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An Energy Service Decision-Support Tool for Optimal Energy Services Acquisition

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Abstract

There is a need to improve the provision of energy services, and utilizing distributed energy resources (DER) offers significant potential. In this paper, we describe a novel decision-support tool that aims to improve the provision of energy services. The tool is composed of an energy service model and a DER scheduler. The energy service model captures temporal variations of services demand and value and differentiates it from the electric energy consumed by the end-use equipment, and the DER scheduler creates a strategy for how available distributed resources should be operated in order to to maximize the net benefit derived from energy services. The corresponding optimization problem is solved using cooperative particle swarm optimization. The paper presents a case study where this decision-support tool is used to optimize the provision of desired energy services in a 'smart' home that includes a number of controllable loads, some direct energy storage and photovoltaic generation.

Contents

1 Introduction

Energy services are energy forms and processes from where consumers ultimately derive and realize the value of energy carriers like electricity and gas. Some of the common forms of energy services are space conditioning, water heating, illumination, information processing and communications. The conventional approach of providing energy services to consumers (where electricity is the energy carrier) is to generate and make available electricity to meet exogenously determined demand while upholding the security of the power system. In this approach, much of the investment and operational decision making is focused on the supply side of the power system, with lesser regard to the potential contributions of the demand side. Lately, this approach has become increasingly unfavorable due to growing demand, more pressing environmental concerns, and deteriorating load factors [ANT,].

The problems that electric power systems are facing have contributed to a paradigm shift during the final decades of the 20^{th} century: consumers put value to the energy services they use, not to the amount of electricity the end-use equipment that deliver these services consume [Masters, 2004]. Hence, the provision of energy services, not kWh of electricity, is the key challenge for the industry [Haas et al., 2008].

A promising approach to improve the provision of energy services is to facilitate a larger role for distributed energy resources (DER). DER are fine-grained equipment and practices usually co-located with or near the consumer that can augment, or in some circumstances assume, the role of the utility in delivering energy services. Numerous financial and technical benefits may be derived from the utilization of DER [Lovins et al., 2002] and their potential to augment the utilities' role of generating and making electricity available to end-users has been continuously increasing [Outhred, 2007]. Examples of DER are distributed generation, interruptible and controllable loads, and consumer-sited direct energy storage.

In this paper, we propose a novel energy service decision-support tool that aims to improve the provision of energy services with electricity as the energy carrier. The tool consists of an approach for modeling energy services and a DER scheduler. The modeling approach is based upon consumers putting value to the benefit derived from their various energy services requirements. In turn, the scheduler maximizes the net benefit derived from these energy services by proposing a strategy for how available DER should be operated. The energy service model created using the proposed modeling approach is used by the DER scheduler to create the strategy.

We demonstrate the effectiveness of the the decision-support tool using a 'smart' home case study. We derive models for five energy services, and schedule the operation of four DER using the scheduler.

The creation of the operation strategy is a complex mathematical optimization problem. We apply co-operative particle swarm optimization (PSO) to solve the problem because simulation-based techniques like PSO generally perform well in these types of problems.

The rest of the paper is summarized as follows: energy services are discussed and the proposed model are described in Section 2, and the factors that could contribute to the optimal provision of energy services and the proposed DER scheduler are described in Section 3. The difference of the proposed decision-support tool from similar research is discussed in Section 4, particle swarm optimization is briefly discussed in Section 5, the case study is presented in Section 6 and the conclusions are summarized in Section 7.

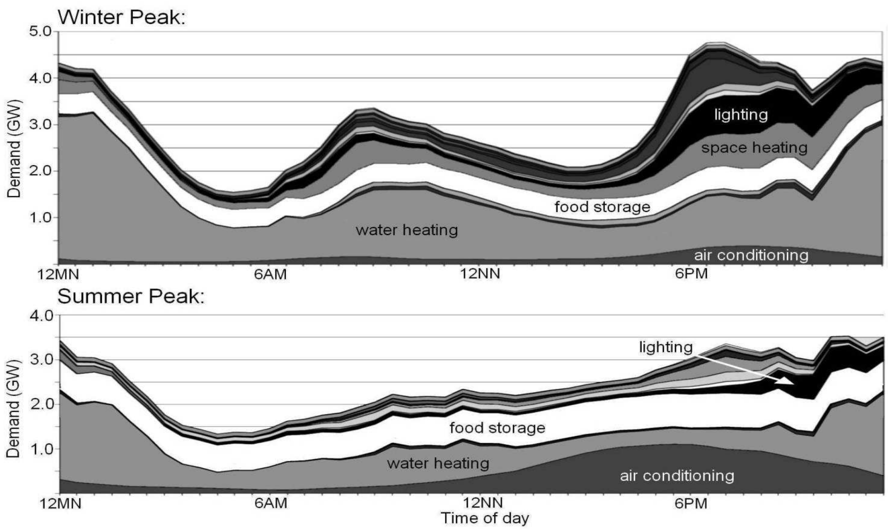

Figure 1: Total peak electricity demand of the residential sector in New South Wales, Australia, broken down by application, in June 2002 and January 2003. These are edited versions of the original figures in [Consultant Pty Limited, 2004].

2 Modeling of Energy Services

Energy services are alternate energy forms, commodities and processes from where consumers ultimately appreciate and derive the value of energy carriers. The demand for an energy service depends on several factors, most notable are occupancy levels, consumer preferences, time of day and day of week, and season of the year. Fig. 1 shows the electricity demand of the residential sector (broken down by application) in New South Wales, Australia during the peak demands in 2002 and 2003 [Consultant Pty Limited, 2004]. The figures show that the demand for different electricity end-use change throughout the day, and the demand during summer is different from the demand in winter. To illustrate, the demand for illumination is highest during in the evening, and there is no demand for space heating in summer.

The value of an energy service originates from the comfort, convenience, products and profits it brings to the consumer. Its benefit to the consumer is either perceived or may be directly quantified, or a combination of both. A residential consumer may be willing to pay several dollars a day for his house to be heated on cold nights (perceived value). On the other hand, a semiconductor processing plant owner could compute the thousands of dollars he would lose for each hour that his plant is not running (directly quantified). The benefit of an energy service to a consumer is affected by several factors. Examples are the time of the day, weather, social externalities, and uncertainties, among others. To illustrate, the benefit of having a bright work area in an office building is certainly higher during the day than during the night. The benefit of watching television is very high if a much-anticipated sporting event is on air.

Energy services may be modeled by specifying the temporal variation of its demand and benefits. The demand may be described by specifying the required temporal changes to a variable directly related to the service, like the hourly temperature in a room or the volume of hourly consumption of hot water. It may also be described by the actual energy consumption of the end-use equipment used to deliver

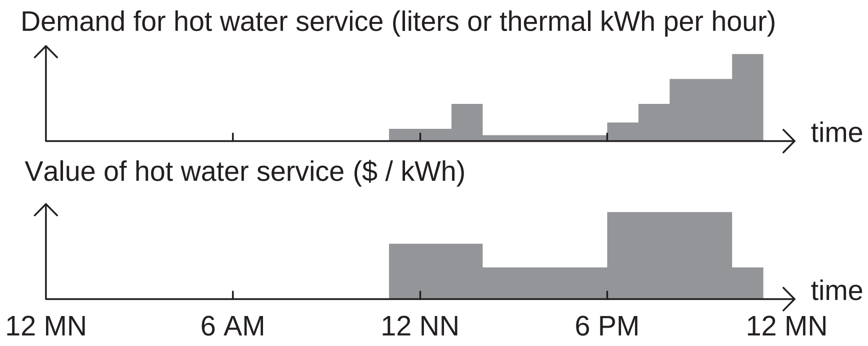

Figure 2: An example of how to use the proposed energy service model to describe the demand for and benefit of hot water service in a restaurant.

the service. However, the latter approach is accurate only if the equipment instantly converts electricity to that energy service. To illustrate, the hourly consumption of hot water can not be inferred from the electricity consumption of water heaters in Fig. 1 because some households use storage-type heaters.

Benefit may be assigned to an energy service in several different ways. The simplest approach is to assign a fixed value to a service regardless of the amount of consumed electric energy or duration of delivery. As an example, we can assume that the benefit of having a bright room is $10/day. To incorporate the total amount of energy that realizes an energy service and the duration of the service to the representation of benefit, we can assign a monetary value to each unit of energy that realizes the service for each hour that it is utilized. As an example, to quantify the benefit of hot water service, we can put a dollar value to the thermal energy content of each liter of consumed hot water every hour. The thermal energy content of water may be thought of as the "energy equivalent" of the hot water service.

This approach allows a distinction to be made between the energy that realizes the energy service and the actual electricity consumption of the end-use equipment. We are putting value on the energy service itself and differentiating that value from the cost of electricity consumption. The temporal variation of benefit of a service can therefore be represented by the hourly variation of the value of each unit of "energy equivalent."

It is generally difficult to determine the monetary equivalent of an energy service. In most instances, its value is easier to perceive when electricity is not available, that is, during a power interruption. At the power system level, several methods have been proposed to determine the Value of Lost Load [Willis and Garrod, 1997] [Kariuki and Allan, 1996] [Yongxiu et al., 2007] and different electricity industries use different values. The determination of the monetary value to be assigned to each unit of "energy equivalent," therefore, involves similar complexity. Some users can readily identify the benefit of a particular service while others can not. Nevertheless, the proposed model enables the users to adjust the benefits until they are satisfied with the efficiency of service provision. It is also worth mentioning that the conventional method of service provision is to assign a high benefit to all services, and the provision is optimized by minimizing the cost of electricity provision to consumers.

Fig. 2 shows how the modeling approach can be used to represent the demand for and benefit of hot water service in a restaurant. The demand may be represented by the volume of hourly hot water consumption or by the required hourly amount of "energy equivalent." The benefit is represented by the hourly variation of the monetary value assigned to each unit of "energy equivalent." The figure depicts that the restaurant owner puts value to the hot water service when hot water is used or when the restaurant is open, and does not care if hot water is available when the restaurant is closed. There are hours when consumption is low but benefit is high, and there are hours when consumption is high but benefit is low.

In energy services where electricity is instantly converted to service (like illumination), or where benefit is derived not from the converted energy form but from the resulting process (like information processing), the actual electricity consumption may be taken as the "energy equivalent."

The demand for shiftable and interruptible services like washing and pool pumping may not be represented as a change of some variable or "energy equivalent." In place of an hourly variation of demand, a narrative description may be given. For example, the demand for the dish washing service may be described as "the dish washing service requires 1 kW of electricity over a period of 1 hour, and the washer may run anytime between 8 PM and 11 PM."

The relationship of the "energy equivalent" of a service, $U_{ES}(t)$, to the actual electric energy consumption, $P_e(t)$, should be determined for each service to be provided. The relationship heavily depends on the physical processes occurring within the end-use equipment and the service itself. The determination is straightforward if the equipment instantly converts electricity to the end-use energy or process. Examples of such equipment are light bulbs and some appliances. If the efficiency of the equipment in converting electricity to an energy service is η, then,

$$U_{ES}(t) = \eta P_e(t). \tag{1}$$

In some services, the conversion from electricity to service is not instantaneous, that is, there is some form of storage involved. In space heating service, for example, the room is not immediately heated at the flick of the heater's switch. It would take several minutes or hours before the temperature reaches the desired level. In the case study in Section 6, the relationship of the "energy equivalents" of space and water heating services to the electric energy consumption of heaters are derived.

3 Scheduling of DER for Optimized Energy Service Provision

The net benefit derived from energy services may be maximized by planning (or scheduling) the operation of controllable DER. The net benefit is equal to the total benefits derived from the services less the cost of electricity consumption. The proposed DER scheduler would create a strategy for how controllable DER should be operated. It maximizes the net benefit by taking advantage of these key points:

1. *Temporal mismatch between energy service demand and electricity consumption.* The presence of some form of storage could dissociate the period of service demand from the period of electricity consumption. This enables the operation of end-use equipment ahead of actual service consumption. Space conditioning and water heating are good examples.

2. *Flexible energy services.* Some services could have variable durations and shiftable starting times while some services may be interrupted and the rest of the service may be delivered at a later time. Examples of such services are washers and pool pumps.

3. *Co- and tri-generation technologies.* These technologies improve the economic efficiency of service provision by concurrently providing several services, and by utilizing energy that is otherwise

lost.

4. *Active storage options*. The ability to store electricity when the cost is low, and using it when the cost is high could reduce the cost of provision. Furthermore, the asymmetry between durations of heat surplus (through solar or waste heat harvest) and demand provide opportunities for using heat storage systems.

5. *Temporal variation of the cost of electricity.* The DER scheduler takes advantage of this by scheduling consumption during the periods with low rates. The scheduler then contributes to the minimization of peak demands.

The benefits derived from the services are determined from the temporal variation of demand for and value of the "energy equivalent." The cost of consumption is determined using the prevailing electricity tariff. The DER operation strategy will be in the form of a schedule, or a set of recommended actions at each interval of the simulation horizon. The scheduler will also quantify the savings incurred by operating the DER using the strategy, and this result may be used for making investment decisions.

The scheduling is essentially an optimization problem that aims to find the DER operation schedule x that maximizes the benefit of the energy services less the cost of electricity consumption. The mathematical formulation of the optimization problem is to maximize

$$\sum_{t=1}^{T}\left[\left(\sum_{i=1}^{S}\lambda_{\mathsf{ES},i}(t)U_{\mathsf{ES},i}(t,\boldsymbol{x})\right)-\lambda_e(t)P_e(t,\boldsymbol{x})\right] \quad (2)$$

subject to the operational constraints of the DER.

In (2), $\boldsymbol{x}$ is the DER operation schedule, $\lambda_{ES,i}$ and $U_{ES,i}$ are the benefit and demand for the "energy equivalent" of the i^{th} service, λ_e is the hourly cost of electricity, P_e is the total hourly electricity consumption, *T* is the number of hours in the simulation period, and *S* is number of energy services.

Many techniques may be used to solve the mathematical optimization problem. The presence of storage and shiftable demands suggest that the objective function in (2) is non-linear, non-convex and non-continuous. Simulation-based heuristic techniques, therefore, offer great potential in finding the optimal or a near-optimal solution. In the case study, we used particle swarm optimization as the optimization tool.

4 Similar Research

Previous research work has presented DER control techniques that optimize the provision of energy services. In [Ha et al., 2006], space heating equipment and shiftable loads are controlled to minimize the cost of energy consumption in a household using tabu search. Multi-agent systems and tabu search were used to solve a similar problem in [Abras et al., 2008]. In [Ha et al., 2007], multilevel optimization was used to implement direct load control in a cluster of houses: linear programming was used to control the energy allocation to each house, while dynamic programming was used to control the heaters and ovens in a house. In [Negenborn et al., 2008], model predictive control was used to control the operation of a Stirling engine and a gas heater to supply the electricity and heat demands of a residential building. In [Marnay et al., 2008], electricity and natural gas, and co-generation technologies are used to service heating and electricity end-use loads. Decision-making has also been extended to the investment regime.

The proposed decision-support tool differs from the approaches above by recognizing that consumers put different levels of value to different services, and by allowing the users to assign monetary benefits to them and include these benefits in the optimization of the DER operation schedule. The proposed energy service model assigns the benefit to the the service itself and not to the energy consumption. By putting value to the services, their provision has been transformed from cost minimization to net benefit maximization. The decision-support tool also tends to prioritize the provision of high-valued services and opens up the possibility that services may not be provided if the cost of provision exceeds their benefit. It also involves the scheduling of multiple DER with complex operational requirements and models. These features are demonstrated in the case study in Section 6.

5 Particle Swarm Optimization

Particle swarm optimization is a population-based search technique that mimics how a group of simple particles could achieve complex collective behaviors [Kennedy and Eberhart, 1995]. The goal of the swarm is to locate the best solution according to a certain objective function f, and each particle is a candidate solution. The movement of a particle around the solution space is affected by its momentum, the pull of the best solution located by the swarm so far (global best), and the pull of the best location that the particle has reached (personal best). The movement of a particle is described by its velocity $V(v_1, ..., v_n)$ and position $P(p_1, ..., p_n)$. If *Gbest* and *Pbest* are the global best and personal best positions, the i^{th} coordinate of *V* and *P* are computed by

$$v_i^{t+1} = \omega \cdot v_i^t + c_1 \cdot \textit{rand}() \cdot \left(p^t_{\textit{Gbest},i} - p_i^t\right) + c_2 \cdot \textit{rand}() \cdot \left(p^t_{\textit{Pbest},i} - p_i^t\right) \tag{3}$$

$$p_i^{t+1} = p_i^t + v_i^{t+1}. \tag{4}$$

In (3), ω is the contribution of the particle's momentum to its velocity in the succeeding iteration, c_1 and c_2 are the weights of the pull of the global and personal bests, and *rand*() is a uniform random number generator from 0 to 1.

The PSO procedure is summarized as follows:

1. *Initialization*. The position and velocity of all particles are randomly initialized, and the initial global and personal bests are chosen by evaluating the objective function. The initial positions may be pre-processed to accelerate convergence or to improve the probability of locating the solution.

2. *Particle movement*. The velocity and position of all particles are updated using (3) and (4).

3. *Fitness evaluation*. The fitness of all particles are evaluated, and the global and personal bests are updated if needed.

4. *Iterate*. Steps 2 and 3 are repeated until the maximum number of iterations is reached or a stopping criterion is satisfied. The global best particle at the end of the simulation is taken as the solution to the optimization problem. In some cases, the historical values of the global best are recorded, and the best is chosen.

The canonical version of PSO has been shown to be effective in generating near-optimal solutions to challenging problems. Some of its applications to power system optimization include reactive power and voltage control, economic dispatch, state estimation and optimal power flow [del Valle et al., 2008].

PSO was extended to solve binary-valued optimization problems in [Kennedy and Eberhart, 1997]. In binary PSO, a position coordinate p_i is either 0 or 1. The velocity is also computed using (3), but the values of v_i^{t+1} are constrained within a range $[-V_{max}, V_{max}]$. To determine the value of p_i^{t+1}, v_i^{t+1} is mapped to a probability using a sigmoid function (5) and the result is compared to a random number. That is, if $S(v_i^{t+1}) > rand()$, then $p_i^{t+1} = 1$, otherwise, $p_i^{t+1} = 0$.

$$S(v_i^{t+1}) = \frac{1}{1 + exp(-v_i^{t+1})} \tag{5}$$

Binary PSO is used to solve optimization problems that involve binary-valued decisions like interruptible load dispatch (interruptible load is curtailed or not) [Pedrasa et al., 2009b] and equipment siting (asset is to be installed in a particular node or not) [Hajian et al., 2007]. A hybrid of canonical and binary PSO has been used to create a generator dispatch schedule in [Ting et al., 2006]: binary PSO is used to solve the unit-commitment problem while canonical PSO is used to solve the economic dispatch problem.

PSO, like any other optimization algorithm, suffers from the curse of dimensionality. The method could fail if it is optimizing several and possibly competing variables. This may be overcome by using cooperative co-evolution [Liu et al., 2001]. A cooperative version of PSO is described in [van den Bergh and Engelbrecht, 2004].

Cooperative PSO solves a high-dimensional optimization problem using a divide-and-conquer approach. The vector to be optimized is divided into several component vectors, and a swarm is created to optimize each component. To illustrate, assume that $f(\boldsymbol{X})$ is to be maximized and $\boldsymbol{X} = [\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_i, ..., \boldsymbol{x}_n]$. One swarm is then assigned to each component of $\boldsymbol{X}$ to find the best value of that component. Further assume that $\boldsymbol{x}_{ij}$ is the j^{th} particle of the i^{th} swarm. To determine if $\boldsymbol{x}_{ij}$ is a personal or global best, the objective function is evaluated by concatenating $\boldsymbol{x}_{ij}$ with the global bests that the other swarms have produced so far, that is, the "fitness" of $\boldsymbol{x}_{ij}$ is

$$f_i(\boldsymbol{x}_{ij}) = f([\boldsymbol{x}_{\mathit{Gbest},1}, \boldsymbol{x}_{\mathit{Gbest},2}, ..., \boldsymbol{x}_{ij}, ..., \boldsymbol{x}_{\mathit{Gbest},n}]). \tag{6}$$

At the end of the simulation, the solution is the concatenation of all global bests, or

$$\boldsymbol{X}_{\mathit{solution}} = \left[\boldsymbol{x}_{\mathit{Gbest},1}, \boldsymbol{x}_{\mathit{Gbest},2}, ..., \boldsymbol{x}_{\mathit{Gbest},i}, ..., \boldsymbol{x}_{\mathit{Gbest},n}\right]. \tag{7}$$

The DER operation strategy in the case study is created using cooperative PSO. The component vectors with real coordinates are optimized using canonical PSO, while those with binary coordinates are optimized using binary PSO.

6 Case Study

6.1 Description of the Case Study

The energy service modeling approach is used to model the services required in a 'smart' home, and the DER scheduler is used to determine how DER may be controlled to optimize the provision of the services. The DER in the 'smart' home are listed below and the first four are to be scheduled.

1. Plug-in hybrid car. 5.9 kWh capacity, 1 kW maximum charging/discharging rate, 90% charging/discharging efficiency, may be discharged down to 30% of capacity, 0.1% coulomb loss per hour.

2. Space heater. Provides the space heating service, maximum heating power is 1.8 kW.

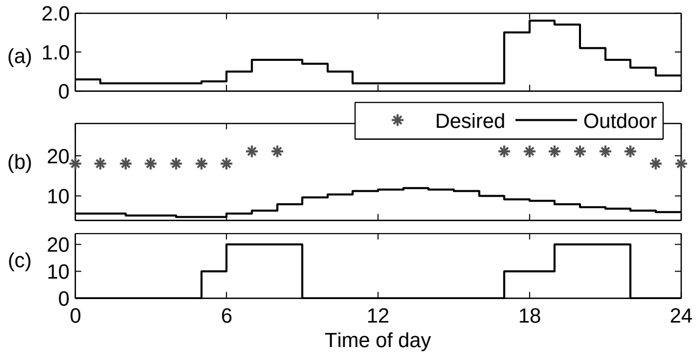

Figure 3: Hourly demand for the energy services: (a) Must-run service power consumption, in kW; (b) Heating service: required hourly temperature, in ℃, the ou tdoor temperature is also shown; (c) Hot water service: hot water consumption, in liters.

3. Storage water heater. Storage capacity is 80 liters and the heating element is rated 1.2 kW.
4. Pool pump. For pool maintenance. Rated 1.1 kW, may be run as 3 separate 2-hour periods.
5. PV module. Peak output = 2.0 kW.

All energy services aside from car battery charging, space heating, hot water, and pool pumping are lumped together into an aggregate must-run energy service. The must-run service includes food storage, food preparation, illumination, and entertainment, among others. The hourly electricity consumption of the must-run service is shown in Fig. 3(a).

The residents prefer that the temperature is within 1 C° from the desired temperature. The hourly desired temperature is shown in Fig. 3(b). The residents leave at 8 AM and returns at 5 PM so the desired temperature in that period is not indicated. The demand for hot water is shown in Fig. 3(c).

The residents may or may not use the hybrid car when they leave the house. If they use the car, its batteries are fully discharged (30% of capacity) when they return at 5 PM. If they leave the car at home, the scheduler could use the car battery as an energy storage equipment, hence, it is regarded as another controllable DER.

The residents have the following outlook on the services they require: (a) the electric car should be fully charged by 8 AM, (b) the space heating service is very important when they are at home but they do not care about the temperature in the house while they are away, (c) the hot water service is very important but has no value during the times it is not consumed, (d) the must-run service should run regardless of the prevailing price of electricity, and (e) the pool pump should run at most 6 hours anytime from 8 AM to 10 PM.

The simulation horizon is 1 day, divided into 24 1-hour periods. The simulation starts and ends at midnight. At each hour, the scheduler would determine

1. the charging or discharging rate of the car battery,
2. the heating power of the space heater,
3. whether the water heater will be connected to the electricity supply or not, and
4. whether to start a 2-hour pumping period or not.

Table 1: Electricity Tariff

Tariff	Rate ($/kWh)
Time of Use (ToU)	
Peak (2 – 8 PM)	0.3025
Shoulder (7 AM – 2 PM, 8 – 10 PM)	0.1089
Off-peak (10 PM – 7 AM)	0.0605
Capacity charge ($/kW)	0.11325
Feed-in (net)	0.60
Critical peak price (CPP)	
Medium alert (5 – 8 PM)	1.00

6.2 Case Scenarios

The DER scheduler would formulate an operation strategy under different situations. The value of scheduling is determined by simulating a baseline case where the DER are manually controlled and comparing it to cases where the DER are scheduled.

In the baseline case, the residents use the car and charge the battery starting at 10 PM, the start of the evening off-peak. The space heater is manually controlled to achieve the desired temperature. At 6 AM, the thermostat is adjusted to 21 ℃ so that by 7 AM, the temp erature is near the desired value. It is also lowered to 18 ℃ at 10 PM, an hour before the desired red uction at 11 PM. It is programmed to turn on at 3 PM with the thermostat set at 21 ℃, so at 5 PM, the te mperature is near the desired value. The pool pump timer is set to run from 9 AM to 3 PM, while the PV output is highest. The water heater is permanently connected to the ac mains.

The DER are scheduled in the succeeding cases. Scenarios with different tariff arrangements are explored, as well as the case where the car is, or is not, available. The electricity tariffs are summarized in Table 1. These are regulated retail rates in Sydney, Australia (ToU and capacity) [Eny,] and the state of Victoria (feed-in) [Vic,] as of January 2009. The critical peak pricing rates are those used by Energy Australia in their Strategic Pricing Study [CPP,].

6.3 DER Scheduler Mathematical Formulation

The optimization problem, based on (2), is to find $\boldsymbol{x} = [\boldsymbol{x}_{car}\ \boldsymbol{x}_{heat}\ \boldsymbol{x}_{water}\ \boldsymbol{x}_{pool}]$ that maximizes

$$\sum_{t=1}^{T} \left(\begin{array}{l} \lambda_{ES,must\text{-}run}(t) U_{ES,must\text{-}run}(t) + \lambda_{ES,car}(t) U_{ES,car}(t, \boldsymbol{x}_{car}) \\ +\lambda_{ES,heat}(t) U_{ES,heat}(t, \boldsymbol{x}_{heat}) + \lambda_{ES,water}(t) U_{ES,water}(t, \boldsymbol{x}_{water}) \\ +\lambda_{ES,pool}(t) U_{ES,pool}(t, \boldsymbol{x}_{pool}) - \lambda_e(t) P_e(t, \boldsymbol{x}) \end{array} \right). \tag{8}$$

In (8), $\boldsymbol{x}_{car}$ and $\boldsymbol{x}_{heat}$ are 24-element vectors whose coordinates are the hourly battery charging/discharging rate and the hourly heating power of the space heater. $\boldsymbol{x}_{water}$ is also a 24-element vector but with binary coordinates: the i^{th} coordinate is equal to 1 if the water heater is to be connected to the ac mains, otherwise it is 0. $\boldsymbol{x}_{pool}$ contains the starting times and state of each 2-hour pumping period:

$$\boldsymbol{x}_{pool} = [Start_1\ \ Start_2\ \ Start_3\ \ State_1\ \ State_2\ \ State_3]. \tag{9}$$

The i^{th} pumping period would run starting at $Start_i$ if $State_i = 1$. If $State_i = 0$, the i^{th} pumping period

Table 2: Mapping of Perceived Values of Services to Monetary Values

Importance of energy service	Value ($/kWh)
High	0.75
Medium	0.20
Don't Care	0.00
Expense	-0.50

will not run.

The hourly grid import P_e is computed by adding the consumption of all services less the PV output:

$$P_e = P_{e,\textit{must-run}} + P_{e,\textit{car}} + P_{e,\textit{heat}} + P_{e,\textit{water}} + P_{e,\textit{pool}} - P_{PV}. \quad (10)$$

The constraints of the optimization problem are: (a) the battery charging and discharging rates should not exceed the maximum value; (b) the stored energy in the batteries should be between 30% and 100% of capacity; (c) the space heater power is non-negative and should be less than the maximum output; and (d) the pool pumping periods should not overlap.

6.4 Energy Service Models

Before the optimization problem in (8) can be solved, benefit ($\lambda_{\textit{ES,i}}$) should be assigned to the energy services and the relationship between the temporal variation of demand ($U_{ES,i}$) for the "energy equivalent" and actual electricity consumption ($P_{e,i}$) should be determined.

Benefit is assigned to the services based on the perception of the residents to their importance. Table 2 maps the relative importance of a service to a dollar value to be assigned to each kWh of "energy equivalent." The monetary equivalents are chosen arbitrarily but are loosely based on the electricity tariff shown in Table 1. The unit value of important services (*High*) is higher than the peak rate while the unit value of medium-valued (*Medium*) services is smaller than the peak but higher than the shoulder rates. These imply that important services should be delivered even at peak period while medium-valued services may be curtailed. Although the residents could have different perceptions to the relative importances of the high-valued services, we can choose a single value as long as this value exceeds the peak rate. *Don't Care* value is assigned to services which the residents do not care whether they are delivered or not, and *Expense* value is assigned to services that they do not wish to have.

The monetary benefit $\lambda_{ES}(t)$ assigned to the "energy equivalent" of the services are summarized in Fig. 4. These values are based on the outlook of the residents to the services they require. They prefer that the car is fully charged at 8 AM, so a *High* value is assigned to the car charging service at 8 AM. They do not care about the state of the batteries at other times so on those periods, a *Don't Care* value is assigned. A *High* value is assigned to the space heating service when it is required. The residents do not care about the indoor temperature from 8 AM to 5 PM so a *Don't Care* value is assigned during that period. The value assigned to water heating is *High* when the they are at home, and *Don't Care* when they are away. *Medium* value is assigned to the pool pumping service from 8 AM to 9 PM. An *Expense* value is assigned from 10 PM to 7 AM to prevent the pump from running. The must-run service should be provided so a *High* value is assigned at all time periods.

We assumed that the space heating service is delivered if the room temperature is within 1 C°from the desired temperature. Therefore, the value of $\lambda_{\textit{ES,heat}}(t)$ in (8) is set to zero if the room temperature

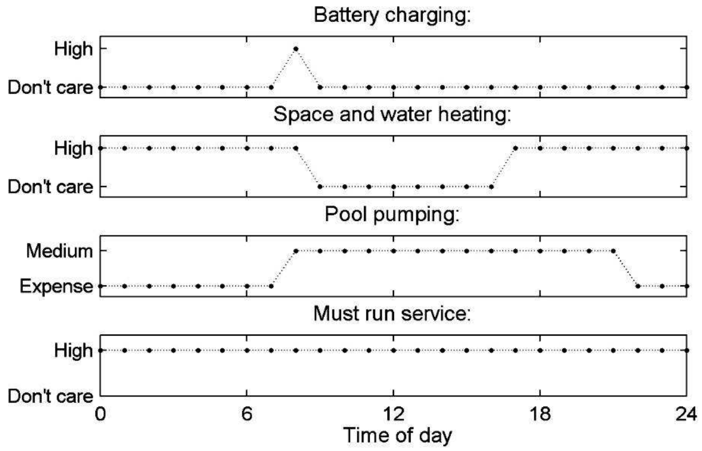

Figure 4: Benefit assigned to each kWh of "energy equivalent" ($\lambda_{ES}(t)$).

is outside this range.

The "energy equivalent" of the car charging service, $U_{ES,car}$, is the energy stored in the batteries. The stored energy at each hour is derived from the charging schedule ($\boldsymbol{x}_{car}$), charging and discharging efficiencies, and losses. The electricity consumption of the car charging service is equal to the charging rate of the batteries, or

$$P_{e,car}(t) = \boldsymbol{x}_{car}. \tag{11}$$

If the residents use the car, they plug it immediately to the ac outlet when they return at 5 PM. If they do not use the car, they leave it plugged to the ac mains.

The "energy equivalent" of the space heating service is the amount of heat energy in the air so that its temperature is equal to the desired value. This heat energy is equal to the heating load of the room. The total heating load, $Q(t)$, is given by

$$Q(t) = \frac{1}{R}\left[\theta_{des}(t) - \theta_{out}(t)\right] = U_{ES,heat}(t). \tag{12}$$

The heating load is equal to the heat flowing out of the building shell. It is proportional to the difference between the desired (θ_{des}) and outdoor temperatures (θ_{out}) and inversely proportional to the thermal resistance of the building shell, R [Sauer et al., 2001]. The outdoor temperature is shown in Fig. 3(b). Infiltration of external air is ignored.

The actual temperature, θ_{in}, is determined by using it in (12) in place of θ_{des}, and the resulting expression is combined with (13) to get (14). Equation (13) relates the change in temperature to the amount of thermal energy introduced to the air.

$$C\frac{d\theta_{in}(t)}{dt} = P_{heat}(t) - Q(t) \tag{13}$$

$$C\frac{d\theta_{in}(t)}{dt} = P_{heat}(t) - \frac{1}{R}\left[\theta_{in}(t) - \theta_{out}(t)\right] \tag{14}$$

In (13) and (14), *C* is the heat capacity of indoor air. The discrete-time equivalent of (14) using 1 hour time steps is

$$\theta_{in}(t+1) = \theta_{in}(t)e^{-\Delta/\tau} + RP_{heat}(t)(1 - e^{-\Delta/\tau}) + \theta_{out}(t)(1 - e^{-\Delta/\tau}), \tag{15}$$

where Δ = 1 hour and $\tau = RC$. The values used are R = 18 C°/kW, C = 0.525 kWh/C°, and the initial room temperature = 17 ℃. The space heating thermal models de scribed by (14) and (15) were adapted from [Ha et al., 2006] and is also used in [Pedrasa et al., 2009a].

We assumed that the electric energy consumption of the heater is entirely converted to heat so

$$P_{e,heat}(t) = P_{heat}(t) = x_{heat}. \tag{16}$$

The hot water service is provided using a storage water heater. We assumed that the water stored in the tank has two sections, hot and cold, having different temperatures. The hot section is already raised to the discharge temperature and does not mix with the cold section. When hot water is discharged at the top, cold water comes in from the bottom and mixes with the cold section.

The hourly decision made by the scheduler is whether to connect the heating element to the ac mains or not. If connected, it heats up the cold section and inlet water. Depending on the volume of water to be heated, the cold section temperature could or could not be raised to the discharge temperature within the hour. If it takes more than 1 hour, the cold section temperature at the end of the hour is estimated using (17). However, if it takes less than 1 hour, the thermostat disconnects the heating element, and the energy delivered by the heating element to the cold section is computed using (18). The cold section then becomes part of the hot section and its volume is reset to zero.

$$T_{cold}(t+1) = T_{inlet} + \frac{C_0[T_{cold}(t) - T_{inlet}]V_{cold}(t) + \eta_{coil}P_{coil} - P_{loss}}{C_0[V_{cold}(t) + V_{inlet}(t)]} \tag{17}$$

$$P_{e,water}(t) = \frac{C_0}{\eta_{coil}}\left\{[V_{cold}(t) + V_{inlet}(t)]\Delta T - V_{cold}(t)[T_{cold}(t) - T_{inlet}]\right\} + P_{loss} \tag{18}$$

Equations (17) and (18) simply follow the law of energy conservation: the increase in internal energy should be equal to the amount of injected heat. We assumed that the specific heat of water is constant over the temperature range it is heated. T_{cold} and V_{cold} are the temperature and volume of the cold section, and T_{inlet} and V_{inlet} are the inlet water temperature and volume. P_{coil} = 1.2 kW and η_{coil} = 0.98 are the rated power and efficiency of the heating element. $C_0 = 1.167 \times 10^{-3}$ kWh/L-C° is the specific heat of water. P_{loss} is a small amount of energy corresponding to the heat loss through the tank jacket and it is estimated using the heater specifications [Rhe,]. The inlet water should be raised by ΔT = 50 C°.

There will be time intervals when the demand exceeds the stored volume, and the cold and inlet water are not heated up by ΔT. In these instances, water in the cold section is released and the temperature of the released cold water is approximated using (17). If the heating element is not connected to the supply, (17) is also used to compute the temperature of the cold section, but without the $\eta_{coil}P_{coil}$ term.

The "energy equivalent" of the hot water service is the energy content of the discharged water:

$$U_{ES,water}(t) = C_0\{V_{HW}(t)(\Delta T) + V_{CW}[T_{cold}(t) - T_{inlet}]\}. \tag{19}$$

In (19), V_{HW} is the volume discharged from the hot section while V_{CW} is the volume discharged from the cold section.

The energy consumption of the water heater, $P_{e,water}(t)$ is 0 if it is not connected to the supply. If connected, $P_{e,water}(t) = P_{coil}$ if the time to heat the cold section takes more than 1 hour, or given by (18) if it takes less than 1 hour.

For the pool pump and the must-run services, their actual energy consumptions are assigned as the "energy equivalent:"

$$U_{\mathit{ES,pool}}(t) = P_{\mathit{e,pool}}(t) \tag{20}$$

$$U_{\mathit{ES,must\text{-}run}}(t) = P_{\mathit{e,must\text{-}run}}(t). \tag{21}$$

The electricity consumption of the pool pump can be easily derived from (9).

6.5 DER Scheduling using Particle Swarm Optimization

The optimization problem described by (8) is solved using cooperative PSO. Ten swarms are used to find the strategy $\boldsymbol{x}$: 3 swarms optimize the charging of the battery ($\boldsymbol{x}_{\mathit{car}}$), 3 swarms optimize the space heater power ($\boldsymbol{x}_{\mathit{heat}}$), 3 swarms optimize the water heater schedule ($\boldsymbol{x}_{\mathit{water}}$) and 1 swarm optimize the pool pumping schedule ($\boldsymbol{x}_{\mathit{pool}}$). The 24 coordinates of $\boldsymbol{x}_{\mathit{car}}$, $\boldsymbol{x}_{\mathit{heat}}$, and $\boldsymbol{x}_{\mathit{water}}$ are divided into three 8-coordinate vectors and a swarm is used to optimize each 8-hour vector. Canonical PSO is used to determine the hourly charging and discharging rates of the battery, the heating power of the space heater, and the starting times of the pool pumping periods (Start_i in $\boldsymbol{x}_{\mathit{pool}}$). The pool pump starting times Start_i are discretized by rounding them to the nearest hour. Binary PSO is used to determine whether the water heater is to be connected to the supply or not and if the i^{th} pool pumping period should run or not (State_i in $\boldsymbol{x}_{\mathit{pool}}$).

The parameters used for canonical PSO are $\omega = 0.7298$ and $c_1 = c_2 = 1.4962$, and for binary PSO, $\omega = 1.0, c_1 = c_2 = 7.5$, and $V_{\mathit{max}} = 5.0$. These sets of parameters were effective in generating near-optimal solutions in [van den Bergh and Engelbrecht, 2006] and [Pedrasa et al., 2009b].

The 10 swarms optimizing the DER operation each has 30 particles, and the simulation has 200 iterations. In each iteration, the order at which the four DER schedules are evolved is chosen randomly but the 3 swarms assigned to the heaters and batteries are evolved in chronological order. The simulation period "wraps around" with respect to the battery charging service, that is, the state of the battery at the end of the 24^{th} hour is used as its state at the start of the 1^{st} hour. The constraints are handled using a repair algorithm [Coello, 2002], that is, the coordinates that violate the constraints are corrected at each iteration.

The simulation is run 10 times and the best solution is chosen. The average 10-run simulation time is 294 sec, using Matlab 2008b running on a 2.0 GHz Pentium dual CPU.

6.6 Simulation Results: DER Operational Strategies

The simulation results are summarized in Table 3 and the DER operation schedules of some cases are shown in Fig. 5.

The cost of consumption under different tariff rates for the baseline case are computed and the indoor temperature and DER operation are shown in Fig. 5(a). The excess PV output is exported to the grid and is compensated at ToU rates.

The operation of the DER are scheduled in the succeeding cases. The results show that the cost of provision can be reduced through scheduling, and on some cases, the residents can earn some credit in their electric bill.

Table 3: Summary of Simulation Results

Case number	Case description	Cost ($)	Energy consumption (kWh)	Grid export (kWh)	Peak demand (kW)
Baseline case: manual control of DER, car is used.					
1	ToU	5.75	49.1	2.3	3.62
	ToU + capacity charge	6.20			
	ToU + net feed-in	4.64			
	ToU + critical peak pricing	12.37			
DER are scheduled:					
2	ToU; car is used	4.03	49.9	2.2	4.15
3	ToU; car is parked	1.95	48.1	8.4	4.14
4	ToU + capacity charge; car is used	4.50	50.2	2.7	3.07
5	ToU + capacity charge; car is parked	2.42	47.8	8.4	3.45
6	ToU + net feed-in; car is used*	-2.51	45.4	14.3	5.50
7	ToU + net feed-in; car is parked*	-5.87	44.4	19.8	5.18
8	ToU + net feed-in; car is used + high pump value	-0.88	51.0	12.6	5.18
9	ToU + net feed-in; car is parked + high pump value	-4.76	47.9	19.0	5.49
10	ToU + capacity charge + net feed-in; car is used + high pump value	-0.32	50.9	13.4	4.92
11	ToU + capacity charge + net feed-in; car is parked + high pump value	-3.80	48.3	17.8	4.13
12	ToU + critical peak pricing; car is used	7.59	50.4	1.9	4.16
13	ToU + critical peak pricing; car is parked	1.99	48.9	3.7	5.42

*The pool pump is only run for 2 hours

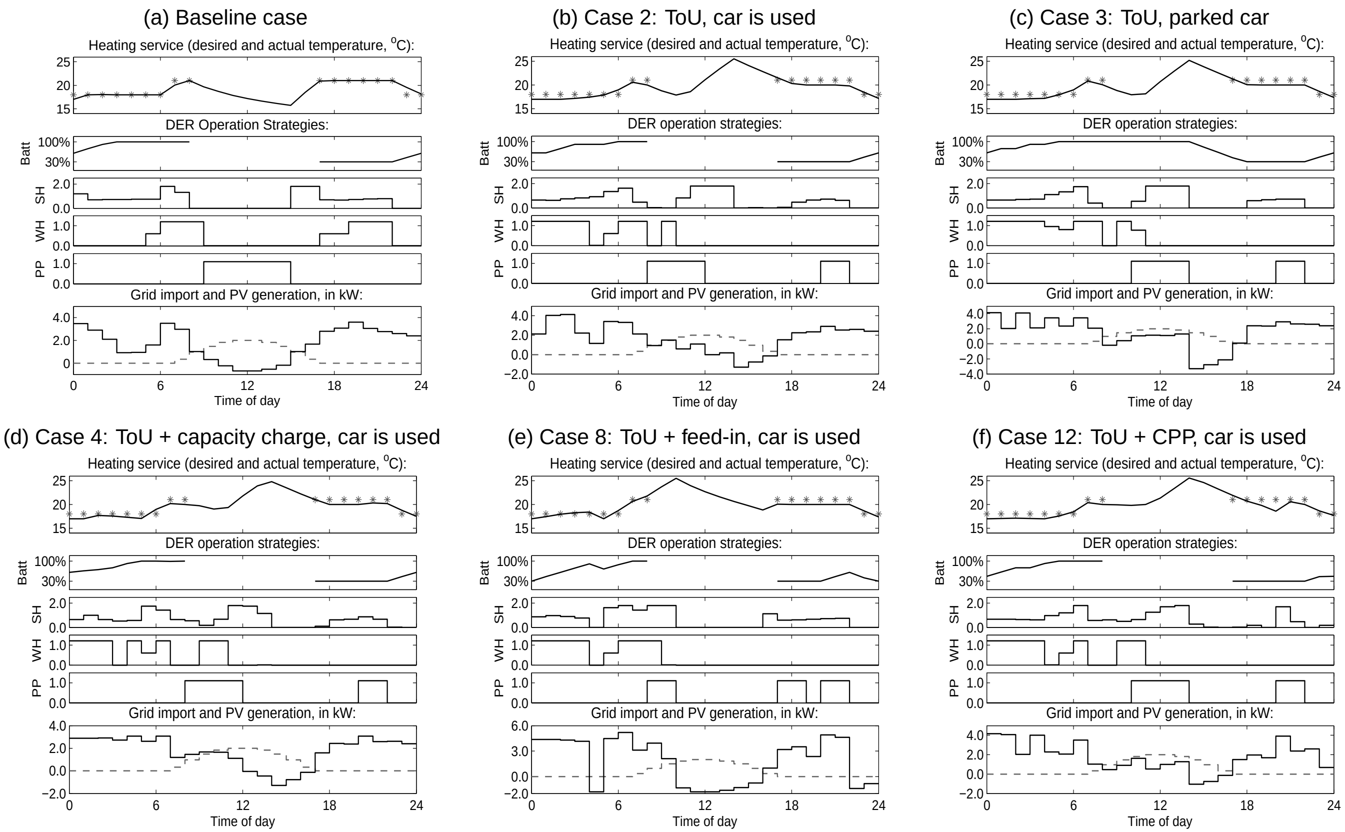

Figure 5: Simulation results for the baseline case and cases 2, 3, 4, 8, and 12. Shown are the desired and actual indoor temperatures, DER schedules, and total grid import and PV output. The DER operation schedules are described by the stored energy in the car battery (Batt, % of full capacity), space heater power (SH, in kW), water heater power (WH, in kW), and pool pump power (PP, in kW). The car is used in all figures except in (c), so the fully charged battery disappears at 8 AM, and returns discharged at 5 PM.

In case 2, ToU rates are applied and the car is used. The results are shown in Fig. 5(b). The cost is minimized by charging the car during the overnight off-peak, pre-heating the house during the mid-day shoulder period, heating the water earlier in the day and operating the pump during the shoulder periods. It is further reduced by not operating any DER at the onset of the peak period so the excess PV output can be exported and be compensated at peak rates. The space heater consumption is also reduced by maintaining the temperature at the lower level of the comfortable range. This heater operation is also evident in some hours of all cases. Pre-heating is also observed in other cases.

In case 3, the residents did not use the car so its battery is now used as an active storage device. The DER operating strategies are shown in Fig. 5(c). The energy stored in the battery is released from 2 to 6 PM to maximize the energy export compensated at peak rate and to displace some energy that is bought from the grid. It is charged again during the overnight peak.

In case 4, capacity charge is levied so the peak demand is reduced by more than 1 kW when compared to case 2. The peak is reduced by charging the batteries at a lower rate, and by controlling the heaters such that their peak consumptions do not coincide. The DER operating strategies are shown in Fig. 5(d). Capacity charge is also levied in case 5 but the car is parked. The strategy for the battery is the same as that in case 3; it discharges from 2 PM to 5 PM to maximize energy export, and recharges again overnight.

In cases 6 to 9, net feed-in rate is available so the strategy is to maximize the energy that could be exported. The pool pumping service is only assigned a *Medium* value so in cases 6 and 7, the DER scheduler recommends that it should only run for 2 hours. If the residents prefers that it should run for 6 hours, then they could assign a *High* value to the pool pumping service. This scenario is covered in cases 8 and 9. The results for case 8 are shown in Fig. 5(e). In this case, the residents could earn a small credit to their electric bill because of the modest feed-in compensation. The export energy is maximized by not operating any DER from 10 AM to 4 PM so that the excess PV output is exported. The house is heated from 8 to 10 AM so that the energy needed to bring the temperature to the comfortable range by 5 PM is reduced. The pump is now operated for 6 hours, and 2 hours of it are in the peak period. Three hours with energy export are achieved during the off-peak by not operating any DER and by discharging the battery. In case 9, a larger energy export is achieved because the car battery is again used to store cheap energy that is released during the export periods.

Capacity charges are imposed and feed-in compensation is available in cases 10 and 11. In these cases, the DER scheduler is able to maximize grid export while limiting the peak demand.

Cases 12 and 13 show how the DER may be scheduled if critical peak pricing is applied: the electricity rate is \$1.00/kWh from 5 to 8 PM, and ToU at other times. In both cases, the house is pre-heated and reaches the maximum temperature at 2 PM. In case 12, the house cools down and the temperature is within the comfortable range at 5 and 6 PM, but drops below 20 ℃ at 7 and 8 PM. During these two hours, the heating service is not provided because the cost of provision exceeds the benefit. The results for case 12 are shown in Fig. 5(f). In case 13, the car battery is used to provide the energy required by the heating and must-run services, resulting in a zero grid import during the critical peak period and the temperature did not drop below the comfortable range.

The simulation results show that scheduling the operation of controllable DER could reduce the cost of provision. The DER scheduler was able to suggest operational strategies that could reduce cost by utilizing the flexibility of the pool pumping and water heating services, the heat storage properties of air, and energy storage capability of the car battery. It was able to suggest strategies that could maximize energy export if feed-in tariff is available, and strategies that could reduce peak demands if capacity charges are imposed. Furthermore, it was able to curtail some services if the cost of provision exceeds the benefit. The total energy consumption is not necessarily reduced because the reduction during peak periods is not equal to the increased consumption during the shoulder or off-peak periods. When the car is parked, however, the total consumption is reduced because the stored charge is used to displace some grid energy. Finally, the scheduler was able to quantify the reduction in the electric bill (or the increase in credits) if the suggested strategies will be followed.

7 Conclusion

Conventional approaches for delivering energy services may be improved by recognizing that consumers put different levels of benefit to different services. Some services should be provided nearly regardless of cost, while some services may be curtailed if the cost of provision exceeds their benefit.

The energy service decision-support tool presented in this paper was able to optimize the provision of energy services by enabling the consumer to assign benefit to energy services, and by scheduling the operation of controllable DER. The energy service model may be used to represent the temporal changes of benefit and demand for services. By assigning monetary value to each unit of energy that realizes a service, or the "energy equivalent," benefit is assigned to the service itself and actual service utilization is differentiated from electric energy consumption. Furthermore, it enables us to incorporate the amount of energy needed to realize the service and the duration of service provision to the assignment of benefit. In the case study, we demonstrated how to use the model to put benefit to services based on the preferences of the consumer.

The DER scheduler was able to optimize the provision of energy services by maximizing the benefit that can be derived from differently valued services while minimizing the cost of provision. Now that benefit can be assigned to energy services, their provision has been transformed from cost minimization to net benefit maximization. In the case study, the scheduler took advantage of the flexibility of some services, the availability of active and passive storage options, and the temporal variation of the cost of electricity as it formulated the DER operational strategies. The scheduling of DER is a complex mathematical optimization problem, and the chosen approach (cooperative particle swarm optimization) was able to produce efficient schedules within brief computation times.

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