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SAS® for Green Energy Solutions in Smart Electric Grid Systems

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ABSTRACT

This research paper proposes a data-analytic approach for making optimum utilization of solar energy generated by solar photovoltaic panels to reduce peak demand on advanced electric grid systems. The proposed best practices of using renewable energy would require less investment in additional carbon-fired (e.g., coal) power plants resulting in less carbon emission, and contributing to a cleaner environment for our future generations.

INTRODUCTION

The modern world is irreversibly dependent on electricity [1]. The Energy Information Administration (EIA) predicts that worldwide electric power generation will grow 2.4% a year between 2004 and 2030. Compounded over that period, this small annual increase will cause generation to nearly double by 2030 – from 2004's 16,424 billion kiloWatt hours (kWh) to 30,364 billion kWh by 2030. To put that growth in concrete terms, the world will need the equivalent of 25,000 additional 500 MW coal-fired power plants. Think about building 25,000 more power plants by 2030. Imagine the amount of capital required; about the wires needed to transmit and distribute the power; about the impact on the environment if many of those plants use coal! In case of the U.S., ensuring proper supply of electric energy is not only essential for daily convenience, but has serious implication to national security, health and public safety as well as to finance, industry and commerce.

WHY RENEWABLE ENERGY?

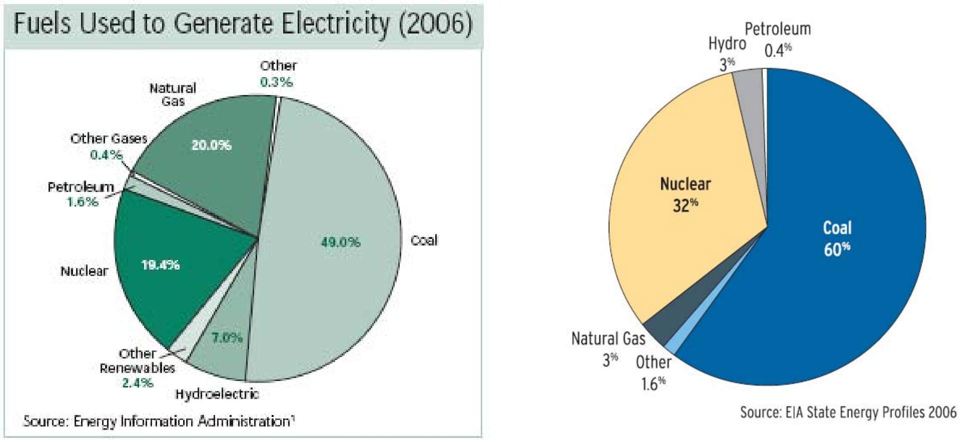
Today we primarily use fossil fuels to heat and power our homes and fuel our cars [2]. It's convenient to use coal, oil, and natural gas for meeting our energy needs, but we have a limited supply of these fuels on the Earth. We're using them much more rapidly than they are being created. Eventually, they will run out. And because of safety concerns and waste disposal problems, the United States will retire much of its nuclear capacity by 2020. In the meantime, the nation's energy needs are expected to grow by 33 percent during the next 20 years. Renewable energy can help fill the gap. Even if we had an unlimited supply of fossil fuels, using renewable energy is better for the environment. We often call renewable energy technologies "clean" or "green" because they produce few if any pollutants. Burning fossil fuels, however, sends greenhouse gases into the atmosphere, trapping the sun's heat and contributing to global warming. Climate scientists generally agree that the Earth's average temperature has risen in the past century. If this trend continues, sea levels will rise, and scientists predict that floods, heat waves, droughts, and other extreme weather conditions could occur more often. Other pollutants are released into the air, soil, and water when fossil fuels are burned. These pollutants take a dramatic toll on the environment—and on humans. Air pollution contributes to diseases like asthma. Acid rain from sulfur dioxide and nitrogen oxides harms plants and fish. Nitrogen oxides also contribute to smog.

Renewable energy will also help us develop energy independence and security. The United States imports more than 50 percent of its oil, up from 34 percent in 1973. Replacing some of our petroleum with fuels made from plant matter, for example, could save money and strengthen our energy security.

In the U.S., as shown in Figure 1(a), around half of the electric energy is generated by coal-fired power plants and around 10% is produced by renewable sources most of which is generated by hydroelectric power plants [3]. As mentioned earlier, coal-fired power plants produce pollutants that can increase cases of smog, acid rain and mercury pollution, and can cause respiratory distress in humans. The significant release of CO_2 from fossil fuel combustion also may increase the potential for global warming. With global warming being an increasing concern around the world, governments are taking steps to reduce carbon emissions by relying more heavily on renewable energy. Fortunately, more than half of the states in the U.S. now have mandated renewable energy requirements in place.

North Carolina possesses no indigenous fossil fuel resources [5]. Millions of dollars leave our economy each year to purchase fossil fuel resources from other states for our electricity production. North Carolina's electricity consumption is among the highest in the nation, producing more than 126 million megawatt-hours of electricity per year. North Carolina's Renewable Energy and Energy Efficiency Portfolio Standard (REPS) requires utilities to meet up to 12.5%

of their energy needs through renewable energy resources or energy efficiency measures by 2021 [4]. They must also begin including solar-generated energy by 2010.



(a) (b)

Figure 1. Fuels Used to Generate Electricity in (a) US and (b) NC

SOLAR ENERGY

Solar electric systems, also known as photovoltaic (PV) systems, convert sunlight into electricity [5]. Solar cells are the basic building blocks of a PV system—consisting of semiconductor materials. When sunlight is absorbed by these materials, the solar energy knocks electrons loose from their atoms. This phenomenon is called the "photoelectric effect." These free electrons then travel into a circuit built into the solar cell to form electrical current. Only sunlight of certain wavelengths will work efficiently to create electricity. PV systems can still produce electricity on cloudy days, but not as much as on a sunny day.

The basic PV or solar cell typically produces only a small amount of power. To produce more power, solar cells (about 40) can be interconnected to form panels or modules. PV modules range in output from 10 to 300 watts. If more power is needed, several modules can be installed on a building or at ground-level in a rack to form a PV array.

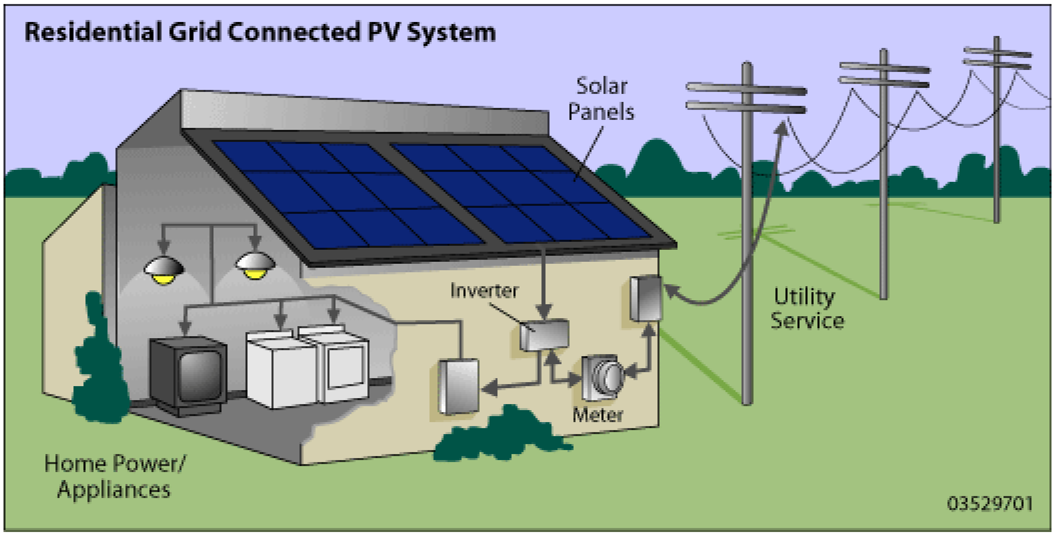


Figure 2. Residential grid connected solar system Photovoltaic (PV)

PV arrays can be mounted at a fixed angle facing south, or they can be mounted on a tracking device that follows the sun, allowing them to capture the most sunlight over the course of a day. Because of their modularity, PV systems can be designed to meet any electrical requirement, no matter how large or how small. You also can connect them to an electric distribution system (grid-connected), or they can stand alone (off-grid). A grid-connected small solar electric or photovoltaic (PV) system (Fig. 2) receives back-up power from a utility's grid when the PV system is not producing enough power. When the system produces excess power, the utility is required to purchase the power through a metering and rate arrangement. *Net metering* is the best arrangement. Under this arrangement, the power provider essentially pays the customer retail price for the electricity that is fed back into the grid.

At the electric power supply end, there can also be solar panels for power generation. There are several “solar farms” appearing around the U.S. In the South-Eastern USA, the largest solar farm is owned by SAS® [4]. Many renewable – wind, solar thermal and marine in particular – are typically located far from population centers. They put a strain on a long-distance transmission system that is already overburdened [1]. From this perspective, solar PV power generation at the customer site is a good option of lowering the peak load on the electric grid system.

TRADITIONAL ELECTRIC GRID

For roughly a century, the developed world has delivered electric power using the same basic four-step approach: (1) generate power in large, centralized plants; (2) step up the power to high voltages and transmit it to regional utilities; (3) step down the power to medium voltages to distribute it locally; (4) step down the power a final time to deliver it to customer premises.

SMART ELECTRIC GRID

A smart grid will employ computers and communications to the existing grid system for remote monitoring and control. In addition, the fragmented grids will be interconnected with a Backbone grid infrastructure for smooth trade of electric energy.

REMOTE MONITORING AND CONTROL [1]

1. Smart meters: A state-of-the-art smart meter shows just how much power was used and when it was used. Many of them can also remotely allow monitoring of power availability and quality, sending back a signal if the power goes down, so the utility knows instantaneously where the fault is and how many customers are affected. Many smart meters also allow the utility to remotely turn service on or off (for instance, when a new tenant moves into an apartment building) without the need to send out a lineman.
2. Two way communication: Smart devices don’t add much value unless they can communicate. They can talk to each other in many different ways – over the Internet, over the power lines themselves, over cell phone networks, via satellite, and so on. In the real world, most smart grids use a mixture of communications methods.
3. Remote monitoring and Control: Advanced control systems let computers make low-level decisions automatically while allowing human operators to visualize and control large areas from a central station. Advanced control systems help in several ways: by handling routine, split-second decisions automatically; by giving operators more visibility and control; by sorting through masses of data to uncover exceptions and problems; by using advanced algorithms to optimize the system; and many more.

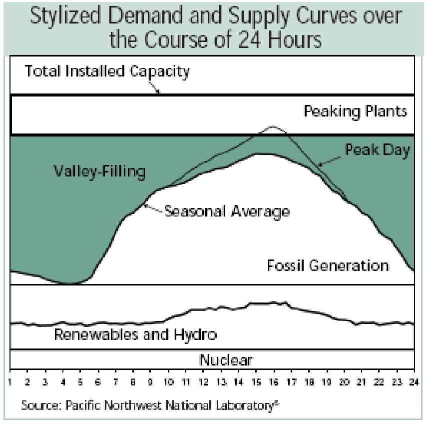
BACKBONE GRID [3]

Currently the electric grid system is largely fragmented. Interconnecting these fragmented grid systems by an overlaid backbone grid infrastructure will let cheap power chase high demand areas across the country. It would squeeze significantly more electricity out of every dollar of invested capital and every dollar spent on raw fuel. Any plant linked to a grid that spans four time zones need not be idle often. With a backbone grid, a plant located in, say, Lebanon, Kansas, the geographic center of contiguous US, would be within easy reach of peak loads on both coasts and everywhere in between.

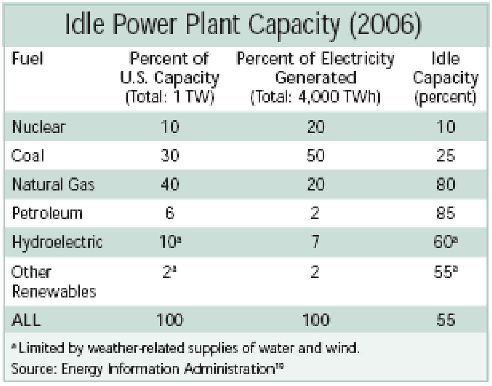
THE PROBLEM

The daily load on the grid is highly variable. In the demand and supply graph shown in Figure 3, it can be seen that there is a peak when the power demand is maximum and there is valley when the demand is low. The cheapest way to meet highly variable demand is to generate base load power in big, expensive plants running on cheap fuel, and to take care of the peaks with smaller, cheaper plants running on expensive fuel. In practice, that currently means generating base load power with cheap coal or uranium, while meeting peaks with expensive natural gas. This minimizes the average, combined cost of capital and fuel.

The issue is that, the power plants need to be constructed to supply the peak power and consequently remain underutilized during the valleys. Currently a significant portion of power plant capacities remain idle in the US as shown in Figure 4. The irony is: we may need more power plants in future to satisfy the growing peak demands of the customers even though a large portion of their capacities may remain unutilized. One of the key challenges of solving the impending power crisis in the US is to supply the peak demand without constructing more carbon-fired power plants and that is where renewable energy sources can contribute significantly. This paper will introduce two methods by which analytics can help in making optimum use of solar energy in supplying the peak demand.



Source: Pacific Northwest National Laboratory[6]



Idle Power Plant Capacity (2006)

Fuel	Percent of U.S. Capacity (Total: 1 TW)	Percent of Electricity Generated (Total: 4,000 TWh)	Idle Capacity (percent)
Nuclear	10	20	10
Coal	30	50	25
Natural Gas	40	20	80
Petroleum	6	2	85
Hydroelectric	10[a]	7	60[a]
Other Renewables	2[a]	2	55[a]
ALL	100	100	55

[a] Limited by weather-related supplies of water and wind.
Source: Energy Information Administration[10]

Figure 3. Power demand and Supply curve

Figure 4. Idle power plant capacity

PROPOSED SOLUTION

Instead of constructing yet more carbon-fired power plants, we propose to optimize the use of solar energy for supplying power during peak demand. In one solution, we intend to make optimum use of the solar generators located at the customer ends. In the other solution, we propose to make optimum use of the solar generator at the supply end.

CUSTOMER END SOLAR OPTIMIZATION

In this approach, we propose to store solar energy generated at customer sites at their local storage batteries (if available) and then use it during system peak loads. To accomplish this, the solar generators at customer sites need to be informed when the grid peak demand is expected to occur and analytics can help in predicting the timing of the peak demand as explained below. The complete solution will have to be implemented by the following three steps:

1. Use Analytics to predict the peak demand of the grid. The peak demand of the grid during the day has to be predicted beforehand based on past demand data and taking into account various weather factors including temperature, humidity, etc. Socio economic parameters could also play a role in influencing the peak demand (e.g., special cultural occasions like Thanksgiving, Christmas, etc.). We will first analyze the data to identify the parameters that affect or influence the peak demand. We will then build a model of demand relating it to the

influencing parameters. In analytic terms, demand will be the dependent variable of the model and the important influencing parameters will be the independent or explanatory variables. An example peak demand modeling technique is discussed in a later section.

2. Remotely inform the solar power generator at the customer site about the timing of the predicted peak demand on the grid. The advanced communication mechanism of the smart grid infrastructure would allow this to happen.

3. The solar power generator at the customer site would first store solar energy to the maximum capacity of its local storage batteries and use that energy and any additional real time solar energy that may be generated during the grid peak duration. The contribution of solar power of customers during the peak duration of the grid would help to lower the peak demand on the fossil-fuel fired power plants.

SUPPLY END SOLAR OPTIMIZATION

In this approach, we propose to use the full capacity of the solar generator located at the supply end during peak demand. Power from expensive gas fueled generators should be used to cover shortfall in peak demand only after making full utilization of supply end solar power. To accomplish this, the gas-fired power plant has to be configured such that it supplies only the shortfall in peak demand and let the solar generator supply to its maximum capacity. Analytics will be required to predict the expected solar power generation during the peak demand so that the gas-fired power plant can be configured to supply the rest of the load. The complete solution would involve the following steps:

1. Use Analytics to predict the solar power generation at supply end. This prediction has to be based on past generation data that may include various weather related parameters, e.g., amount of sunlight, ambient temperature, etc. We will build a model of solar power generation that relates solar power with the weather parameters that influence the solar power generation. In analytic terms, solar power will be the dependent variable of the model and the influencing parameters will be the independent or explanatory variables.

2. Predict shortfall of peak demand that has to be covered by the expensive gas-fired power plants. Configure the gas-fired power plants such that they supply the expected shortfall during peak demand. The solar generator would supply the rest of the peak demand while delivering at its full capacity.

3. The actual power delivered by the solar generator will have to be dynamically monitored. If it shows a tendency of generating less than the prediction, then the gas-fired power plant will need to be dynamically reconfigured to cover the unexpected gap in predicted solar generation.

ANALYTIC MODELING

We have created data set for grid consumption and also for the solar power generation and used SAS® 9.1.3 for modeling as described below. As mentioned in an earlier section, the first step for lowering the peak is to analytically predict the peak demand. The following sections explain how peak power demand can be predicted based on weather parameters. The next two steps are concerned with communication and control between the power supply end and the customer end and therefore are not directly related to the Analytic part and will not be covered in this paper.

CUSTOMER END SOLAR OPTIMIZATION

In order to lower the peak by making optimum use of solar power, the idea is to predict when the grid peak time will occur based on weather parameters. The following sections describe how this would be done. The customer site solar generators would then be informed about the predicted system peak time so that they can use their stored energy during peak hours and contribute to reducing the overall system peak demand.

DATA

Partial Power demand data from a given power plant, assumed to supply a small town, is provided below. For simplicity, this data takes into consideration only a few of the usual weather parameters and no socio-economic factors (e.g., Thanksgiving, Christmas, etc.) are considered at this time.

TABLE-1: Example electric power demand from a power plant

Day	time_slot	Demand_MW	Temp	Humid	Press	wind_mph	UVind	Precip
1	0	90	70	89	32.99	1	4	20
1	1	90	70	88	31.29	1	2	45
1	2	90	70	87	30.58	1	2	49
1	3	90	70	87	31.71	1	6	66
1	4	90	70	96	32.30	1	2	80
1	5	90	70	66	31.76	1	6	69

CODE

```
proc corr data= town_power plots;
run;

proc reg data=town_power;
       eq_Wind_Temp: model MW = wind_mph Temp;
       plot r. * p. / cframe=ligr;
run;
```

OUTPUT

The output of proc corr shows that significant correlation exists between response variable Demand_MW and dependent variables wind_mph and Temp.

TABLE-2: Pearson Correlation Coefficients
N = 240 Prob > |r| under H0: Rho=0

	Demand_MW	Temp	Humid	Press	wind_mph	UVind	Precip
Demand_MW	1.00000	0.40714 <.0001	0.00460 0.9435	0.01142 0.8604	-0.65631 <.0001	0.00177 0.9783	-0.10551 0.1030

The output of proc reg indicates that 92.15% of data was captured by the model as shown by value of R-Square. The intercepts indicate that Demand_MW increases for decreasing wind and increasing temperature. Because of the simplicity of the data, a simple linear regression is found to be enough for modeling the demand MW. More complicated real world data would require a more complex model.

PREDICTION

Using the parameter estimates of the regression output we can form a linear regression equation of Demand_MW consumption by the customer under consideration as follows:

Demand_MW = -195.47 – 28.683 * (wind_mph) + 4.423 * Temp (1)

When the detailed (e.g., hourly) weather forecast of a future date is known, by using the forecasted wind_mph and the Temp values in eq.(1) the peak load in MW can be predicted. As an example, for simplicity, let us assume that the weather parameters are given in am and pm granularity as shown in Table-3. Using the values of wind_mph and Temp from Table-3 in eq.(1), we can see that the predicted Demand_MW at pm is higher than that at am (85.456 vs. 59.185). In this particular example, the prediction identifies that peak demand will occur at pm and not in the am.

TABLE-3: Predicted peak power (MW)

wind_mph_am	Temp_am	Pred_Demand_MW_am	wind_mph_pm	Temp_pm	Pred_Demand_MW_pm
5	90	59.185	1	70	85.457

SUPPLY END SOLAR OPTIMIZATION

Supply end solar modeling will be done to predict how much solar power would be generated during peak demand of the grid. Full capacity of the solar generator will have to be utilized during the peak demand of the grid. The solar generation needs to be predicted to calculate the expected shortfall in peak demand that has to be supplied by the expensive gas-fired power plants. An example analytic technique is discussed below for modeling the solar power generation that can be used for predicting the solar generation.

DATA

Example partial data of historical power generation from a solar generator is given below.

TABLE-4: Solar generation at supply end

Obs	month	day	time	Sunlight	Temp	solar_MW	Humid
1	6	1	0	1	60	4	60
2	6	1	1	1	70	3	70
3	6	2	0	2	60	7	70
4	6	2	1	2	70	6	60
5	6	3	0	3	60	10	70

CODE

```
proc corr data= solar.SolarPanel;
run;
proc reg data=solar.SolarPanel;
       eq_sunlight_temp: model solar_MW = sunlight temp;
       plot r. * p.;
run;
```

OUTPUT

The output of proc corr shows that significant correlation to exist between response variable solar_MW and dependent variables sunlight and temp.

The output of proc reg indicates that 98.86% of data was captured by the model as shown by value of R-Square. The parameter estimates indicate that solar_MW increases with stronger sunlight and decreasing ambient temperature. Because of the simplicity of the data, a simple linear regression is found to be enough for modeling the demand MW. More complicated real world data would require a more complex model.

TABLE-5: Pearson Correlation configuration

	sunlight	temp	solar_MW	Humid
solar_MW	0.97980 <.0001	-0.20000 0.1255	1.00000	0.06667 0.6128

PREDICTION

Using the parameter estimates of the regression output we can form a linear regression equation of MW consumption by the customer under consideration as follows:

Solar_MW = 7.0 + 3.0 * (sunlight) – 0.1 * (temp) (2)

When the detailed (e.g., hourly) weather forecast is known, by using the forecasted sunlight and the temp values in eq.(2) the solar MW generated can be predicted at hourly interval. For simplicity, let us assume that the sunlight and Temp parameters during peak demand are as shown in Table-8. The predicted solar_MW expected to be generated can be calculated by using eq.(2) and this value (8 MW) is also given in the same table (Table-8).

TABLE-6: Predicted solar MW generation

Obs	sunlight	temp	solar_MW
1	3	80	8

SYSTEM LEVEL SOLUTION

An end-to-end solution architecture for the proposed system is provided below. The distinctive features of the solution are as follows:

4. The Analytic engine is located at the back-end of the supply end.
5. Front-end software modules are required to realize this client-server system.
6. The client of the software SYSTEM is at the customer end, possibly embedded within the Smart Meter.
7. The server of the software system is at the supply end, shown as the Intelligent Energy Controller.

The embedded client at the customer end Smart Meter has to be built as a “Thin client” with minimum memory foot print and low CPU computation load requirements. SAS® will also need to build suitable API (Application Programmer’s Interface) and reference designs for the equipment manufacturing vendors to be able to integrate the thin client easily into the customer end devices (e.g., the Smart Meters in this case).

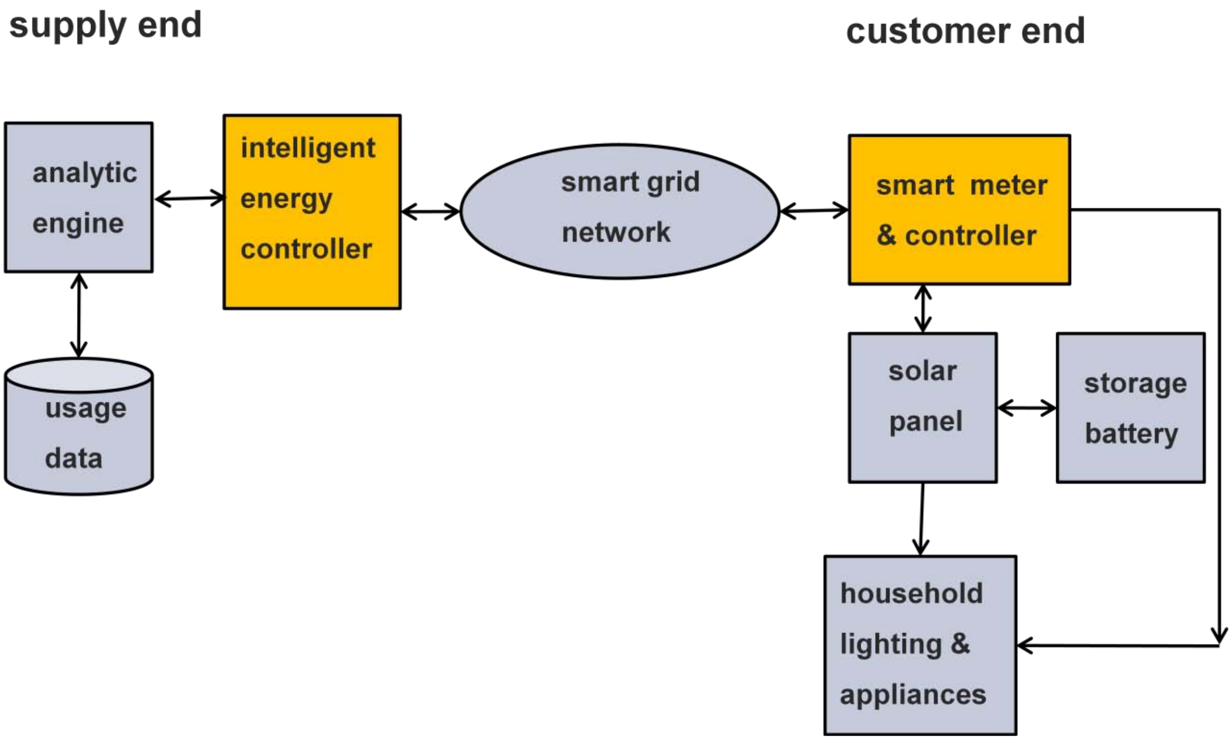


Figure 5. End-to-end system level solution

NEW BUSINESS OPPORTUNITIES FOR SAS®

The business value of the proposed system level solution would be that part of SAS® is now embedded into low computation customer end devices, e.g., the Smart Meters in this scenario. This opens up new product development business opportunities for SAS® in the form of end-to-end system level solution. SAS® will need to enter into partnership with utility equipment manufacturing vendors to integrate the proposed thin client into the customer end device (the Smart Meters). This has at least two major positive benefits for SAS®:

1. The licensing agreements have potential of generating significant revenue by embedding SAS® thin clients into millions of household electric meters.
2. The client-server system level solution can be seen as the next phase of SAS® cloud computing where SAS® Institute not only processes customer data in a hosted Solution-on-Demand environment but also takes actions based on the outcome of the data analysis. Part of these actions may actually involve controlling or fine tuning remote equipments (e.g., the Smart Meters) for efficient operations.

CONCLUSION

This research paper discussed possible use of analytic methods for making optimum utilization of solar power for lowering the peak demand on the emerging smart electric grid infrastructure. Although the analytic method was described particularly for solar power generation, it is equally applicable to other forms of renewable energies, including wind and biomass. One key point to note is that analytic methods need to be integrated within a complete system level solution rather than being a stand-alone technique. The examples mentioned in this paper were (i) updating customer site solar generator with analytically predicted time of peak demand and (ii) Controlling output of gas-fired power plant based on analytically predicted solar power generation during peak demand. These examples are proof of the crucial role analytics could play in a complete system level green energy solution of a smart grid system. Another key point to note is the dynamic nature of analytics that would become increasingly important in future green energy solutions. For example, even though prediction can be made on peak demand or green energy

generation based on analytic modeling, still those are predictions based on various parameters that can change drastically. So there will always be the need to monitor the real time data with the predictions and make dynamic adjustments to the system if significant discrepancies start to emerge. Thus there is a need to consider integration of analytic modeling techniques at a dynamic level with the overall system level solution for a smart grid.
This is just the beginning of using analytics in creating green energy solutions for the emerging smart grid infrastructure. The success of green energy solution for smart grid will shape the future of our nation. Using analytics in green energy optimization is just the beginning of an exciting endeavor, the prospects are limitless—but we have to act now.

Furthermore, it was shown how an end-to-end system level solution may create tremendous business opportunities for SAS® to introduce new products and services and generate yet to explore revenue stream.

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