive plans. The comprehensive plan is the legal foundation that legitimizes local land-use regulations. As such, it is important for plan authors to establish a policy foundation in the comprehensive plan for development regulations that affect solar energy use. Ideally, the local comprehensive plan is a primary guide not only for updates to development regulations but also for the creation of local capital improvements plans, which detail planned capital expenditures over a multiyear period. By extension, comprehensive plans with goals, objectives, policies, and actions that support solar development can pave the way for future public facility construction or rehabilitation and private development projects that incorporate passive solar design or solar energy systems.

Solar in subarea plans

Subarea plans are plans that include goals and objectives for a discrete geographic area within a jurisdiction. Some common types of subarea plans include plans for specific sectors, neighborhoods, corridors, or special districts, such as transit station areas, redevelopment areas, or areas designated for historic preservation. These plans may cover a wide range of topics relevant to the plan area, essentially functioning as smaller-scale comprehensive plans, or they may be strategic in nature, focusing on a subset of topics with special urgency. The limited extent of subarea plans has both advantages and disadvantages. Because comprehensive plans can seem abstract or diffuse to residents, business owners, or institutions that identify more with specific neighborhoods than with a city as a whole, planners often have an easier time identifying and engaging key stakeholders when a plan has clear implications for these stakeholders' homes, businesses, and shared public spaces. The other clear potential advantage of subarea plans is that these plans can be more specific about how goals and objectives apply to individual parcels of land. On the flip side, strong emotions can lead to a loss of objectivity, making it difficult for communities to prioritize scarce resources. When considering the limited extent and greater specificity of subarea plans in the context of planning for solar energy use, plan authors have opportunities to discuss the neighborhood- or parcel-level implications of policies and actions aimed at increasing adoption of solar technologies. Subarea plans can provide greater detail about preferred locations for solar installations and go into more depth about the regulations, incentives, and potential competing interests that may either support or inhibit local solar market growth.

5. The power audit

Here is a sample power audit. Notice the "No." column. This shows how many of those appliances typically are operating at the same time. This is important. If you have 12 ceiling lights, but on average, only five are turned on at once, you'd enter 5, not 12, in the "No." column to get an accurate estimate of the typical load. The "Total KW" column is simply the KW load multiplied by the quantity in the "No." column. Notice the "Hours on per day" and "KWH per day" columns. Estimate how many hours per day each appliance is used. Multiply the "total load" KW by these hours to get the total power (KWH) used by that appliance in a typical day. Example: In Table 1, the five 26W ceiling fixtures together draw 130W (0.13 KW), and all five are estimated to be turned on for 8 hours each day. Multiplying 0.13 KW by 8 hours yields a daily power consumption of 1.04 KWH.

Table 1: Sample power audit

Appliance	No.	KW (Load)	Total KW (Load)	Hours On per Day	KWH per Day
Ceiling light, two 13W CFLs apiece	5	0.026	0.13	8	1.04
Desktop computer	1	0.175	0.175	4	0.7
45" LCD television	1	0.22	0.22	5	1.1
Well water pump	1	1.3	1.3	0.2	0.26
Refrigerator	1	0.275	0.275	4	1.1
Microwave	1	1.8	1.8	0.1	1.8
Washing machine	1	0.3	0.3	0.1	0.03
			Total solar load: 4.2 KW		**3.31 KWH per day**

In this audit, the total solar load is 4.2 KW if all the listed appliances are operating at the same time. This is a worst- case condition, but one for which the inverter should be sized, and is a factor in determining the number of solar panels. This audit shows that 3.31 KWH are consumed per day. The KWH per day value affects how many arteries you will need, and is another factor in determining the number of solar panels.

6. Panel interconnections

PV panels come with short (3' or 4') positive and negative cables permanently attached to a junction box that is wired to the internal solar cells. Each cable has a polarized industry-standard compatible connector. Connectors are used throughout the solar industry to interconnect PV panels. They are polarized (male and female), so it is possible to connect a positive cable only to a negative cable for series wiring, or to a panel-mounted positive connector of the opposite gender (e.g., on a combiner box). Connectors are weatherproof, and have latches to ensure a positive connection that won't pull loose. You will need longer cables to reach the combiner box (below) than are supplied with PV panels. Extension cables are available for this purpose, and how to use them is explained in the section on the combiner box.

Grid-tie considerations

Grid-tied means being connected to the grid and capable of selling excess solar energy to the electric utility. A grid- tied inverter sends AC power produced from a renewable source (e.g., solar, wind, hydro) to the grid via the *input* cable. Normally we think of an inverter putting AC power on its *output* cable to run appliances, but in this case it puts it on its input cable.

Power System Operation Planning

Given the unit-commitment and dispatching of the conventional generators assessed in the sale/purchase session of the energy market, and given the forecast of load and renewable PV and wind power, assessment of the balancing reserve involves:

i. Uncertainty evaluation based on the load demand, the wind and solar power generation and the generation supplied by thermal units;

ii. Probabilistic combination of the abovementioned uncertainties and consequential evaluation of the needed balancing reserve to match the demand for a given confidence level of 95%.

Regarding the confidence level of 95%, this value was considered taking into account other international experiences; in any case, this parameter can be changed maintaining the same methodological approach proposed here. Under a set of operational conditions such as composition of generators, generator characteristics, automatic generation control and economic load dispatch, an operator plans a generation schedule typically for the next day. In the schedule, start and stop timing and generation level of each generator are decided to fit the predicted demand of various levels during the day. The operation plan of a power system, called as unit commitment, is a result of large-scale optimization planning considering economy, stability and security of the power system operation. The economy is mainly dependent on the operational cost of each power plant including fuel cost and generation efficiency of a thermal unit. The operational stability is mainly related to the total capability of all generators to change its output. The security is ensured through the reserved generation units which may work in a sudden increase of demand or in a sudden loss of generation due to a generation failure. If there is not enough balancing capability in a power system, it may be necessary to curtail the variable PV generation to secure the stability of the system operation, even if it reduces the economy of the system. In the context of operation planning, the natural variation of PV generation increases the requirement demand-and-supply balancing capability of a power system which results in partial operation of some power plants. The uncertainty of PV generation requires additional operation of generation units with lower economy in preparation for the event of reduced PV generation. These changes bring about the reduced economy of the existing generators and the increase of stresses of the generators there are many countries where electricity is traded in a power market. The trades are made for various, short or long time frames. In the competitive circumstances, the plan of unit commitment is decided partially in the market. In the unit commitment including the power market operation, PV forecast plays a crucial role to decide the performance of a power system operation. In the power system operation planning, in order to keep the viability of the analysis, we need to include the parameters such as maintenance schedule of power system elements.

Power System Augmentation Planning

In years, demand and generation mix changes in a power system. In order to reduce CO2 emission in the energy sector, it is widely recognized that energy demand will increase as economy grows in general, the existing power demand will reduce through energy efficiency, much of energy demand will be electrified, and more energy will be supplied by variable renewable generation, which leads to a larger power demand and supply structure with a higher share of variable renewable generation including PV. In the current practices of power system augmentation planning, a planner, following criteria such as economy, reliability, environmental, stability and security, optimize the future power system. When a power system augmentation is planned including RE such as PV, it is usually aimed to find the optimum path to integrate RE into a power system. In order to develop such a future power system, the power system augmentation planning must have the new functionalities so as to accommodate substantial variable renewable generation, while satisfying the existing planning criteria and constraints. The impacts of PV penetration on the power system come with the variation and limited predictability of PV generation, and the reduction of the operational amount of dispatch able generators. In the power system augmentation planning, the parameters which are used in the operation planning are necessary to estimate the operational performance of each augmentation scenarios. In the augmentation planning, the time horizon is the most important parameter. A major thermal generation needs several years of legal procedures and construction period. The distributed generators also need long time for being properly disseminated. The augmentation planning usually has 10 to 20 years of study period.

7. Planning: Comprehensive Approaches

Comprehensive planning approaches that integrate transmission, distribution, generation and system performance goals, from distribution to bulk power system across an entire network, greatly facilitate and reduce the implementation costs of variable renewable energy integration. The coordination and integration of planning processes helps regulators prepare for the potential impacts that variable generation may have on the system and evaluate the available options to optimize generation and transmission costs. Resource planning takes many different forms around the world. However, the experience in different countries shows that there are a few practices that can be applied in many different regulatory contexts. Three key principles that have been identified include:

1. Integrating the planning of generation, transmission, and system performance
2. Ensuring institutions and markets are designed to enable access to physical capacity
3. Building from local and regional planning to better integrate and coordinate information across jurisdictions.

Planning processes that optimize generation, transmission and other resources across an entire network greatly reduce the need and cost of variability mitigation mechanisms.

Operation Planning

Under the increased variability and uncertainty due to PV and wind generation penetration, in order to preserve reliability in an economic way, it is crucial to improve the predictability and flexibility in the operation of a power system. Given the unit-commitment and dispatching of the conventional generators assessed in the sale/purchase session of the energy market and given the forecast of load and renewables PV and WIND, the steps of the assessment of the balancing reserve are:

- The uncertainty evaluation based on the load demand, the wind and solar power generation and the forced outage risk of thermal units;
- The probabilistic combination of the above mentioned uncertainties and the consequential evaluation on the needed balancing reserve to match the demand for a given confidence level. Figure 2 depicts the basic flow scheme of the adopted methodology for the balancing reserve calculation for one day ahead.

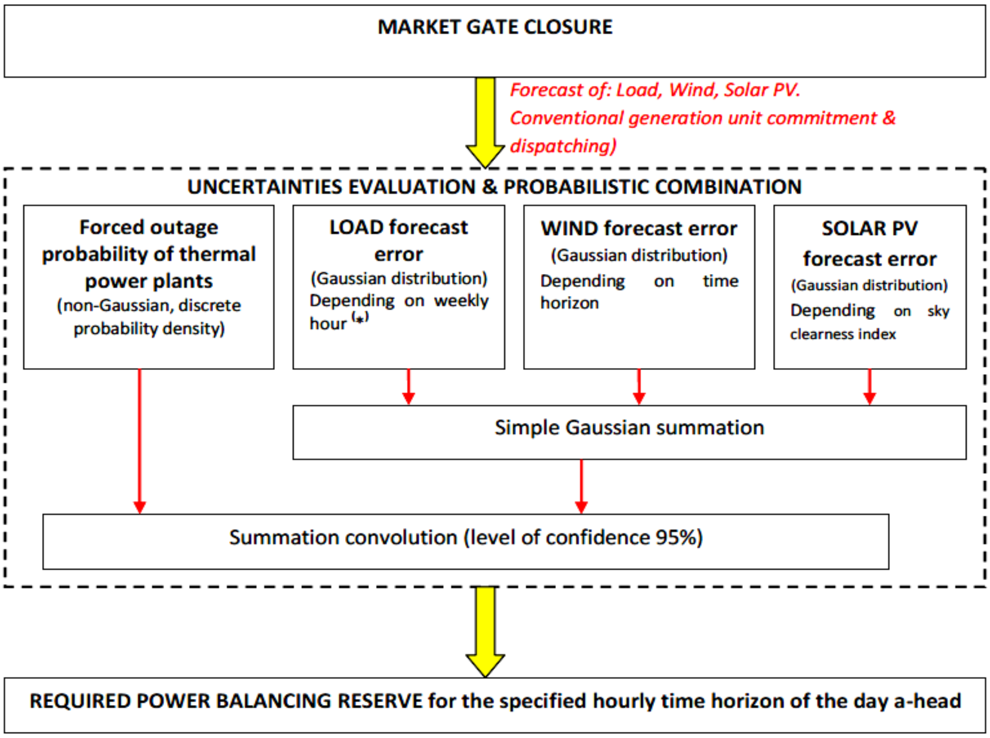

Fig. 2 Flow scheme of the methodology for the evaluation of the hourly balancing reserve.

Augmentation Planning

In the last few decades, the increasing penetration of variable generation technologies – most notably wind and solar – has required changes in the way the electricity grid is operated. The daily and seasonal variability patterns observed in wind and solar technologies present a challenge to their efficient integration into existing electrical grids. Given the complexity of modern grids, it is necessary to employ computational simulation models to fully understand the effects of introducing increasing variable generation levels, devise effective mechanisms that facilitate their integration, and optimize costs. The design and complexity of the optimal variable generation integration model will depend on the goals of each study, as well as the levels of added solar PV capacity. Some of the study components presented in this section may be omitted for studies looking at shorter time horizons, or relatively low levels of increased solar PV penetration, for example. Before designing a solar PV integration study it's important to consider its main goals. Examples include:

- Evaluating the costs of integrating variable renewable energy source into the system
- Identifying variable renewable energy integration impacts on grid operation

Measuring the amount of variable renewable energy the existing system can absorb before changes in operation or physical configuration are needed To address the complexity, the model structure can be divided in elements corresponding to relatively independent tasks as depicted in Figure ES5. Modularity also helps to scale down the model complexity to match actual needs.

Most solar PV integration studies will follow an iterative process where a few of the steps are repeated, using outputs from certain modules to modify previous assumptions, or as inputs for other modules.

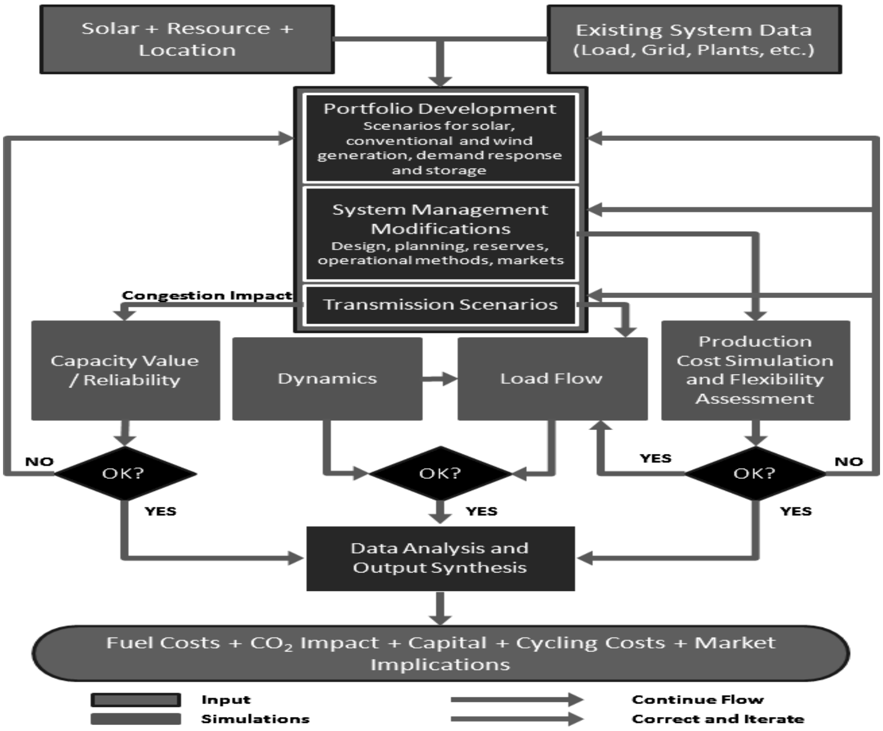

Fig. 3 PV and Wind integration study recommended practices diagram.

In normal operation, hydropower plants support the power grid, and the PV power system outputs active power and reactive power in accordance with the requirement of the scheduling institute. When the grid is down, the two dual-mode PV units support the grid alone. Figure 4 shows a photo of the 2 MW PV station.

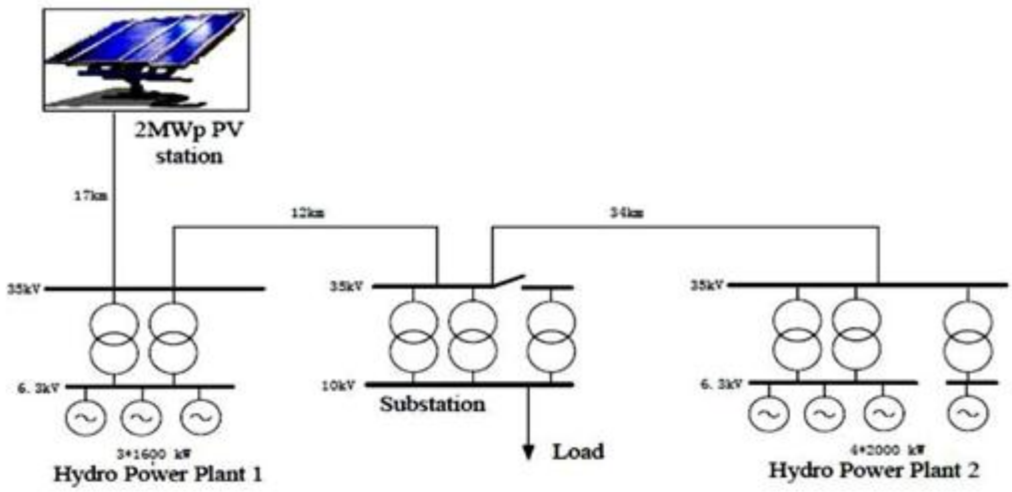

Fig. 4 Hydro/photovoltaic hybrid power system

The annual generating capacity of this power system is nearly 3 million kWh; its lifetime generating capacity is nearly 70 million kWh. Compared with traditional power plants, the hydro/PV hybrid power system can save about

24.5 thousand tons standard coal, which saves 64 thousand tons of CO2, 588 tons of SO2, and 172 tons of nitrogen oxide emissions; the beneficial effect of reducing carbon emissions is obvious.

8. Estimation of solar electricity generation

The solar electricity generation was estimated with the above conditions. The electricity generated annually and monthly is estimated by assuming a PV system performance ratio, the losses are accounted as follows for a PV system with nominal DC power of 1.0 kWp.

i. Estimated losses due to temperature and low irradiance: 9.7%

ii. Estimated loss due to angular reflectance effects: 2.4%

iii. Other losses (cables, inverter etc.): 12.0%

iv. Combined PV system losses: 24.2%

Table 2: Monthly and Total Annual electricity production for fixed angle PV system, inclination=31 deg., orientation=0 degrees with the above conditions.

Month	E_m in kWh/kWp
Jan	69.1
Feb	84.9
Mar	129
Apr	144
May	167
Jun	166
Jul	175
Aug	172
Sep	147
Oct	118
Nov	82.8
Dec	65.3
Total Annual electricity production in kWh/kWp	**1520**

Em: Average monthly electricity production from the given 1 KWp PV system (kWh)

Therefore, it is estimated the AC power electricity production for a PV system will be 1520 kWh/kWp with an estimated accuracy of ±5%.

9. Issues and Solution for PV and other Generation RES Electrification island power system operation approach

In Figure 5, the basic block diagram of Electrification system is presented as it is expected to operate in its final scheme including Hydrogen production, storage and electricity production associated with Hydrogen. In a real application, the electrification system should be supported by a monitoring and a decision support system that will take into account forecasts for load, weather (solar, wind, etc.) and state of charge of batteries, hydrogen storage, etc. and provide an operation schedule and strategy for the following minutes and hours.

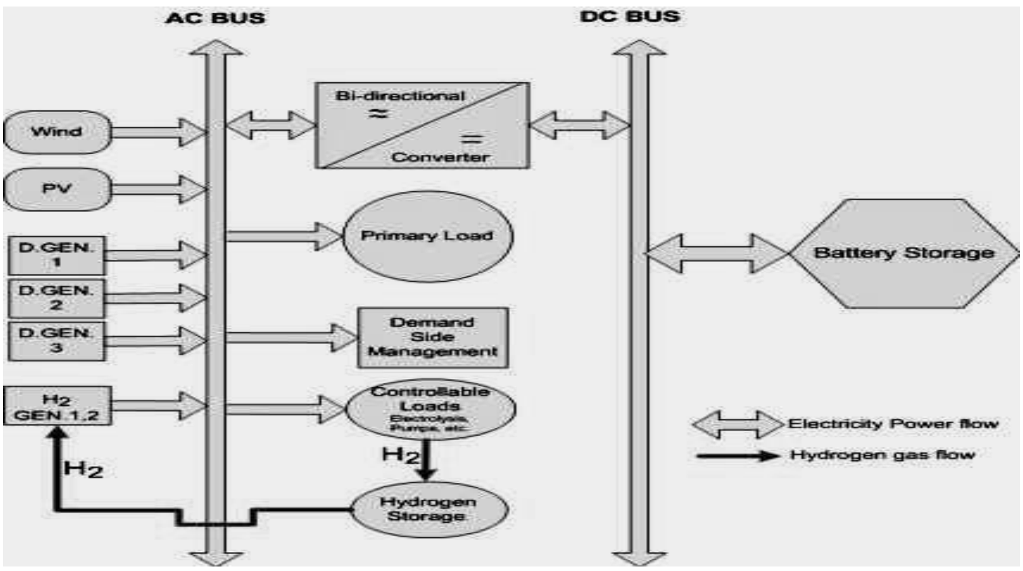

Fig.5 Basic block diagram of RES and Hydrogen based Electrification system.

The main components for the management of the overall power system and decision logic are a Data Acquisition system and a Central Supervisory Control. Additional systems(SCADA), such as dynamic compensation components and adjusting devices for security necessary for the proper dynamic operation of the network are also considered. The additional systems, depending on the architecture of the proposed power system may also include: flywheels, rotary capacitors and additional bi-directional converters with local storage. Interventions may be also needed to the existing diesel generators of the power station such as: upgrade or replacement of the engine rpm regulators to comply with the dynamic support characteristics and communication of the existing SCADA26 system of the power plant with the central monitoring, control and management system. For this purpose, the central management system given the forecasts for load and RES availability and the state of charge of the battery system should be able to make a prediction of short term RES production and island system demand, providing appropriate signals for the management of power production and of the controllable loads. In Figure 6, a logic block diagram for the forecast, state estimation and scheduling of the island electrification system components is presented. As RES units are being generally characterized by variability in their production, the penetration of RES in the conventional power systems' generation mix is limited due to technical constraints introduced by the conventional units. With limited control capabilities, operators are obliged to follow conservative procedures, rejecting part of\ the available resources. To overcome this limitation, advanced management systems with effective control capabilities need to be implemented.

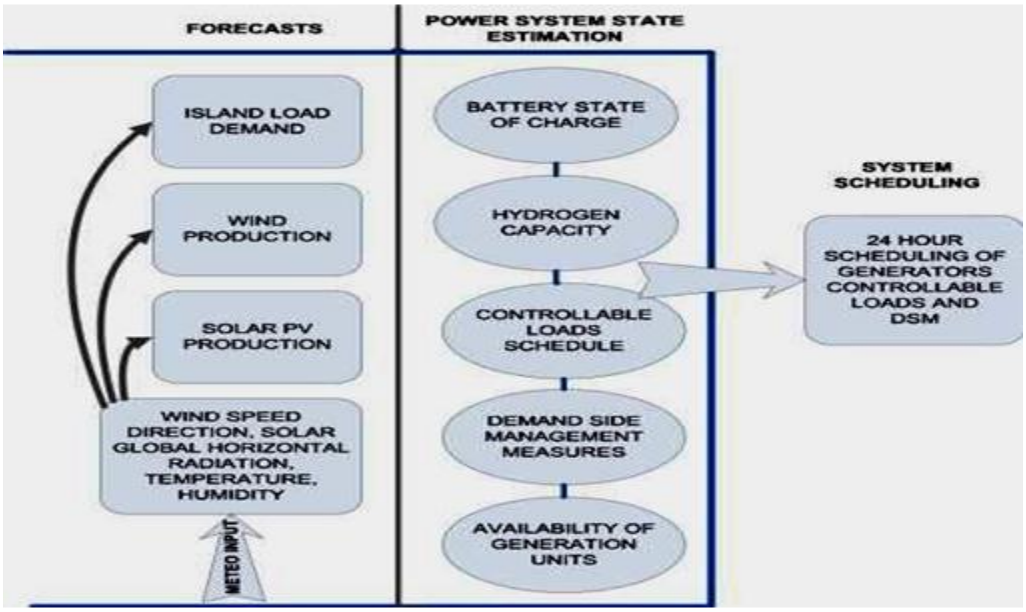

Fig.6 Block diagram for forecasts, state estimation and scheduling

10. Load Forecasting for Power System Planning using ANFIS

Load forecasting has been an integral part in the efficient planning, operation and maintenance of a power system. Short term load forecasting is necessary for the control and scheduling operations of a power system and also acts as inputs to the power analysis functions such as load flow and contingency analysis. Owing to this importance, various methods have been reported, that includes linear regression, exponential smoothing, stochastic process, ARMA models, and data mining models. Of late, artificial neural networks have been widely employed for load forecasting. However, there exist large forecast errors using ANN when\ there are rapid fluctuations in load and temperatures. In such cases, forecasting methods using fuzzy logic approach have been employed. In this paper, an approach for long term load forecasting problem, using fuzzy logic combined with ANN approach is proposed. The fuzzy logic technique has been used to classify the data's. The neural network is used to calculate the increment factor of load due to other parameters like growth in industries, increase in number of customers etc.

Adaptive Neuro-Fuzzy Method

Adaptive neuro-fuzzy method (or Adaptive neuro-fuzzy inference system, ANFIS) has been became a popular method in control area. In this section, we give a brief description of the principles of Adaptive neuro-fuzzy inference system (ANFIS). The basic structure of the type of fuzzy inference system could be seen as a model that maps input characteristics to input membership functions. Then it maps input membership function to rules and rules to a set of output characteristics. Finally it maps output characteristics to output membership functions, and the output membership function to a single valued output or a decision associated with the output. It has been considered only fixed membership functions that were chosen arbitrarily. Fuzzy inference is only applied to only modeling systems whose rule structure is essentially predetermined by the user's interpretation of the characteristics of the variables in the model. However, in some modeling situations, it cannot be distinguish what the membership functions should look like simply from looking at data. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen so as to tailor the membership functions to the input/output data in order to account for these types of variations in the data values. In such case the necessity of the adaptive neuro fuzzy inference system becomes obvious. The neuro-adaptive learning method works similarly to that of neural networks. Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set. It computes the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. A network- type structure similar to that of a neural network can be used to interpret the input/output map so it maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs,. The parameters associated with the membership functions changes through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure (performance index). This error measure is usually defined by the sum of the squared difference between actual and desired outputs. ANFIS uses a combination of least squares estimation and back propagation for membership function parameter estimation. The suggested ANFIS has several properties:

1. The output is zeroth order Sugeno-type system.
2. It has a single output, obtained using weighted average defuzzification. All output membership functions are constant.
3. It has no rule sharing. Different rules do not share the same output membership function, namely the number of output membership functions must be equal to the number of rules.
4. It has unity weight for each rule.

11. Simulation results

The electrification systems that achieved the lowest cost of electricity production over a lifetime of 25 years for each primary load and average wind speed simulation case. As the PV system will have a modular design through the use of several grid connected inverters, in scenario 3, 4 and 7, 8 the lowest levelized cost of electricity using 2 wind turbines are presented for the low primary load (3.345 MWh/day) and higher primary load (5.352 MWh/day) cases respectively. It is noted, that the increase in the cost of electricity with 2 wind turbines, in the higher primary load case is much smaller than the lower load case.

Primary Load in MWh/day	Annual Average wind speed in m/sec	Scenario	PV (kW)	Number of Wind Turbines 330kW/each	Gen1 Max. Capacity (kW)	Gen2 Max. Capacity (kW)	Gen3 Max. Capacity (kW)	Number of 2V Cells of 6 kWh each	Converter (kW)	Dispatch strategy	Initial capital in Euro	Operating cost (Euro/yr)	Total Net Present Cost in Euro
3.345 (1220 MWh/year)	9	1	300	1	90	220	90	480	300	LF	1,632,000	116,237	3,117,895
		2	500	1	90	220	90	480	300	LF	1,932,000	96,680	3,167,897
		3	200	2	90	220	90	480	300	LF	2,082,000	123,409	3,659,587
		4	100	2	90	220	90	480	300	LF	1,932,000	135,650	3,666,059
5.352 (1953 MWh/year)	9	5	700	1	90	220	90	720	300	LF	2,448,000	195,845	4,951,560
		6	700	1	90	220	90	840	300	LF	2,556,000	187,378	4,951,325
		7	500	2	90	220	90	600	300	LF	2,640,000	183,159	4,981,385
		8	500	1	90	220	90	600	300	LF	2,040,000	253,704	5,283,186

Primary Load in MWh/day	Annual Average wind speed in m/sec	Scenario	Cost of Electricity in Euro/kWh	Renewable fraction	Excess Electricity kWh/yr	Unmet Load kWh/yr	Total Diesel Gen. prod in kWh/yr	Diesel used in Liters	Gen1 operation hrs	Gen2 operation hrs	Gen3 operation hrs	Battery Autonomy hr	Battery Through-put kWh/yr	Battery Life yr
3.345 (1220 MWh/year)	9	1	0.200	0.925	796,747	0	91,268	29,601	697	318	271	12	198,797	20
		2	0.203	0.959	1,041,996	0	50,368	16,199	346	186	135	12.4	215,699	20
		3	0.234	0.952	2,190,942	0	58,125	18,674	387	226	156	12.4	155,454	20
		4	0.235	0.932	2,067,169	0	83,025	26,711	555	321	233	12.4	162,425	20
5.352 (1953 MWh/year)	9	5	0.199	0.907	684,129	3,133	181,494	65,974	1,205	561	572	11.62	361,783	20
		6	0.199	0.915	662,900	3,133	165,875	60,211	1,099	510	516	13.56	378,910	20
		7	0.200	0.935	1,926,926	2,546	127,627	46,380	847	391	409	9.69	272,761	20
		8	0.212	0.857	516,040	3,600	280,118	102,007	1,781	901	910	9.69	291,030	20

Table 3: Selected HOMER simulation results according to the above assumptions and sensitivity analysis

LF: Load Following mode, CC: Cycle Charging mode

The optimum PV system capacity, for the lower primary load (3.345 MWh/day – scenario 1, 2, 3, 4) for the current electricity use, according to the simulation is in the range of 500 to 100 kWp, while all proposed systems have a high renewable fraction higher than 92% with a levelized cost of electricity production for 25 years in the range of 0.200 to 0.235 Euro/kWh. In Figure 7, the monthly average electric production according to all generator units for scenario 7, as in Table 3 are presented. This scenario is projected to be the one that represents the most probable case in energy load use, while fulfilling the requirements for high RES penetration and higher reliability in making use of RES with a competitive electricity production cost.

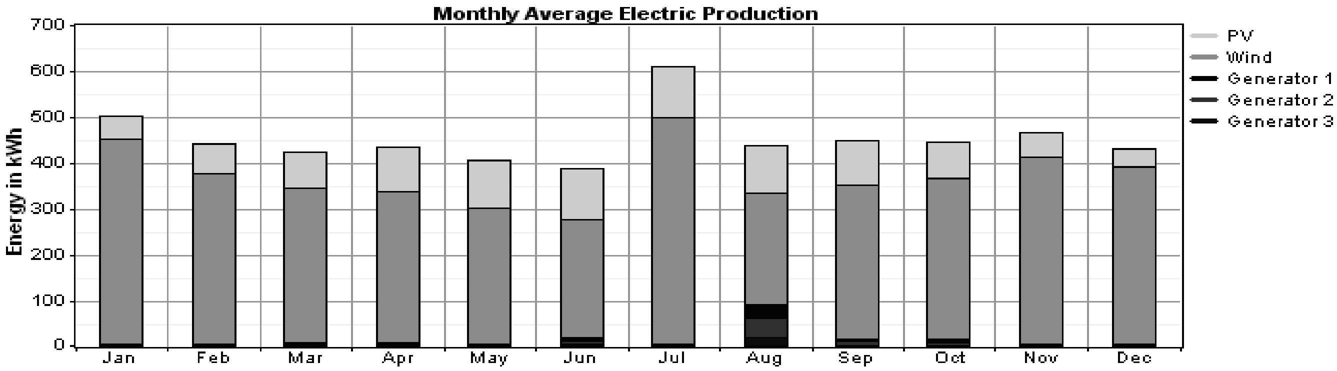

Fig.7: Monthly average electricity production for all generating units.

In Figure 8a, b, the power output over the year of the wind turbines and the PV system are presented, in Figure 8c the battery bank state of charge is presented.

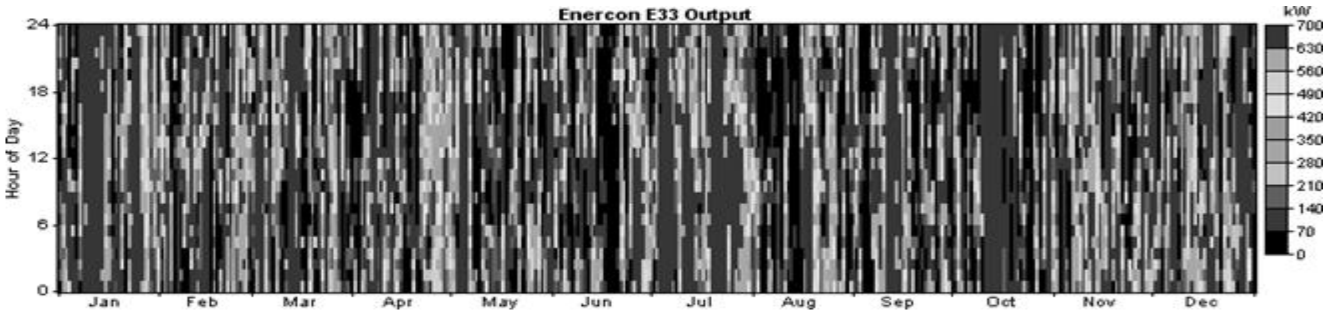

Fig. 8a: The power output over the year of the wind

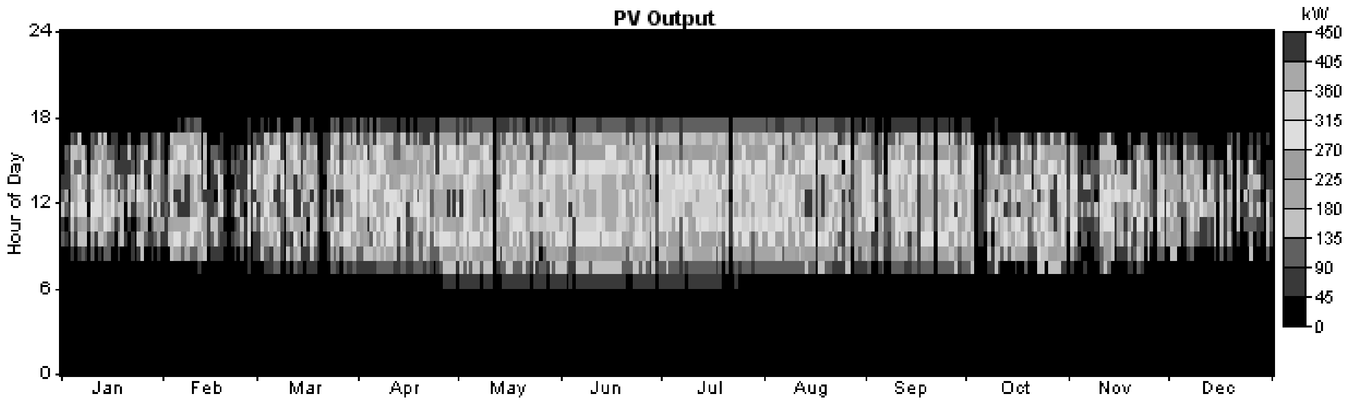

Fig. 8b: The power output over the year of the PV system

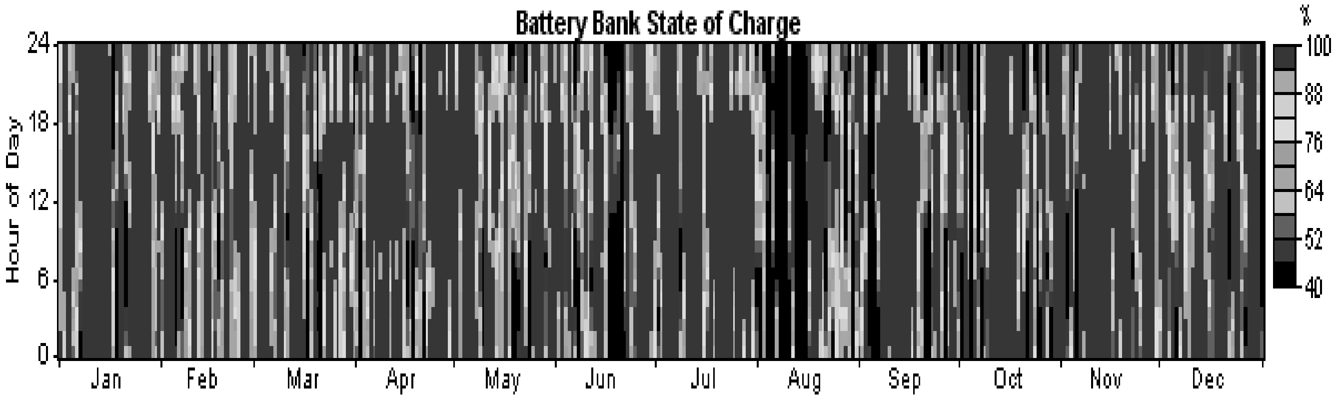

Fig.8c The annual fluctuation of the battery bank state of charge

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