Reducing Generation Cost by Optimum Load Scheduling in Smart Grid Considering System Loss

Shuvangkar Das
Dept. of Electrical & Electronic Engineering
Bangladesh University of Engineering & Technology
Dhaka, Bangladesh
sshuvo93@gmail.com

Partha Protim Saha
Dept. of Electrical & Electronic Engineering
Bangladesh University of Engineering & Technology
Dhaka, Bangladesh
parthabuet11@gmail.com

Md. Forkan Uddin
Dept. of Electrical & Electronic Engineering
Bangladesh University of Engineering & Technology
Dhaka, Bangladesh
mforkanuddin@eee.buet.ac.bd

Eklas Hossain
Electrical Engineering & Renewable Energy
Oregon Tech
OR-97601, USA
eklas.hossain@oit.edu

***Abstract*—Reducing electricity generation cost, and peak demand, are two key requirements for smart grid. Load scheduling is an effective way to reduce the peak demand for reducing generation cost. In this paper, the problem of scheduling the loads of a substation is analyzed considering system losses - which is modeled including transmission loss and transformer loss - to minimize the electricity generation cost. An optimization algorithm is then formulated to determine the optimal schedule of the loads within 24 hours of a day. The problem is solved for various load scenarios by using optimization tools including MINOS, FilMINT, and CPLEX. The numerical results show that optimal load scheduling reduces the average generation cost by more than 34% compared to that of a conventional system. However, this reduction decreases with increasing number of load. System loss also has a significant impact on the reduction of generation cost by optimal load scheduling.**

Keywords—Smart grid, substation, load scheduling, system loss, optimization, non-linear programming

I. Introduction

A smart grid (SG) is an intelligent electricity network which integrates the actions of all users connected to it and makes use of advanced information, control, and communications technologies to save energy, reduce cost, and increase reliability and transparency [1, 2]. The researchers in the field of SG already paid a significant amount of attention on demand management and load management strategies. In [3-6], the researchers proposed various techniques such as time-of-use (TOU), emergency demand response program (EDRP), linear programming computation, and multi-agent paradigm, for managing the energy demand by the consumers. Load scheduling/management was very well studied in [7-12]. However, these researches did not consider system loss as well as power factor of the appliances in their studies. Since system loss has an impact on the total energy consumption of the system, it is essential to consider the system loss as well as power factor of the appliances for the optimal and appropriate load scheduling. In this paper, the problem of reduction of electricity generation cost by the optimal scheduling of electric loads is investigated considering the system loss and power factor of the appliances. An SG system consisting of a substation and loads connected to the substation are considered. The contributions of this paper are: it models the losses of the system in terms of currents and power factors of the appliances of the consumers; formulates an optimization problem to determine the optimal scheduling of the operating times of the consumer appliances to minimize the electricity generation cost, the problem is found to be solvable through an integer non-linear programming (INLP); and solves the optimization problem numerically for different scenarios of the system and demonstrates that optimal load scheduling can reduce a significant amount of generation cost compared to the generation cost of a conventional system.

Load scheduling is one of the methods to reduce electricity bills of end users. The related works can be classified as: (i) Demand management, (ii) Load management, (iii) Energy consumption management, and (iv) Demand response. Mohesnian-Rad et al. in [9] presented an optimal, autonomous, and incentive-based energy consumption scheduling algorithm to balance the load among residential subscribers that shared a common energy source. In this paper, they reduced peak to average ratio and total cost. Yue et al. in [10] considered the load demand scheduling problem of multiple end users. The objective of these end users was to minimize the electricity generation cost. Hu et al. in [5] discussed optimizing energy loads by managing consumer energy demand in Denmark. Using a linear program, they modeled the energy costs of a consumer during the day with an objective to minimize those costs. Ma et al. in [12] introduced a concept of cost efficiency based residential load scheduling framework to improve the economic efficiency of the residential electricity consumption. Results showed that the proposed scheduling algorithm can effectively reflect and affect user's consumption behavior and achieve the optimal cost-efficient energy consumption profile [12]. In addition to load scheduling, there are some papers on energy consumption scheduling too. Mohesnian-Rad et al. in [9] proposeed a model considering that consumers will not change their consumption habits without incentive. They explained that most of the energy consumption in the United States occur in buildings and there are two general approaches for energy consumption management in buildings: reducing consumption and shifting consumption [9]. The algorithm they proposed solved the energy consumption schedule for each household in the target neighborhood, then communicated it back to the local controller. Roos et al. in [13] added some insight into the electricity cost saving potential of real-time pricing (RTP) through intelligent demand management. A significant amount of work was carried out in the past regarding RTP. Mohesnian-Rad et al. in [4] proposed a model for residential consumers that also used real-time pricing (RTP) as discussed in [13]. The authors assumed that each residential consumer was equipped with a smart meter with an energy scheduling unit similar to the electromagnetic compatibility (EMC) devices discussed in [6, 13, 14]. The authors devised a linear program that reduced consumer electricity costs while also minimizing the time between when a device is called to turn on and when the linear program schedules the appliance to turn on. Since the electricity costs might not be known for the entire day to the end user, the authors proposed an equation that predicted the electricity costs during the day based on past electricity cost data. By utilizing the schedule proposed by the linear program, an end user could experience reduced electricity costs [4]. Jond et al. in [11] proposed a household appliance scheduling scheme for smart meters that would be used in future smart grids. Simulation results verified the proposed algorithm's efficiency in order to address peak load problem [11]. Barbato et al. presented a distributed demand management system which used game theoretical approach which reduced peak demand by 20% [15]. Mohsenian-Rad et al. reduced total energy cost, and peak to average ratio using distributed algorithm (game theoretical approach) while considering load model of appliances. Their approach reduced total energy cost to 37.8% [9]. In [16], Chavali et al. proposed an approximate greedy iterative algorithm which influenced the user to schedule appliances to operate when price of electricity was lower, and added a penalty if the schedule was violated. Yue et al., in [10], proposed a distributed method of load scheduling, where the users scheduled their own tasks. They finally showed that the performance of distributed method was a bit degraded than central method, whereas central method requires huge amount of communication. Koutsopoulos et al. proposed two online demand schedule policies based on stochastic model in [17]. In the first method, a controller served demand request depending on users' current power consumption; while in the second one, the controller activated a new request immediately if the power consumption dropped below threshold.

The model proposed in this paper will deal with commercial load scheduling similar to the papers presented by the authors we have discussed. This model will shift the electrical loads from peak times to partial peak or low peak times, similar to [5, 8, 9]. Some of the main differences of this paper from the existing works are that we have considered appliance power factor, and then, we have considered conduction losses of the distribution wire. Moreover, we have included the transformer losses in the calculation.

The rest of the paper is organized as follows: in section II, the system model, load model and loss model are presented. The optimization problem is formulated in section III with numerical results being presented and discussed in section IV. Finally, section V concludes the work.

II. System Model

A. Smart Grid System

A SG system is considered consisting of a substation, loads of N consumers, smart load scheduling devices (SLSD), smart meter (SM) and transformers. Each consumer connected to the substation has a SLSD, a SM with bi-direction data flow and household appliances. The SM is also connected to the local area networks (LAN) so that it can communicate with the central server installed in the substation. Let the set of the consumers connected to the substation be N. The set of appliances such as light, fan, washing machine, refrigerator etc. is denoted by A. A typical scenario of the SG system is shown in Fig. 1, where N consumers each with a SM and a SLSD are connected to a substation. For simplicity, we assume that an appliance is operated by its owner once in a day and the operation of the appliance is continuous.

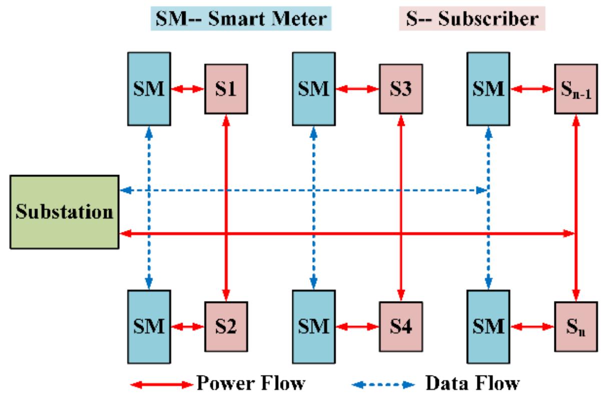

Fig. 1. A typical scenario of smart grid consisting of a substation and N consumers.

B. Energy Consumption Model

In this sub-section, we model energy consumption considering all types of losses and energy consumption. The energy consumption in kWh for the appliance $a \in A$ of subscriber $n \in$ N in one hour is given as:

$$E_{n,a} = V_n I_{n,a} \cos(\theta_{n,a}) \times H \tag{1}$$

Where, H = time (1 hour), $I_{n,a}$ is the appliance current in Ampere which varies from appliance to appliance, V_n is the subscriber household voltage in kV which depends on the distance of subscriber from the substation and $\theta_{n,a}$ is the appliance power factor angle. For resistive load power factor is close to unity, and for inductive and capacitive load power factor is less than unity. Moreover, maximum load profiles of the households are resistive or inductive.

The energy consumption model is made taking the 24 hours in a day denoted by set $H = \{1,2,3\ldots.24\}$. To model total energy consumption due to appliances loads in a given hour, let us define a binary variable $x_{n,a}^h$ regarding the operation of appliance $a \in$ A of consumer $n \in N$ during the hour $h \in H$. The value of $x_{n,a}^h$ is 1 if the appliance a of consumer n operates during the hour h; otherwise the value is zero. Thus, the total power consumption in kilowatt-hour unit by all the consumers in a given hour $h \in H$ can be written as:

$$\mathcal{E}_h = \sum_{n\in\mathbb{N}} \sum_{a\epsilon A} V_n I_{n,a} cos\theta_{n,a}\, x_{n,a}^h \tag{2}$$

C. Subscriber Current Model:

The consumer current model can be modelled by using the decision variable $x_{n,a}^h$. The current for subscriber $n \in N$ during time $h \in H$ is given by :

$$I_n^h = \sum_{a\in A} x_{n,a}^h I_{n,a} \angle\theta_{n,a} \tag{3}$$

As we are using optimization which cannot solve for complex number, we will consider only the magnitude of the current model. For any vector in polar coordinate system

$(r\angle\theta)$, the corresponding Cartesian coordinate system is $x = rcos(\theta), y = rsin(\theta)$, while the magnitude can be expressed as $r^2 = x^2 + y^2$. Then the user current for a particular appliance considering magnitude equation will be:

$$(I_n^h)^2 = \left(\sum_{a\in\mathbb{A}} I_{n,a} cos\theta_{n,a}\, x_{n,a}^h\right)^2 + \left(\sum_{a\in\mathbb{A}} I_{n,a} sin\theta_{n,a}\, x_{n,a}^h\right)^2 \quad (4)$$

D. Energy Loss Model

For the energy loss model, the main losses in a substation can be considered as line loss and transformer loss. Transformer losses can be categorized into two types, such as copper loss, and core loss. Electricity-carrying wires are made of copper and aluminum in general. The line loss mainly occurs due to the conduction loss in the resistance of the current-carrying conductors. The line losses of the consumers are different due to the different lengths of their lines from the substation and the different line currents. Let the distance of consumer $n \in N$ from the substation be l_n and the radius of the copper wire of the consumer be r_n. Thus, the resistance of the wire of consumer n is given by:

$$R_n = \frac{\rho l_n}{\pi r_n^2} \quad (5)$$

Where, ρ is the resistivity of wires. Thus, the total line loss in a given hour h can be written as:

$$L^h = \sum (I_n^h)^2 R_n \quad (6)$$

The transformer loss is the combination of two losses: copper loss and core loss. Copper loss in a transformer occurs due to the primary and secondary side copper resistances. The transformer copper loss in a given hour h can be expressed as:

$$P_{Cu}^h = (\sum I_n^h)^2 R_{eq} \quad (7)$$

Where, R_{eq} is the equivalent resistance of the transformer referred to secondary side. Note that, $R_{eq} = R_s + \frac{R_p}{k}$; if R_s and R_p are the transformer resistances of the secondary and primary side, respectively; k is the turns ratio. The core loss is the summation of eddy current loss and hysteresis loss which are fixed. Let the core loss for the substation transformer is P_{core}.

E. Total Energy Consumption:

Including core loss with previous losses, the total energy loss of the system in a given hour h can be written as:

$$L_t^h = L_h + P_{cu}^h + P_{core} = \sum (I_n^h)^2 R_n + (\sum I_n^h)^2 R_{eq} + P_{core} \quad (8)$$

Let $R_n' = R_n + R_{eq}$. Thus, the total energy loss of the system in a given hour h can be re-written as:

$$L_t^h = \sum_{n\in N} (I_n^h)^2 R_n' + P_{core} \quad (9)$$

Including the energy loss with the energy consumption of the consumers, the total energy consumption of the system in a given hour h can be obtained as:

$$E^h = \epsilon^h + L_t^h = \sum_{n\in\mathbb{N}} \sum_{a\epsilon A} V_n I_{n,a} cos\theta_{n,a}\, x_{n,a}^h + \sum_{n\in N} (I_n^h)^2 R_n' + P_{core} \quad (10)$$

III. Problem formulation

In this section, the optimization problem is formulated to reduce the generation cost and describe the solution approach of the problem.

A. Generation Cost Model:

For generation cost model, let us consider that the generation cost of power is a function of the total energy supplied by the substation. Further, we assume that the daytime and nighttime costs for per unit energy generation are different. The generation cost is modelled as [9]:

$$Cost = \sum_{h\in H_d} BE_h + \sum_{n\in H_n} CE^h \quad (11)$$

Where, B and C are the per unit cost of electricity generation during daytime and nighttime, respectively; and H_d and H_n are the sets of the time in hours during daytime and nighttime, respectively.

For the optimal scheduling problem, let $T_{n,a}$ be the time in hours when consumer $n \in N$ operates its appliance $a \in A$. The set of the time in hours is defined as $\{2,3,...,24 - T_{n,a}\}$ by the set $H_{n,a}^c$. Let the matrix for variables $x_{n,a}^h$, I_n^h and E^h be denoted by $\boldsymbol{x}$, $\boldsymbol{I}$ and $\boldsymbol{E}$, respectively. The optimization problem to minimize the generation cost can be expressed as:

$$\min_{x,I,E} \sum_{h\in H_d} BE^h + \sum_{h\in H_n} CE^h \quad (12)$$

$$E^h = \sum_{n\in N, a\in A} x_{n,a}^h V_n I_{n,a} \cos(\theta_{n,a}) + \sum_{n\in N} (I_n^h)^2 R_n' + P_{core} \quad (13)$$

$$(I_n^h)^2 = \left(\sum_{a\in\mathbb{A}} I_{n,a} cos\theta_{n,a}\, x_{n,a}^h\right)^2 + \left(\sum_{a\in\mathbb{A}} I_{n,a} sin\theta_{n,a}\, x_{n,a}^h\right)^2 \ \forall\, n \in N, \forall\, h \in H \quad (14)$$

$$\sum_{h\in H} x_{n,a}^h \geq T_{n,a} \qquad \forall\, n \in N, a \in A \quad (15)$$

$$\sum_{h'_c \in \{h_c, h_c+1, \ldots\ldots, h_c+T_{n,a}\}} x_{n,a}^{h_c} \geq T_{n,a} x_{n,a}^{h'} (1 - x_{n,a}^{h'-1}) \quad (16)$$

$$\forall\, n \in N, a \in A, h'_c \in H_{n,a}^c \quad (17)$$

$$x \in \{0,1\}; I \geq 0\,; E \geq 0 \quad (18)$$

The objective function in (12) represents the cost for generating the energy supplied by the substation. The constraints in (13) show the energy supplied by the substation in different hours of a day. The constraints in (14) provide the currents of the consumers during different hours of a day. The constraints in (15) ensure that the appliances of each consumer to be scheduled as long as the operating hours of the appliances are requested. The constraints in (16) guarantee that an appliance of a consumer will operate continuously during the operating hours. The constraints in (17) are the boundaries of the variables of the optimization problem. The constraints in (18) are the boundary of the variables of the optimization problem. The problem (12)-(18) is a non-linear non-convex problem.

IV. Numerical analysis

In this section, the load scheduling problem for several scenarios of the power system is solved, and compared with a baseline case. For baseline case, it is assumed that all the consumers operate their appliances as they want and there is no control over scheduling the loads. This base is required to perform a comparison of the performance of the proposed algorithm. In the case of baseline study, users randomly turn on/off appliances. Also there is peak demand at certain times. Peak demand is economically harmful for power generation as at the time of peak demand new generation stations have to be connected with the grid to serve the peak demand. Therefore, a baseline cost is considered by randomly selecting appliance and considering peak demand. This process is illustrated in Fig. 2.

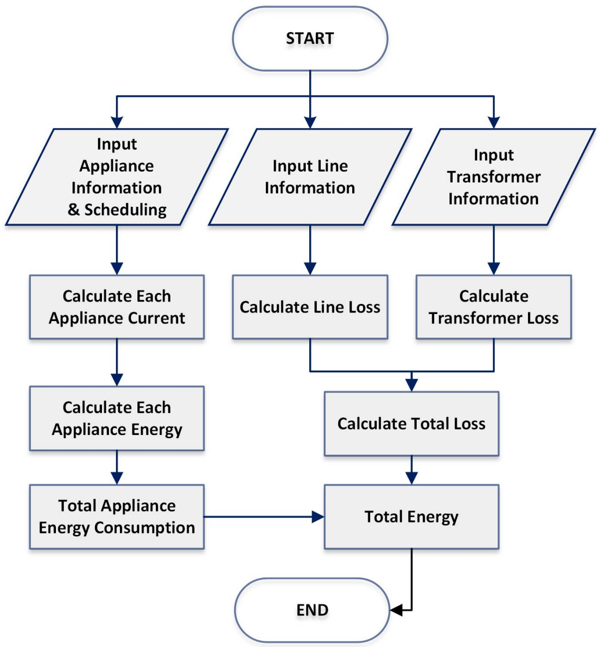

Fig. 2. Procedure for the baseline cost calculation.

Five power system scenarios are considered to evaluate the performance of optimal load scheduling and to provide various engineering insights. Five scenarios for the are considered for approaching to the solution. For each scenario, it is assumed that the appliance current $I_{n,a}$ is less than 1 Ampere, and user voltage V_n varies between 200 and 220 Volts. From Table I we can see that power factor varies between 0.4-0.95 for different appliances. The operating time period of an appliance, i.e., $T_{n,a}$ is taken to be 1, 2, or 3 hours based on the daily usage. The value of H is taken to be 24 hours where H_d and H_n are considered as $\{5,6,7,8,9,10,11,12,13,14,15,16,17,18\}$, and $\{19,20,21,22,23,0,1,2,3,4\}$, respectively. For a scenario, the distance of the consumers are taken randomly between 0.1 to 2 kilometers, the radii of the wires of the consumers are randomly taken between 0.0001 to 0.01 meters, the values of V_n's are calculated by deducting line drop from 220 Volts, the values of $I_{n,a}$'s are calculated from the kiloWatt-hour uses of the appliances mentioned in Table II by using the values of V_n, and the power factors of the appliances are taken randomly between the ranges mentioned above. For determining the power generation cost, the values of B and C are taken to be \$0.1875 and \$0.09375 USD, respectively. To determine the system loss, the values of R_n are calculated from (8) using the randomly generated l_n and r_n values. Since P_{core} is constant, its value is neglected in computation. Fig. 3 shows the proposed optimization algorithm. The requirement of this process is to minimize generation cost, by considering the major losses including conduction loss, loss due to power factor, transformer loss etc. By this proposed algorithm, generation cost is reduced by 34% compared to the baseline. The solver here is selected by using the cost function $Cost(E_h)$ which indicates the cost of generating or providing energy by the substation at each hour $h \in H$ [18]:

$$Cost_{h_1}(E) \neq Cost_{h2}(E), \forall h_1, h_2 \in H \,\&\, h_1 \neq h_2 \qquad (19)$$

In other words, the cost of the same energy can be different at different times of the day. In particular, the cost can be less during night compared to daytime. The cost function $Cost(E_h)$ is a convex function [18]. So, it has only one global optimum point. A convex function can be a piece-wise linear function or a smooth differential quadratic function. The cost function we assume is general and represents either the actual energy cost or simply a cost model by proper load scheduling. In our optimization problem, the objective function is linear but the constraints are non-linear. So we adopted non-linear mixed inter type optimization solver. The decision variable $x_{n,a}^h$ is three-dimensional. Therefore, if we consider N=1000 families, A =10 appliances, H=24 hours, then the number of variables will be 240,000. The case will be similar for rest of the variables as well.

TABLE I. TYPICAL POWER CONSUMPTION AND POWER FACTOR RANGE OF DFFERNET APPLIANCES [19]

Appliance Name	Typical Power Consumption	PF Range
Washing Machine	500-540W	0.55-0.59
Electric clothes Dryer	2-6KW	
Air Conditioner (Wall Mount)	1.1-1.25KW	0.95-0.97
Air Conditioner (Central AC Unit)	1.84-2.34KW	0.9-0.92
CFL Light	25W	0.4-0.95
Refrigerator	135-400	0.92-0.99
Dishwasher	250-300	0.62-0.65
Electric Ranger/Oven	1.3-3KW	0.95-0.98
Electric Water Heater	4-5KW	--

TABLE II. NUMBER OF CONSUMERS, APPLIANCES AND LOADS FOR DIFFERENT POWER SYSTEM SCENARIOS

Scenario	Number of consumer, N	Number of appliance, A	Loads	Daily usage (kWh)
I	3	4	Refrigerator-freezer	1.32
			Electric stove	2.01
			Heating	7.1
			Dishwasher	1.49
II	5	3	Electric stove	2.01
			Heating	7.1
			Dishwasher	1.49
III	10	4	Refrigerator-freezer	1.32
			Electric stove	2.01
			Heating	7.1
			Dishwasher	1.49
IV	20	5	Refrigerator-freezer	1.32
			Electric stove	2.01
			Heating	7.1
			Dishwasher	1.49
			Clothes dryer	2.5
V	50	6	Refrigerator-freezer	1.32

			Electric stove	2.01
			Heating	7.1
			Dishwasher	1.49
			Washing machine	1.94
			PHEV	9.9

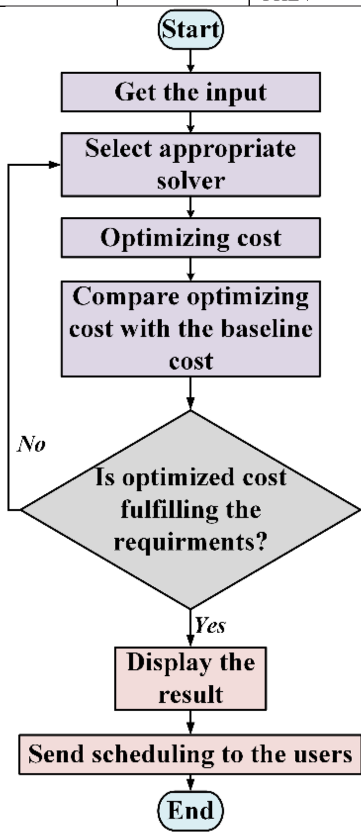

Fig. 3. Proposed optimization algorithm.

The optimization problem is a non-linear non-convex problem and hence, obtaining the global optimal solution is a challenge. Optimization tools including MINOS [20], FilMINT, and CPLEX are used to obtain the optimal solution and hence, it is not guaranteed that the obtained solution is the global optimal. The model and run files are generated in AMPL and the data files are generated using MATLAB tool for MINOS. To determine the advantages of optimal load scheduling, ten instances for each power system scenario are generated with MATLAB by randomly varying the system parameters as mentioned above. The generation cost under the baseline case is determined for each instance of all the scenarios. The generation cost under optimal load scheduling is determined by solving the optimization problem for all the considered instances. The baseline and the optimal energy consumption for a 24-hour period is shown in Fig. 4 which shows almost constant consumption pattern for the optimized solution, very much better compared to the peaks and valleys of the base case. Fig. 5 shows the ability of the optimization technique to put the cost down for any amount of load appliances. The percentage reduction of generation cost by the optimal load scheduling is determined by:

$$\%Reduction = \frac{Cost_b - Cost_o}{Cost_b} \times 100 \qquad (20)$$

Where, $Cost_b$ and $Cost_o$ are the generation costs for the baseline and the optimal load scheduling cases, respectively. The average reduction of generation cost by the optimal load scheduling for all the power system scenarios is presented in Fig. 6. The results show that the reduction of generation cost decreases with increasing index of network scenario. This can be attributed to the fact that the number of consumers increases with increasing the index of scenario, as shown in Table II, and hence, the variation of the total demand among the different hours of a day decreases and the opportunities from optimal load scheduling also decreases. However, the average percentage of reduction of generation cost is significant for all the scenarios. Thus, optimal load scheduling provides a significant advantage in reducing the generation cost. Note that in this study a simple cost function for electricity generation is considered which has only two steps of generation cost: daytime and nighttime. The reduction of generation cost will be higher if cost function with higher cost variations in the different hours of a day is considered. To determine the effect of system loss on reduction of generation cost, an instance from the power system scenario-III can be considered to determine the generation cost with and without system loss for both baseline and optimal load scheduling cases. Fig. 7 shows the comparison of the generation cost with and without system loss under the baseline and the optimal cases. The results clearly show that the generation cost increases due to the system loss. From the results, it can be calculated that the cost reduction is as high as 34% when the losses are considered, and this value rises to 40% when these losses are ignored. This performance is significantly superior than the one demonstrated in [9], where 30% cost reduction was achieved without considering the generation losses. The discrepancy between the two reduction values (with and without considering the losses) obtained from this work clearly indicates that determining the reduction of generation cost without considering the system losses can be misleading. However, the optimal scheduling of the loads without system loss will not be the optimum one as a real system always operates with system loss.

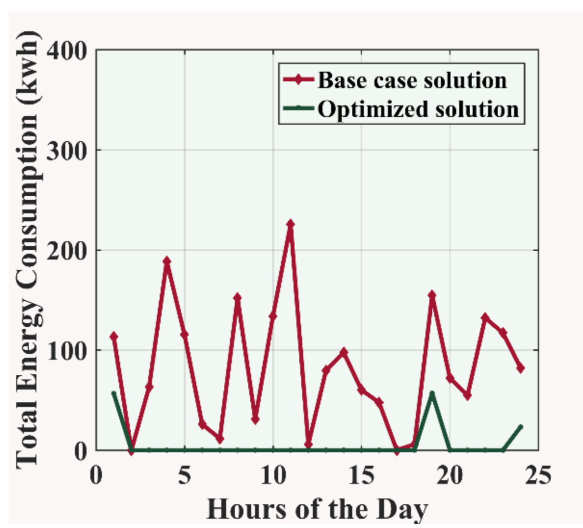

Fig. 4. Energy consumption reduces significantly over a day when optimized with the proposed method, the demand curve gets very flat too.

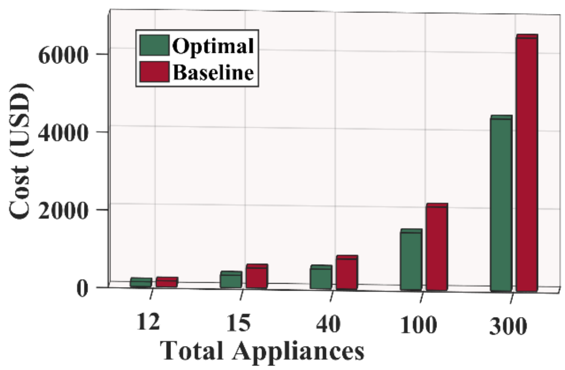

Fig. 5. Change in optimal and baseline cost with increasing number of appliances. The optimal method reduces cost regardless the changes in appliance quantity.

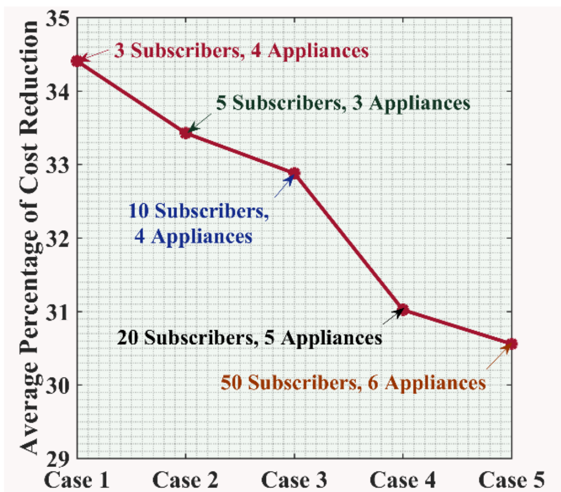

Fig. 6. Average generation cost reduction by the proposed optimal load scheduling strategy for the different scenarios.

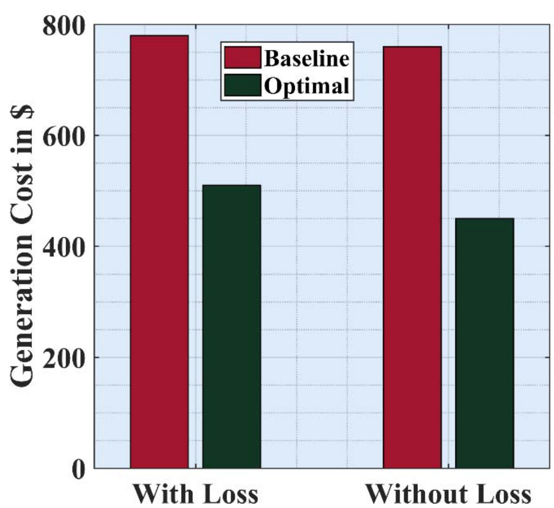

Fig. 7. Generation cost is less for a particular instance, whether system loss is considered or not.

V. CONCLUSION

Load scheduling plays an important role in reducing electricity generation cost, and in peak shaving. In this paper, optimal scheduling of electric loads of a substation for minimizing generation cost has been studied considering the system loss. An optimization problem has been formulated for optimal scheduling of loads by numerically analyzing the problem for various scenarios. It has been demonstrated that optimal load scheduling can reduce the generation cost significantly, and there is a significant impact of the system loss on the reduction of generation cost by optimal load scheduling. Future research related to this work can be the development of a simple heuristic solution of the optimization problem such that the problem can be solved by using a computer of low processing power. Future expansion on this work can include detailed studies on the computational power required to run the proposed system at a substation, and comparison of its computational load with existing methods.

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