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OPTIMIZATION OF RESIDENTIAL ELECTRICAL CONSUMPTION WITH ELECTRIC CONSUMPTION SCHEDULING AND DISTRIBUTED ENERGY STORAGE DEVICES

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ABSTRACT

In this paper, we develop a residential grid-level optimization model, which incorporates both electrical consumption scheduling (ECS) systems and energy storage devices (ESDs), so as to lower the peak-to-average ratio (PAR) of electricity demand and reduce the costs of electricity supply and consumption. This model consists of three levels: household consumption optimization (solo opt), grid consumption optimization (base opt) and ESD allocation optimization (ESD opt). To evaluate this model, a realistic residential population of 180 households subdivided into subpopulations by household sizes and income levels was simulated using a bottom-up randomization approach, with electricity supply from conventional thermal generation (CTG). The results show that PAR can ideally be reduced to 1 with an optimal allocation of ESDs among households with positive bills savings.

Keywords: Demand Side Management; Electrical Consumption Scheduling; Energy Storage Devices; Convex Optimization; Genetic Algorithm

1. INTRODUCTION

In order to meet the ever-growing demand for electricity, the consumption of limited fossil fuels has been increasing steadily over the past few years [1]. At the same time, the generation of electricity also contributes significantly to the greenhouse gas emissions [2]. With these factors in mind, improvements to current generation and distribution systems are needed to produce electricity more efficiently.

All power grids are required to have a spinning reserve, which refers to the unused capacity which can be activated on decision of the system operator and is provided by devices synchronized to the grid network [3]. Spinning reserve is used to increase the power grid's load to either compensate losses in capacity due to breakdowns, or to meet increased demand during peak hours. Due to such reserved capacity unutilized during average demand hours, generators usually run inefficiently at lower capacity. The greater the difference between the peak demand for electricity and the average demand, the less efficient a generator operates as more capacity is reserved to meet peak demand. Thus, the power grid would be more efficient when the peak-to-average ratio (PAR) of electricity demand is reduced.

Demand side management (DSM) is the planning, implementation and monitoring of utility activities that are designed to influence customers' use of electricity [4]. The objective of demand side management is to reduce peak demand such that PAR can be reduced. DSM can be achieved with the implementation of Energy Consumption Schedulers (ECS) in a smart grid where two-way communications exist between the grid and household consumers [5]. This communication allows for the real time monitoring of electrical consumption and pricing. An ECS consists of a smart meter and a controller which can schedule the usage of each household appliance based on consumption information. This thereby shifts the load away from peak hours and lowers the PAR, thus improving grid efficiency.

There have been many papers aiming to reduce the high PAR in the power grid through DSM load shifting method. These papers adopt many different methods of optimization such as heuristic, mixed integer linear programming and agents-based modelling [4, 6-9]. Many papers also include the use of energy storage devices (ESDs), which are rechargeable batteries that store electrical energy through electrochemical reactions [10], in their optimization [11-14]. ESDs should assist in lowering the demand during peak hours as these can store energy during non-peak hours for use during peak hours. However, those authors assumed every household owns ESD and investigated the effect of ECS

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and ESD combined on total energy cost and PAR. This paper aims to develop and evaluate an approach to lower the PAR of electricity demand and reduce the costs of supply and consumption of electricity, by determining an optimal appliance usage schedule for a simulated residential population, while investigating the optimal number and allocation of ESDs in a fixed number of households with different consumption patterns.

2. METHODOLOGY

2.1 Optimization Model & Framework

There are three levels of optimization as shown in Fig. 1a. The solo optimization (opt) is the most inner layer and represents the optimization at the individual household level. The base opt is the next layer where the optimization is performed at the residential grid level. Lastly, the ESD opt uses a genetic algorithm that searches for the optimal ESD allocation amongst households within the residential grid.

The solo and base opt is an autonomous demand-side energy management scheme based on the research done by Mohsenian-Rad et al. [15], in which time is discretized into 24 one-hour periods. Using a game-theoretic approach, it is possible to develop an incentive-based pricing scheme whereby each household communicates their energy consumption vector (ECV) with one another. Through an iterative convex minimization problem (each problem is one solo opt), it is shown that the global minimum for the total energy generation cost (T_{EC}) can be achieved. Moreover, by minimizing T_{EC}, the bills to each consumer as well as PAR would be minimized simultaneously.

A single convex minimization problem (a solo opt) is performed by a household whose objective is to minimize their total electricity bills by shifting shiftable electrical appliances using an ECS. It is important to note that the ECS only shifts usage of shiftable electrical appliances which households do not mind shifting (such as electrical vehicles or washing machines whereby their exact usage time periods do not matter). Other authors have quantified the cost of inconvenience as dissatisfaction cost [14]. For simplicity in our analysis, we do not consider the cost of changing habits in the objective function as households are only shifting shiftable appliances.

The base opt is simply the iterative solving of the solo opt for all households in a round robin style (Fig. 1b) till the total electricity cost converges to the global minimum [15]. Each full round of base opt is carried out using an ESD allocation vector (0 being the household represented by the vector's index not having an ESD and vice versa) and outputs a final T_{EC}, PAR, and bills ($\boldsymbol{b}$) for each consumer. Hence, the base opt can be seen as a black box function that maps a particular ESD allocation vector ($\boldsymbol{\psi}$) to its grid properties as such:

$$[T_{EC} \;\; PAR \;\; \boldsymbol{b}]^T = B(\boldsymbol{\psi}) \qquad (1)$$

With the black box function, any heuristic optimizer could be used to search for an optimal $\boldsymbol{\psi}$ that gives the best grid properties. Before running each base opt, each household can be assigned an ESD (or not) and is indicated by a binary variable (1 or 0). If a household has been allocated an ESD, the ESD constraints will be activated for that particular convex minimization that the household will perform in each solo opt, in addition

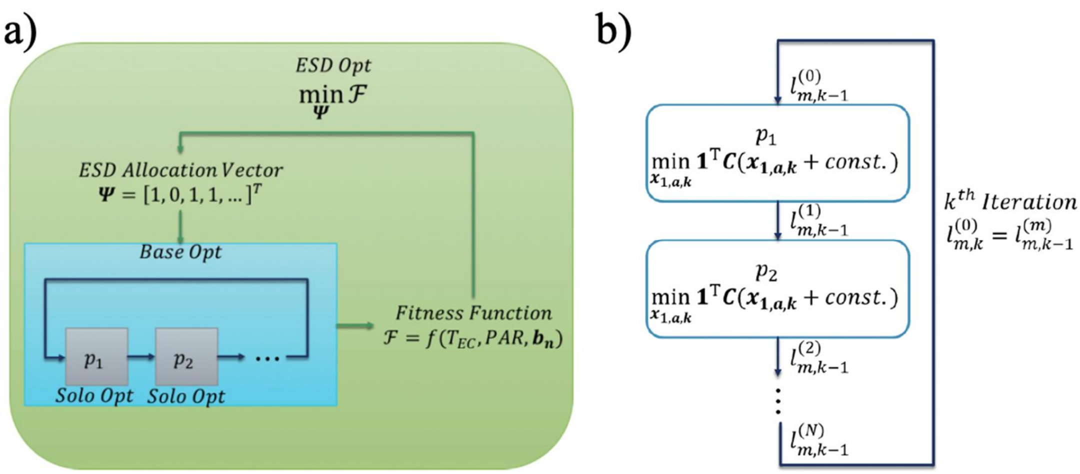

Fig 1 Optimization model. a) The three levels of optimization in the model. b) Depiction of the base opt procedure.

a)

$$\min_{\boldsymbol{y},\boldsymbol{x}} C_T = \min_{\boldsymbol{y},\boldsymbol{x}} \sum_i y_i C(x_i) = \min_{\boldsymbol{y},\boldsymbol{x}} \boldsymbol{y}^T C(\boldsymbol{x})$$

s.t. Generator Constraints:

$\boldsymbol{y}^T \boldsymbol{x} = E_T$	Total energy supplied = Total energy demanded
$E_i^{min} \leq x_i \leq E_i^{max}, \forall i$	Each generator operates within possible capacity.
$y_i = \{0,1\}, \forall i$	Binary variable to determine if generator is off or on.

b)

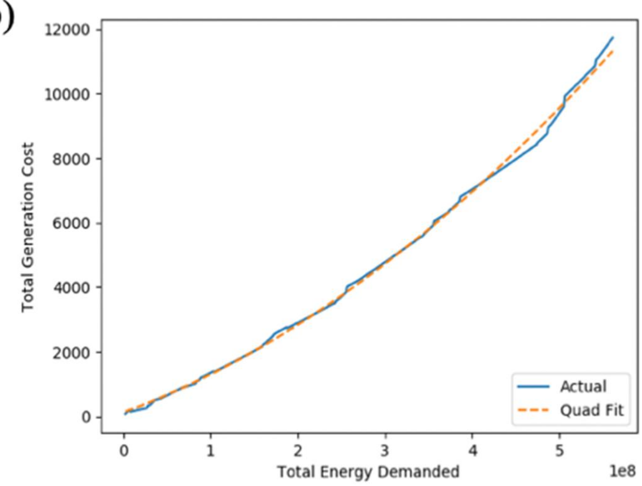

Fig 2 Cost function of CTG. a) MICP model for solving optimal C_T. b) Regressed CTG quadratic cost function.

to the ECV constraints that all households have. Since T_{EC} and b_n are related [15], only T_{EC} and PAR need to be considered. A fitness function can be defined to achieve a particular property, for example:

1. To minimize sum of energy generation and ESDs cost (first fitness function; FF1):

$$F(T_{EC}) = T_{EC} + N_{ESD} C_{ESD} \qquad (2)$$

2. To minimize the sum of energy generation and ESDs cost, as well as reducing the PAR to a desired level (second fitness function; FF2):

$$F(T_{EC}) = T_{EC} + N_{ESD} C_{ESD} + M|PAR - PAR^D| \qquad (3)$$

where PAR^D is the desired PAR level and *M* is some sufficiently large positive constant.

While FF1 will reduce the sum of electricity and ESD costs, since the allocation of each subsequent ESD carries a diminishing marginal benefit, the heuristic optimization will generally allocate an ESD to an insufficient number of households to reduce PAR to a low enough value (i.e., close to 1). Hence, the additional term is required to add a penalty for PAR being too high. This forces the algorithm to provide a solution with more ESD allocations, equivalently, a solution with the PAR closer to the desired level. If *M* is made large enough, the PAR can be made arbitrarily close to the desired level. In our later analysis, we defined our desired PAR level equal to 1 to evaluate if we can obtain a feasible optimal ESD allocation and the accompanying cost savings. A low PAR equates to larger fixed cost savings in the design stage of a plant and will be further discussed in Section 3. We used a genetic algorithm (GA) as the heuristic optimizer. The GA was implemented in Python using the DEAP library [16].

2.2 Producer-Side Modelling

To develop a realistic cost function, we implemented an optimal dispatch of conventional thermal generators (CTG) [17]. The power supplier is assumed to have 9 CTG with the following quadratic form $C(x) = a_i + b_i x + c_i x^2$, each with their own set of coefficients and range of energy production. The producer then optimizes which generators to turn on and their energy production rates to meet the required energy demand whilst minimizing T_{EC}.

Mixed Integer Convex Programming is conducted for many different values of E_T (~10,000 points) to obtain their respective optimal C_T, and a quadratic regression of these points is performed to obtain an overall quadratic cost function (Fig. 2). This allows for a realistic cost function as well as a more computationally efficient solving of the convex minimization in the solo opt.

Lastly, the range of CTG energy generation can be rescaled to match the range of electrical consumption by our simulated residential population by rescaling the quadratic cost function as $C(x) = \left(a_i N^k + b_i N x + c_i N^2 x^2\right)/N$, where *N* is an empirical scaling factor and $0 < k < 1$ is an empirical exponent factor for fixed costs.

2.3 Consumer-Side Modelling

In our research, 35 household electrical appliances have been identified and categorized into shiftable and non-shiftable appliances. As it is difficult to obtain sufficient large and complete datasets for our optimization model, we have developed a version of the bottom-up randomization methodology modified from [18, 19] to achieve variability in generating realistic datasets for testing our model. Three subpopulations, each containing sixty simulated households, are created and differentiated by varying appliance ratings, ownership and usage, to simulate differences in household sizes and income levels for economic analysis on the optimal ESD allocation. The three subpopulations (1, 2, and 3) are in descending order of economic wellbeing. This translates to differences in their electricity consumption with richer households generally consuming more electricity. For shiftable appliances, appliance ratings and usage durations for each household are sampled from normal distributions (the distribution mean being typical literature values), within a pre-specified percentile interval depending on subpopulation. Appliance ownership is also randomly assigned depending on subpopulation. Thereafter, the earliest usage start time α, latest end time β, daily usage duration γ and daily shiftable load δ can then be generated for each household, which serves as constraints for the solo opt. For non-shiftable appliances, hourly energy consumption data for all such appliances are instead aggregated after undergoing a similar randomization procedure for appliance ratings and ownership.

2.4 Energy Storage Device (ESD) Modelling

ESDs will be used by individual households to store energy during off-peak hours for use during peak hours. Such systems usually include an AC-DC rectifier to charge the battery from the grid, a battery to store the energy, as well as a DC-AC rectifier to convert the battery's DC output to AC for household use. In this case, charging the battery would contribute to the ECV, with the charging hours and charging rate being scheduled by the ECS. Likewise, the ECS will also schedule when to discharge the batteries to minimize total generation cost. There are several constraints for any ESD. These include the capacity of the ESD, the maximum charging rate of the ESD, as well as the maximum discharge rate of the batteries. To simplify our model, only a single model of ESD will be used, and the daily cost of the ESD will be calculated using a straight-line depreciation model as follows:

$$\text{Daily depreciation expense} = \frac{(\text{ESD cost} + \text{Installation cost}) - \text{ESD Scrap value}}{\text{Total number of warranted cycles}}$$

In this case, the scrap value of the ESD will be assumed to be 10% of the ESD device cost, and it is assumed that each battery will only cycle once per day. Furthermore, a 100% round-trip efficiency of the ESD (i.e., how much of the energy used to charge the batteries is recovered during discharging) is assumed. Likewise, degradation of the cells used in the batteries will also be ignored for their entire life cycle.

Only complete ESD systems which can be seamlessly integrated into the household without any other equipment will be considered for this study, and specifically, the Tesla Powerwall 2 was chosen for this study by considering cost, capacity, as well as maximum charging and discharge rates [20, 21].

3. RESULT AND DISCUSSION

3.1 Increasing ESD Allocation

Increasing the fraction of households having ESDs (i.e., unit increase in ESDs allocated) was found to have diminishing benefits to reducing electrical costs. In a simplified model of 60 consumers. We found that allocating 30 ESDs allowed for electrical cost savings of about S$500 compared to electrical cost when no ESDs were allocated. However, allocating another 30 more ESDs (i.e., all consumers have ESDs) only saved approximately by another S$100. Since the daily depreciation cost per day for owning a unit of ESD was found to be S$2.60 [20], the optimal fraction of consumers (value between 0 and 1) is a non-trivial solution we solved using Genetic algorithm.

3.2 Results of Base Opt and ESD Opt

Consistent with results from [15], we managed to also reduce the total electricity cost for each consumer (i.e., 2.57% savings) and PAR after base opt for our consumer model to S$1624.51 and 1.66 respectively (Table 1).

Our ESD opt utilized genetic algorithm with specified parameters (i.e., 100 generations of 100 population). We tabulated the results from optimizing ESD allocation from two different ESD opts, one minimizing PAR and one without (Table 1). The table also showed the results from base opt as baseline comparison.

Using FF1, we saw a drop in PAR and total generation cost from base opt as expected. But with FF2, we could further decrease PAR to 1 while minimizing total generation cost. Unsurprisingly, the optimal number of ESDs solved (~70) was much higher than from the first fitness function (~26). However, there was a trade-off for reducing PAR to 1. Despite an increased in bill savings (excluding cost of ESDs) to each consumer to nearly 11.3% up from 2.57% from base opt. The effective savings if we included the cost of allocated ESDs dropped to 1.1%, which made each consumer worst off than without the ESD allocation. However, reducing PAR to 1 from base opt alone (i.e., only ECS in effect) is an

Table 1 Summarized results from Base opt and two ESD opt types, one w/o minimizing PAR (FF1) and one w/ minimizing PAR (FF2).

	Base Opt (1)	ESD opt w/o PAR (1)	ESD opt w/o PAR (2)	ESD opt w/o PAR (3)	ESD opt w/ PAR (1)	ESD opt w/ PAR (2)	ESD opt w/ PAR (3)
Savings excluding ESDs (%)	2.57	8.27	8.57	8.27	11.3	11.3	11.3
Savings including ESDs (%)	2.57	4.58	4.58	4.58	1.15	1.15	1.00
ESD Allocation	0	25	27	25	69	69	70
Fraction of consumer model	0	0.139	0.15	0.139	0.383	0.383	0.389
ESD allocation to each group 1,2,3	0,0,0	12,11,2	16,9,2	15,9,1	27,27,15	29,25,15	24,27,19
Total Initial Cost (S$)	1760	1760	1760	1760	1760	1760	1760
Total Generation Cost (S$)	1624.5	1529.5	1524.5	1529.5	1478.4	1478.4	1478.4
Total Cost (S$)	1624.5	1594.5	1594.7	1594.5	1657.8	1657.8	1660.4
PAR	1.66	1.4	1.37	1.4	1	1	1
Largest Cost Savings (S$)	-	1.48	1.53	1.48	2.03	2.03	2.03

impossible task [22]. Hence, with ESDs being implemented to selected households, reducing PAR to 1 became possible which may generate benefits that outweigh the cost from lowered individual savings of ~1.1%.

Interestingly, for both ESD opts, ESDs were allocated to households of richer background (i.e., owning more household appliances and hence consuming more electrical energy). We found that ESDs were more likely to be allocated to households from group 1; number of ESDs allocated decreases from group 1 to 2 to 3. This observation is in line with our logical understanding that ESDs can store more and later discharge for more energy-intensive households, thereby generate greater cost savings. We summarized the performance of our ESD opt in terms of total generation cost as well as PAR. In all, we repeated each ESD opt type (both fitness functions) 3 times and we can visualize the consistent results obtained from our genetic algorithm optimization for ESDs allocation (Fig. 3). Note that in 2 full iterations of 180 households/consumers each, we were confident that the results obtained were at optimal.

3.3 Economic Analysis

Based on the exact cost savings (in nominal terms) for our consumer model after ESD, the largest cost savings generated for a household was given as S$1.53/day for FF1 and S$2.03/day for FF2. Both cost savings were still less than the per day depreciation cost for one unit of ESD, S$2.60, and hence not a single consumer would be willing to self-purchase an ESD to reduce his/her electrical cost. However, our ESD opt was found to optimally allocate a non-zero fraction of 0.1425 and 0.3851 of households for FF1 and FF2 respectively. The allocation could achieve a more socially optimal

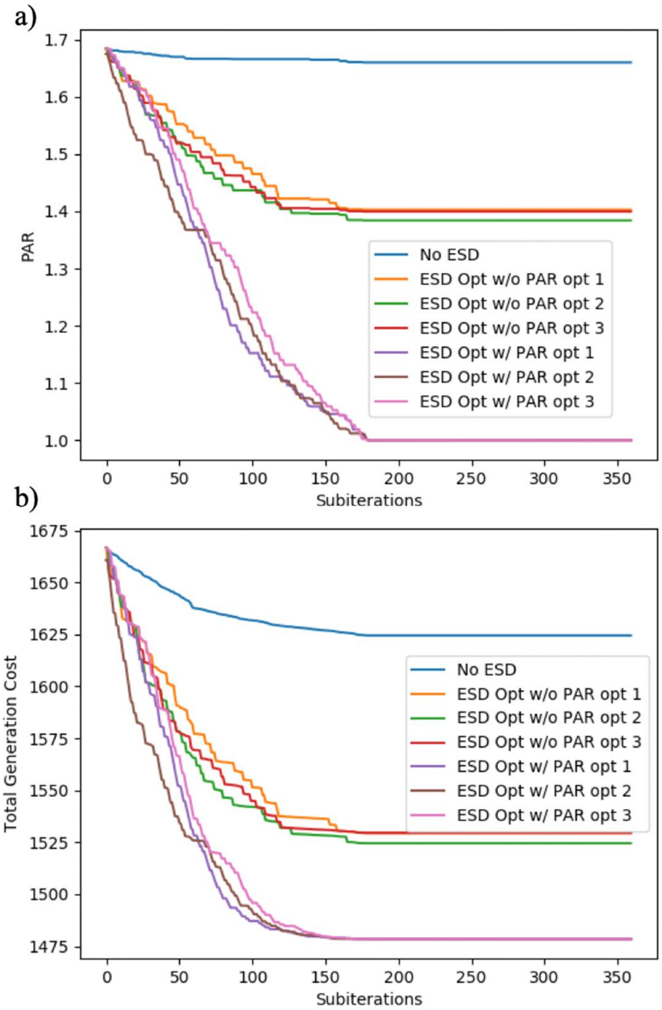

Fig 3 PAR and total generation cost. a) PAR for every iteration for a total of 360 iterations with base opt and 6 ESD opt runs. b) Total generation cost for every interaction for a total of 360 iterations with base opt and 6 ESD opt runs.

result which we saw an overall reduction in electrical cost savings for everyone (i.e., households without ESDs also get to enjoy savings). Hence, households with ESDs have positive spillover effects onto other households without ESDs as total generation cost can be further reduced. In that note, the responsibility of supplying ESDs lies with electrical companies or public body to possibly subsidize ESDs due to positive externalities present.

Lastly, at a power plant design stage, if it can be forecasted and guaranteed that PAR would be at a certain low level (i.e. close to 1) through the usage of an optimal ESD allocation using FF2, the power plant needs not to invest in extra spare capacity to meet peak load demands. Thus, this reduction in fixed cost will lead to more cost savings for both consumers and producers.

4. CONCLUSION

In our study, we incorporated the optimization of ESD allocation on top of ECS and found improvements to further reducing total generation cost and PAR which translated to higher bill savings to each consumer. Our work showed that the implementation of optimal allocation of ESDs into the grid can potentially reduce PAR to an ideal value of 1 (i.e., perfectly flat profile load demand profile). In our future work, we can quantify the benefits from reducing PAR and better evaluate the results obtained from FF2. While the results showed a decrease in bill savings for each consumer compared to base opt, the cost savings derived from a perfectly flat load profile can be quantified (i.e., savings from eliminating the need to build peak generators) and pass on these cost savings onto consumers. This would be important in the design stage of building new electrical grids in urban cities.

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