Intelligent Connector (I-Connector) Design and Demand Response in Smart Grid

Dung Nguyen, Hyungtaek Chang, Claudio Talarico, Anita Annamalai, He Zhou, and Janet M. Roveda

Abstract—**Despite the significant effort spent the efficient and reliable delivery of energy to individual households remains an unsolved challenge. One of the key roadblocks is the high complexity of the smart grid system. In this paper we propose a new architecture for the management of the energy flow between smart grid and households. The proposed design strives to dynamically balance and optimize the amount of energy between the grid and the various smart homes. The preliminary experimental results show that the proposed design can capture the major characteristics of a smart home system, and when combined with higher level optimization tools has the potential to provide significant energy saving.**

Index Terms—**Energy management, smart grid systems, renewable energy resources, intelligent connector.**

I. Introduction

For the past fifty years, the electricity grid has been the key source of energy for households around world. However, ever since, the infrastructure for the energy generation and delivery has seen little improvement [1]. Looking forward, we face several major roadblocks before we can connect renewable resources into the current electricity grid. First, the current grid system is dominated by ageing transmission lines, transformers, and traditional power plant stations that makes the grid very unreliable. Second, it follows an outdated one-way grid-to-buildings energy distribution paradigm. Third, we receive very little information from the grid itself. The power plants collect information through sensors, however each house-hold and building have little information on their daily usage until monthly bills are received. The current grid system suffers from a poor information acquisition scheme. Recently, with the development of smart meters, appliances, and renewable energy sources, the requirements on grids have changed significantly. For example, the new renewable energy requires a two-way structure that allows energy to flow in and out of the grid continuously and with changing amplitude. Most appliances are only equipped with local sensors that cannot send their data to a central location for analysis (i.e. a central control board, a computer, or a community level server). A new real time monitoring, sensing, analyzing, and control framework needs to be put in place for a household to be automatic and smart. Last, the current electricity grid only regulates the supply side (grid side). Once equipped with renewable energy resources, the grid is no longer the center of the energy system. The energy system becomes a vast network of distributed resources. Under this situation, a highly efficient grid requires the demand side and supply side being balanced at all times.

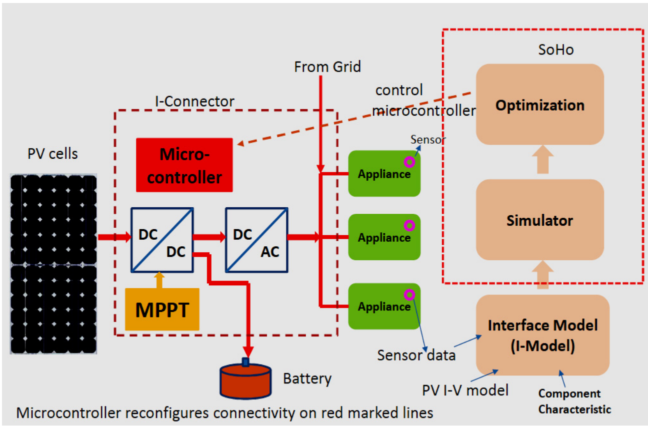

Fig. 1. General architecture for the new smart grid design

This paper discusses a new real time monitoring, sensing, analyzing, and control framework that facilitates data flow and energy flow management and integrates both power electronics hardware and software for smart grid and smart buildings. We intend to build a two-way structure that allows energy to flow in and out of the grid continuously and with changing amplitude. The proposed new smart system design strives to balance the demand side and supply side at all times. Instead of regulating the supply side (grid side) as in the traditional system, we need a two-side regulation scheme: we should be able to reconfigure household automatically, as well as regulating the grid. Fig. 1 demonstrates the general flow of the proposed project. The Intelligent Connector (I-Connector) controls the hardware system in the household. It receives optimization results from the simulation based Optimization with Hierarchical Options (SoHo). The Interface Model (I-model) [2], [3] prunes data from sensors and smart meters at the households to provide a fast optimization framework. The contributions of this paper include:

1) A new smart connector (I-Connector) that allows multiple direction energy flow and two-way regulations. In addition to the exiting peaking power tracking scheme, the proposed smart connector allows reconfigurable connection and stable output considering photovoltaic (PV) panel output uncertainty.
2) A new simulation based Optimization with Hierarchical Options (SoHo) scheme to schedule multiple buildings

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from different locations under different solid-state transformers (SST). The new development allows the users to take advantage of differences such as solar intensity, cost per watt, and resource availability at multiple locations. This new algorithm decides the configurations of components at each household, and is applicable to different platforms.

The end result is a prototype system that embeds software and hardware automation for smart buildings and smart grid. We would like to point out that even though converters, inverters, and demand response tools have been released on the market, how to build intelligent systems is still an unsolved challenge. Through this paper, we intend to provide first-hand experiences to illustrate how these systems communicate with household hardware, and how these tools cope with large volumes of data coming from sensors and real time monitoring. The Broader Impact of this research is to bridge the gap between existing tools and underlying energy physical systems using the cyber presentation/interface [4], [5]. Instead of using different module to define/model different components (i.e. PV cell, wind mills, batteries, appliances, and inverters), an unified model for data, energy, and timing is the key solution to reduce the complexity of the smart grid design. Such a model will allow us to focus on only the key metrics: demand response, load balancing, scheduling, and abnormal situations due to uncertainties. Our preliminary experimental results showed that the Intelligent Connector (I-Connector), the proposed Interface Model (I-Model) [2], [3], and the simulation based Optimization with Hierarchical Options (SoHo) can capture the major characteristics of a smart home system, and when combined with higher level optimization tools has the potential to provide significant energy saving.

II. I-Connector for Households

Inverters and Converters for PV cells are not new concepts or designs. Ever since we had PV cells, we have also developed their converters and inverters. However, we would like to point out that current industrial and academic inverter designs are focused on power electronic circuits and their control circuits. Their vision on households is still traditional: for a single household, its PV panels and batteries are resources for this household ONLY. This is different from the reality. It is obvious that once connected to the electricity grid, we have a large network of distributed resources (PV cells and batteries from multiple buildings) [6]-[8]. The key problem becomes how to manage this vast network of PV cells and batteries well. This large network of renewable resources has the potential to provide significant energy savings.

To further explain this concept, let us consider a PV-Inverter-Converter system at a household. Assume the maximum power point tracker (MPPT) improves the PV output power efficiency by 30%. However, the grid load balancing indicates that due to demand decrease, we do not need additional electricity at the moment. Then, it is not helpful for the electricity generated by the PV to be directly ported back to the grid. In other words, in this case the MPPT efficiency improvement of 30% becomes irrelevant. Coordinated optimization strategies almost always overshadow the standalone power saving strategy. There are numerous practical examples [9], [10] of demand, supply, and load balancing that confirm this scenario. Henceforth, there is a strong need of smart inverters and converters that not only provide single household solar-electricity conversion, but also offer a hardware system that allows intelligent collaborations among different users, different locations, and communities.

To facilitate communication and coordination, the proposed design directly takes commands from a simulation based optimization tool instead of local control circuits. This is very different from the existing auxiliary circuits that inverters are often equipped with. The operation of the auxiliary circuits is not optimized with respect to total power and cost. This affects all circuits related to switch mode power supply, measuring and protection circuits, and microcontrollers. For the rest of this section, we describe a new DC-DC converter and its control scheme for the proposed I-Connectors. Fig. 1 illustrates that the new I-connector combines the functionalities of the inverter, converter, regulator, and reconfiguration in one box. It includes voltage regulators such as DC-DC regulators and DC-AC regulators, a MPP tracker for the PV panels, and a microcontroller. Our ultimate goal is that costumers are no longer concerned whether the source of energy is from the grid or the solar panels; from a customer perspective there should be no disconnection in the energy provided even in the case there is uncertainty about the availability of solar energy.

Today's most popular PV cells use multi-crystalline silicon based technology. However, under solar "uncertainty", PV cells have rather dramatic changes in their electricity production. Even a small amount of partial shadow may lead to de-lamination, power losses, and a very irregular voltage-current characteristic. It is a must to have MPPTs with decoupling capacitance Cpv to help improve the output of the PV cells. To improve the quality of MPPT, we investigate the sensitivity of PV output power to the changes in voltage and current at the output. This helps to establish the interface between PV cells and the DC-DC converter. In all cases, we expect wide environment changes, and thus wide change in output voltage, current, and power provided by the PV cells. In the US, lighting and low-power appliances run at 120 volts plus or minus 10%; meaning 108 volts to 132 volts at 60 Hz. In the prototype system we designed, the I-Connector consists of a microcontroller (TMS320C200), a bidirectional DC-DC converter, a DC-AC inverter, and an MPPT. The interface between the optimizer (software) and the smart connector is the load sequence. The sequence represents load power consumption in the time domain. The load power consumption curve is the input to the power electronic system. The load power, the available input PV power, and the load scheduling are given as inputs to the microcontroller circuit, which control the switches to shift the operation modes of the DC-DC converter. The DC-DC converter has been designed to produce a regulated output voltage of about 170V, which is then fed into the input of the DC-AC inverter. The output of the DC-DC converter can also be directly connected to DC loads or to the input of another DC-DC converter, which sets the value required by the appliances. When there is an excess of energy generated by the PV modules, it can be stored in storage devices, which can later be used as an input source. Alternatively the excess energy can be sold back to the grid. The DC-AC inverter ideally produces an output of 110VAC, which is then supplied to the loads. The grid also acts as one of the inputs of our multiple-input multiple-output (MIMO) physical energy management system. Since DC-AC inverters achieves over 95% efficiency and MPPTs improve PV efficiency to the upper limit, the key innovation we focused on is the DC-DC converter design. The DC-DC converter is designed both for high efficiency and high input swing range. The proposed DC-DC converter also provides an effective way to perform as a surge protector and as a fast backup source when solar uncertainty occurs. Due to the variation of weather conditions, the output of the PV modules directly connected to the input of the DC-DC converter has a large dynamic range (50-350VDC). The inverter takes about 170VDC to produce the steady 110VAC required by the AC powered appliances connected at its output. The DC-DC converter must be able to lower down the voltage when it is higher than 170VDC (this can be done with a buck converter) and boost up the voltage level to 170VDC when the input is lower than the required value (this can be done through a boost converter). Fig. 2 shows the circuit designed as well as the control signals.

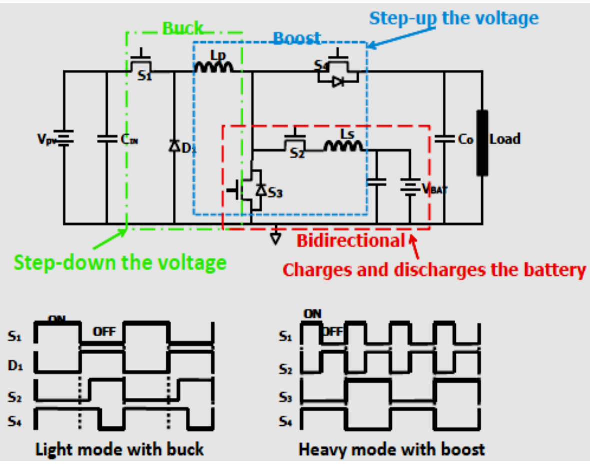

Fig. 2. DC-DC converter designed and control signals

III. Demand Response Using SoHo

Hierarchical Options in SoHo is a tool that helps customers from two different locations (e.g. two cities, or two counties) to coordinate their schedules to achieve maximum savings. Fig. 3 illustrates the flow of SoHo for demand-response negotiation. Two customers A and B from two separate locations (Location P and Location T) coordinate using SoHo through Internet (or other long distance communication methods). These two customers may be under two different solid-state transformers (block SST [11]). Due to different price per watt cost, different solar intensity, and different resources available to the two buildings A and B, the SoHo provides the best saving schedules for both A and B taking advantage of the two locations differences. SoHo is a fast, simulation-based optimizer. The objective function is total cost of energy. The constraints include load balancing constraints from both physical locations under different SSTs, supply constraints from sun, task completion time requirements, resource (including battery) management constraints, and cost upper bounds. The solar intensity changes are incorporated into the solar supply constraints. SoHo runs in two modes: real time optimization, and look-forward optimization. The real time optimization mode in general provides hour-by-hour optimized schedules assuming constant solar intensity for one hour. The look-forward optimization mode uses the solar intensity prediction model as nonlinear constraints to provide schedules for future usage. If the solar intensity changes follow the prediction model, the look-forward optimization scheme will be favored over the real time optimization scheme.

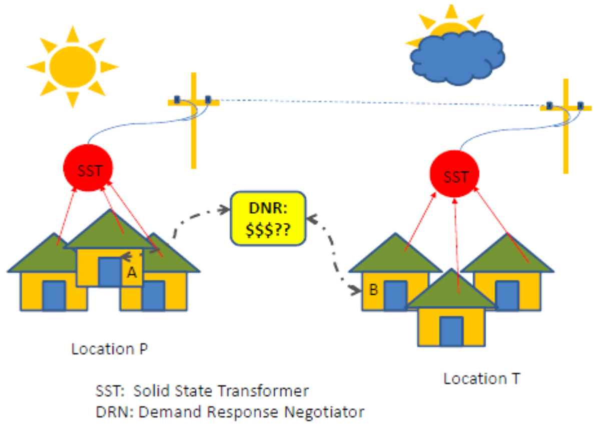

Fig. 3. SoHo demand-response negotiation flow

I-Model and SoHo are new approaches for tackling the demand-response research problem characterizing the smart grid and smart home infrastructure. With these two components, it is possible to implement a hierarchical management framework for smart grid. This is to support large size communities with thousands of households with little concerns on data or information explosion. In addition, it is possible to extend the current I-Model work [2], [3] to provide automatic model generations for general smart appliances, and power electronic systems. In this way, it will be possible to provide a dynamic-data-driven, adaptive multi-scale simulation (DDDAMS) framework to coordinate the management of house-level energy resources and to provide a closed loop control for the household. For example, inside each home, dynamic data is incorporated into the simulation framework. Simulation is launched on servers and steers the measurement process for data update and system control. An appropriate level of simulation fidelity is selected based on the time constraints for evaluating alternative control policies and questions addressed by users. It is clear that with SoHo and I-Model, it becomes possible to build tools to conduct additional research such as user usage patterns, design for smart connectors, and creation of incentives for consumer participation. The insight gained from these tools has the potential to impact the design of future solar power architectures and smart grid networks. While in this paper, the focus is placed on residential applications, the methods and tools developed as part of this effort can be applied to neighborhood and community level monitoring and optimization, as well as a diverse range of systems such as automated greenhouse production, monitoring or automated shop floor, and large-scale supply chain management.

Distributed PV, batteries, and wind mills require flexibility in the modeling of the grid. From the utility side such as power plants, it is important to detect rapid changes within a few minutes. Thus, when supply drops due to an interruption, it is possible to restore using backup power to satisfy the tight requirements such as 60 Hz and 110VAC. Because uncertainty detection is only done from the utility side, most end users never observe the detection in action. Thus, most people always have the wrong impression that the grid is always stable and predictable. In order to have the ability to react to the changes in the supply, it is urgent to make fast progress in advances in the modeling and characterization of both the supply and demand side.

For example, Arizona being a desert, the sun is abundant natural resource whose energy can be captured via PV cells and converted into electrical energy. The surplus energy available from these PV cells can be stored in batteries or other storage devices. This stored energy can later be used as a source of electricity or sold back to the grid. Our objective is to manage the available resources efficiently and effectively so as to save both energy and cost. In order to achieve this, we use the demand-response (DR) model [11]-[16]. Based on a customer's demand, the available sources of energy are scheduled to obtain an optimized solution. Our DR model is not restricted to a single household but is a virtual model connecting customers over different geographical regions. The customer requests a certain number of tasks to be completed during the day. The customer can choose to perform these tasks based on a preference basis or a cost-effective basis or an energy-effective basis. Our scheduling algorithm considers both the criteria chosen by the customer as well as the energy resources available at any given time. Depending on the data available, the customer's requests are scheduled.

The amount of electricity consumed by a customer can be monitored using smart meters. The smart meters provide an estimate of the energy-usage pattern of a customer. Using data accumulated over a given period of time, we can obtain a daily-load curve for the customer. The daily-load curve represents the amount of energy consumed by the customer over a 24-hour period. This is not a constant curve and is subject to variation based on the customer's demands. However, it gives us a rough estimate of the user energy-usage pattern.

Similar information is collected for all customers. This information can be used to combine the customers in groups. Customers with similar demand and daily-load curves can be grouped into a single group subject to the condition that all customers in the group agree to co-ordinate with each other such that energy is conserved (least amount of grid-energy consumed) in a cost-effective way. The customers belonging to the same group are linked via the DR model and their loads can be scheduled based on the total available resources shared among them. It is also important to keep in mind that each customer should benefit from the collaboration rather than being at a financial loss.

As mentioned earlier, the groups are divided based on similar demands. If a particular customer's demands vary for a long period of time, they would not be able to be a part of the existing group any longer and are subject to change to a new group based on their new demand. For smaller variations over a short period of time, mutual understanding between the customers within the group should suffice.

IV. Experimental Results

A. Case Study for Demand-Response Model

Our smart grid system model consists of PV cells, stored energy, and the grid. Based on the availability of these resources, we respond to the customer's demand at any given time and schedule the load distribution. Let us now consider one customer each from the two neighboring cities in Arizona – Tucson and Phoenix.

Let T1 be a random customer in Tucson and P2 be a random customer in Phoenix who shares similar load demands. Due to their similar load demands, we put both these customers in a common virtual group with the objective of being subject to a total power cost of 0. Both have to enter an agreement such that if one gains the other has to lose; but the amount one loses is less than the average amount he would lose without the grouping.

There are five activities that affect both customers:

1) T1 buys power from the Tucson Electric power (TEP - grid) at $1/kWh.
2) P2 buys power from the Phoenix Electric Power (PEP - grid) at $2/kWh.
3) T1 sells power to TEP at 50c/kWh.
4) P2 sells power to PEP at $1/kWh.
5) Self sufficient – no cost power.

Therefore, the tota; cost for T1 and P2 is:

$$Cost_{total} = \sum C_{T1_i} \times S_i + \sum C_{P2_j} \times S_j \tag{1}$$

where, C_{T1i} and C_{P2j} are the costs for Tucson and Phoenix customers respectively, and S_i and S_j are the time periods.

Buying cost for T1 can be calculated as:

$$Cost_1 = +1.0 \times P_{s1} \times S_1 \tag{2}$$

Buying cost for P2 can be calculated as:

$$Cost_2 = +2.0 \times P_{s2} \times S_2 \tag{3}$$

Selling back cost for T1 can be calculated as:

$$Cost_3 = -0.5 \times P_{s3} \times S_3 \tag{4}$$

Selling back cost for P2 can be calculated as:

$$Cost_4 = -1.0 \times P_{s4} \times S_4 \tag{5}$$

A customer is self-sufficient if:

$$Cost_5 = 0 \tag{6}$$

According to the agreement between the customers:

$$Cost_1 + Cost_2 + Cost_3 + Cost_4 + Cost_5 = 0 \tag{7}$$

Hence, when T1 is consuming power, P2 should sell back equal amount of power to PEP and vice versa. So, $P_{s1} = P_{s4}$ and $P_{s3} = P_{s2}$; $S_1 = S_4$ and $S_3 = 4S_2$

B. I-Connector Results

In order to provide efficient and optimal load scheduling, the following parameters should be known: 1) the amount of solar energy available at any given time, 2) the amount of energy stored in the battery at any given time, 3) the cost per unit energy from the PV cells, battery, and the grid and 4) the power transmitting capability of the energy management system (DC-DC converter and DC-AC inverter). Selecting the proper battery is also an important parameter. The battery must be able to store a sufficient amount of energy, and it must have fast enough charging and discharging rates and deep cycle. The optimal energy management system should be designed to achieve minimum transfer and converting power loss. As mentioned earlier, the focus of our algorithm is scheduling optimally the daily load curve. Sensors are attached to each of the user-end appliances to control their ON/OFF operation. Most of the events are scheduled when maximum energy can be obtained from the PV cells. Based on the cost per unit of energy, the power may be supplied solely by the PV cells or in addition with the battery and the grid. During the night, we try to use as less amount of power as possible. At night the energy is distributed by the battery and the grid. The ratio depends on the cost. The load scheduling is done on an hourly basis and fed as input to the control of the energy management system which is comprised of a DC-DC converter and a DC-AC inverter. Based on the PV power and the load power, our DC-DC converter works either as a buck converter or a boost converter. The duty cycle of the converter is adjusted based on the load curve. Excess energy is stored in the battery during the buck mode of operation. During the boost mode of operation, energy is discharged from the battery if load power is greater than the PV power. If both the PV power and the battery power cannot meet the load requirements then the grid needs to be activated. All experimental simulations were carried out in HSPICE. The experiment was conducted for a single PV cell. The output of the PV cell is fed as input to the DC-DC converter. It can be observed that normally it takes more time to transmit energy when there are multiple output sources (battery charging and load) or multiple input sources (PV cells and battery discharging).

I-Models have been simulated in the programming language SystemC as previously mentioned. The input data is collected from eight Sanyo HIT Double panels, which generates close to 170W per panel [17]. The I-Model of DC-DC converter has a boundary condition range of between 50V and 350V due to the voltage limit of the MOSFET switches [18]. The efficiency for DC-DC and DC-AC is also included in I-Model due to the converting and switching loss during the process. Based on the specifications of given components, the boundary condition values are set, which can be modified any of the components is replaced or changed.

Table I to Table V represent the experimental result data of our proposed new smart grid system scheme.

TABLE I: COMPONENT LIST [2]

Component	Model
PV Module	Sanyo HIT Double 190W
Battery	Valve-regulated lead acid
POWER MOSFET	IBM 180nm MOSFET
Microcontroller	Silicon labs C8051F560
	PIC controller (F560DC)
	TI-TMS320C2000

TABLE II: DELAYS FOR DIFFERENT CASES [2]

Case	Delay
Light mode (Buck)	~20us
Light mode (Buck + battery charging)	~30us
Heavy mode (Boost)	~100us
Heavy mode (Boost + battery discharging)	~210us

TABLE III: PV CELL I-MODEL

	λ_i (W/m^2)	V_o (V)	I_o (A)	ESF (W)
1	1200	50	2	800
2	1000	45	2.44	878.4
3	1300	51	3	1224
4	1500	55.3	3.44	1521.8

TABLE IV: DC-DC INVERTOR I-MODEL

	V_i (V)	I_{norm} (A)	V_o (V)	ESF (W)
1	195	3	175	3905.5
2	199.2	3.1	179	3994.8
3	207	3.3	171	3816.2
4	221.2	3.4	165	3682.3

TABLE V: BATTERY I-MODEL

	V_b (V)	I_b (A)	T_{chg} (hr)	T_{dchg}(hr)	ERF (W)	ESF(W)
1	48	40	8.8	0	1267.2	0
2	50	42	14.3	0	2216.5	0
3	51	43	0	5	0	10965
4	52	45	0	4	0	9360

V. CONCLUSION

This paper discusses a new real time, monitoring, sensing, and control framework that facilitates data flow and energy flow management by integrating power electronics hardware and software in both the smart grid system and smart buildings. Instead of following an outdated one-way grid-to-buildings energy distribution paradigm, we propose a two-side regulation scheme. Not only we regulate the grid, but we also reconfigure the households. Our preliminary experimental results showed that the intelligent connector (I-Connector), the Interface Model (I-Model), and the simulation based Optimization with Hierarchical Options (SoHo) proposed capture the major characteristics of smart home systems, and integrated with higher level optimization tools have the potential to provide significant energy saving.

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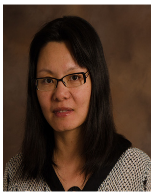

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