Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2017) 25: 3725 – 3737
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doi:10.3906/elk-1606-152

Promoting peak shaving while minimizing electricity consumption payment for residential consumers by using storage devices

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Received: 10.06.2016 • **Accepted/Published Online:** 31.03.2017 • **Final Version:** 05.10.2017

Abstract: Nowadays, smart meters, sensors, and advanced electricity tariff mechanisms such as time-of-use (ToU), critical peak pricing tariff, and real time tariff enable electricity consumption optimization for residential consumers. The main scope of such mechanisms is to promote peak shaving, which leads to minimization of technical losses and avoidance (or delay) of grid onerous investments. This paper proposes a method to determine the optimum capacity of a storage device (SD) that significantly contributes to peak shaving of electricity consumption for residential consumers. Detailed modelling of diverse electric appliances' behavior and consumers' necessities is addressed in order to determine the optimum capacity of the SD. The effects of a small scale photovoltaic panel (PV) owned by residential consumers are also analyzed.

Key words: Consumption optimization, storage, peak shaving, time-of-use tariff, prosumer

1. Introduction

Enhancement of grid infrastructure is among the grid operator's investments necessary to supply demand increase, upgrade lines and substations, and integrate renewable energy sources (RES). According to the Ten Years Network Development Plan (TYNDP) developed by ENTSO-E countries, 150 billion Euros were proposed for CAPEX in 2014 just for grid expansion at European level (European Network of Transmission System Operators for Electricity. 10-Year Network Development Plan 2014). In Romania, over 1 billion Euros are necessary for transmission grid expansion according to the Transmission grid development plan for 2014–2023 elaborated by Transelectrica. Advanced electricity tariff mechanisms are aimed to contribute to peak shaving, as practically proven worldwide. The literature shows that an electricity consumer can save up to 50% of the electricity payment since the off-peak electricity tariff is one-third of the peak tariff [1].

This paper presents a method to determine the optimum capacity of a storage device (SD) that contributes to the peak shaving of a residential consumer. Therefore, the SD is proposed to be supplied by the grid operator for free, since the residential consumer is interested in a time-of-use (ToU) tariff mechanism that incentivizes minimization of his/her electricity bill. However, the ToU tariff will increase the demand peak of the consumer at certain hours when the tariff is low (e.g., after midnight). In response, charging and discharging cycles of the SD are proposed to be programmed by the grid operator (manually or remotely) in such way that the SD

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operates in order to shave the peak. The more the consumer pays attention to schedule his/her consumption at low tariff rates, the more both the consumer and grid operator benefit.

The literature includes many studies that address minimization of electricity bills and peak shaving mechanisms by means of SDs. In [2], the authors describe a simulator that optimizes electricity consumption of residential consumers that have controllable and uncontrollable devices, SDs, and generation sources. The objective function of the optimization process is to minimize payment by optimally connecting/disconnecting the controllable devices based on the electricity tariff. A drawback of this approach could be that most of the consumers might tend to response to the incentive, which would lead to new load peaks.

In [3], the authors apply stochastic optimization based on a scenario approach by Monte Carlo simulation for minimization of estimated payment for the entire day and mixed integer linear programing (MILP) algorithm for optimal management of electricity residential consumption taking into account real time tariffs. In [4], problems regarding the private sensible information related to electricity consumption that could appear while managing the recorded consumption by means of smart metering systems are addressed. The authors of [5] and [6] perform consumption optimization by using genetic algorithms. The optimization method is easy and presents a higher accuracy compared with traditional methods. In [7], the authors foresee major obstacles regarding the advanced tariff systems, such as consumers' lack of information related to the tariff variations and lack of automatic systems for consumption management. In response, the authors propose an optimal and automatic framework for planning residential electricity consumption by making a balance between minimizing the payment and minimizing the waiting time before the operation of each device. In [8], an optimization demand response through peak shaving is proposed. It uses an efficient linear programming formulation for prosumers' demand change. This approach is focused on peak minimization of electricity consumption based on fuel supply for self-generation. In [9], the author proposes a peak shaving energy management system that adapts the house appliances to the available power such as RES and SDs with the help of sensors by monitoring and controlling algorithms. In [10], the effects of energy management are analyzed from the residential consumer perspective. The authors proposed a prototype for a house with PV, lead–acid batteries, controllable appliances, and smart metering and showed the nonlinear relation between electricity flows and SDs' capacity.

Different from the literature, this paper proposes a model for electricity consumption optimization for residential consumers with different modern consumption appliances. The proposed model takes into account a dual approach that considers two objective functions: minimization of consumption peak and minimization of electricity payment. Based on the results of the two approaches, the optimum capacity of a SD, which can effectively improve the consumption optimization process, is determined. The paper is organized as follows. Problem definition is addressed in Section 2, along with the flowchart of the proposed methodology. Section 3 presents formulation of the optimization problem and its simulation results. Calculation of the optimum capacity of the SD, which might be provided by the grid operator for free to ensure peak shaving in order to avoid new peaks, is described in Section 4. The effects of PV on optimizing electricity consumption of residential consumers are addressed in Section 5. Conclusions drawn from this paper are presented in Section 6.

2. Problem definition

The grid operators and residential consumers have different motivations. While the grid operators would like to reduce the consumption peak in order to benefit from reduction in technical losses and from grid investment avoidance or delay, the consumers can be motivated to schedule their appliances as long as they benefit from the ToU tariff rates and obtain some savings. The idea introduced in this paper is to use SDs that are installed at the consumers' premises in order to satisfy both the grid operator and consumers. A flowchart of this methodology is illustrated in Figure 1. The methodology is based on solutions of two different optimization problems: 1) minimization of consumption peak; and 2) minimization of electricity payment. From the grid operator perspective, as far as the peak consumption is minimized, technical losses will decrease as a consequence of their dependence on the loading of the grid. This paper is focused on the concept of utilizing SDs as a planning and operation tool for mutual benefits of consumers and the grid operator. However, its feasibility depends on the cost–benefit analysis performed by the grid operator.

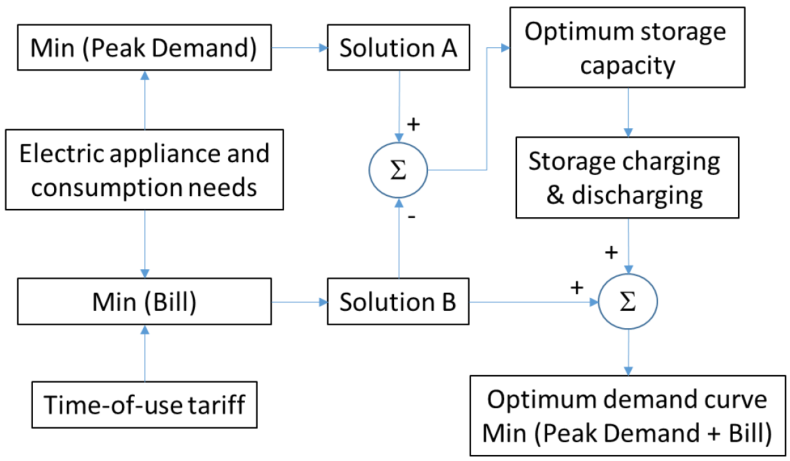

Figure 1. Flowchart of the methodology.

3. Formulation of the optimization problem

The electricity consumption optimization problem is a MILP problem defined by an objective function, variables, bounds, and linear equality and inequality constraints. MILP is a particular form of the more relaxed linear programming (LP) algorithm, by tightening the LP relaxation since some of the variables (x) must be integers.

3.1. Identification of variables

Variables of the electricity consumption optimization problem mainly are related to the hourly consumption of each appliance. The number of variables (n) for hourly consumption is given by the number of appliances (Na) multiplied by daily 24 time intervals. That means $24 \times Na$ variables, plus $24 \times Npu$ variables for the hourly on/off status of uninterruptable programmable appliances (Npu) that cannot be interrupted during their operation and can operate at any time or at certain time intervals with certain consumption. Such appliances include washing machines and heaters. In the case of peak minimization, one more variable is added to represent the consumption peak. Therefore, the total number of variables is $n = 24 \times (Na + Npu) + 1$ and x is an array with Na+Npu rows and 24 columns (1):

$$x = \left[x_1, \ldots, x_i, \ldots, x_j, \ldots, x_{Na+Npu}\right]^T \tag{1}$$

where

x_i=$[x_{i1}, \ldots, x_{ih}, \ldots, x_{i24}]$: Hourly consumption of the appliance i along a day, $\forall$ i$\in$ Na;

$x_j = [x_{j1}, \ldots, x_{jh}, \ldots, x_{j24}]$: Status on/off of uninterruptable programmable appliances, $\forall j \in Npu$;

i: Appliance index (i= 1, …, Na);

j: Status (on/off) index (j= 1, ..., Npu);
h: Hour index along a day (h= 1, ..., 24).

3.2. Objective functions

Hourly electricity consumption (C_h) represents the sum of all appliances' consumption at a certain hour h (2):

$$C_h = \sum_{i=1}^{N_a} x_{ih} \quad \forall h, \tag{2}$$

C_h : Consumption of all appliances at hour h;
N_a: Total number of appliances.

Therefore, the first objective function in the case of electricity consumption peak shaving is to minimize $C_{\max}$ representing the daily consumption peak that is greater or equal to C_h (3). As for the payment minimization case, the daily payment for electricity consumption (P) is formulated by (4). The second objective function is to minimize P.

$$C_h \leq C_{\max} \quad \forall h, \tag{3}$$

$$P = \sum_{h=1}^{24} C_h \times t_h \tag{4}$$

$C_{\max}$: Daily consumption peak;
t_h: ToU tariff vector;
P: Daily payment for electricity consumption.

3.3. Formulating bounds

Bounds are the lower and upper limit constraints for hourly consumption of each appliance. For all Na appliances the lower bounds (lb_i) can be 0, except those appliances that have to operate at some minimum consumption limit, $C_{i\min}$ (5). The upper bound (ub_i) is equal to $C_{i\max}$, which represents the maximum consumption for appliance i (6). Lower and upper bounds of the uninterruptable programmable appliances are 0 and 1 (7).

$$lb_i = \{0, C_{i\min}\}, \ \forall i \in Na \tag{5}$$

$$ub_i = C_{i\max}, \ \forall i \in Na \tag{6}$$

$$lb_j = 0 \text{ and } ub_j = 1, \quad \forall j \in Npu \tag{7}$$

lb_i : Lower bound for appliance i;
ub_i : Upper bound for appliance i;
$C_{i\min}$: Minimum consumption limit of appliance i;
$C_{i\max}$: Maximum consumption limit of appliance i;
lb_j : Lower bound for status of uninterruptable programmable appliances j;
ub_j : Upper bound for status of uninterruptable programmable appliances j.

3.4. Inequality and equality constraints

While some appliances are flexible and can operate at any time, others have no operation flexibility, and so they should operate at certain time intervals with certain consumption. This constraint is formulated by transforming (2) and (3) into (8) for all appliances (Na).

$$\sum_{i=1}^{N_a} x_{ih} - C_{\max} \leq 0, \quad \forall h, \tag{8}$$

Uninterruptable programmable appliances (Npu) can operate at any hour with certain consumption and it cannot be split over several hours. For instance, the dishwasher main program needs just one hour to clean the dishes, while the washing machine needs one hour of operation for cleaning and another consecutive hour for rinsing and drying. Start-up (on) and shut-down (off) of those appliances are represented by $\in x_j \, Npu$ with 1 (on) or 0 (off) values as stated in (9). Constraints for the uninterruptable programmable appliances are represented by (10) and total consumption of each appliance along a day (Ct_i) is represented by (11) for each appliance.

$$\in x_{jh} \, Npu = \{0,\, 1\}\,, \quad \forall h \tag{9}$$

$$\in\in \frac{x_{ih}}{Ct_i} - x_{jh} \leq 0, \quad \forall i \, Na, \, \forall j \, Npu, \, \forall h \tag{10}$$

$$\in \sum_{h=1}^{24} x_{ih} = Ct_i, \quad \forall i \, Na \tag{11}$$

Ct_i : Total consumption of appliance i over a day.

3.5. Classification of electricity appliances

The appliances are categorized based on their interaction with electricity consumers as follows: background, active, and passive appliances [11]. From the consumers' necessities point of view, the appliances can also be divided into two main categories: programmable and nonprogrammable. Some appliances such as the refrigerator, heating, and lighting cannot be programed because their operation shift will cause discomfort to consumers. Other appliances such as the washing machine could be programmed to operate at different time intervals without causing any discomfort. Based on their intrinsic characteristics, some programmable appliances are interruptible (e.g., water heater) and others not (e.g., washing machine). The appliances considered in this paper are summarized in Table 1.

Hourly operation of the appliances over a day is defined based on certain operating constraints. For instance, the electric oven is an active appliance that must be on at 2000 hours and its hourly consumption is 1 kWh. Therefore, its total daily consumption is 1 kWh. It is obvious that the electric oven operates at fixed time intervals (often just before dinner time); thus it is nonprogrammable and noninterruptible.

3.6. Optimization results

For the minimization of electricity consumption payment, we considered a ToU tariff that incentivizes consumption at night (between 2100 and 0459) by 50% discount from the daily electricity tariff (0500–2059). The

Table 1. Characteristics of the electric appliances.

No.	Appliance	Programmable	Interruptible	Background	Active	Passive
1	Oven	-	-	-	x	-
2	Heating	-	-	-	-	x
3	Refrigerator	-	-	x	-	-
4	Water heater	x	x	-	-	x
5	Car battery	x	x	-	-	x
6	TV, audio, aux.	-	-	-	x	-
7	Washing machine	x	-	-	-	x
8	Dish washer	x	-	-	-	x
9	Electric hob	-	-	-	x	-
10	Lighting	-	-	-	x	-
11	Vacuum cleaner	x	-	-	x	-
12	Bread oven	x	-	-	-	x

reference daily load curve depicted in Figure 2 is considered in numeric analysis. It belongs to an urban residential consumer during a winter weekday in Romania where peak consumption occurs due to heating loads. The data were measured with smart meters as described in [12]. Peak of the reference consumption is assumed to be 2.27 kWh as illustrated in Figure 2. Hourly consumption of the appliances is depicted in Figure 3. The total cost of electricity is 3.5 monetary units (m.u.).

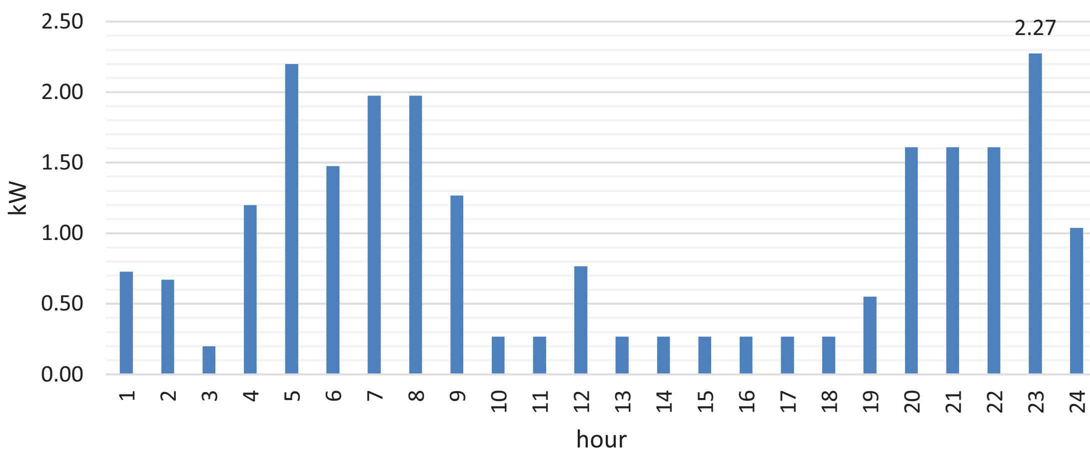

Figure 2. Reference daily consumption.

3.7. Grid operator perspective: minimization of consumption peak

Hourly electricity consumption of the appliances is plotted in Figure 4 for the peak shaving case (i.e. the objective function is minimization of consumption peak). According to the results, the peak consumption is 1.56 kWh and the electricity payment is 3.47 m.u. per day. Essentially, the consumption peak decreased from 2.27 kWh (reference case) to 1.56 kWh (peak shaving case).

3.8. Residential consumer perspective: minimization of electricity payment

Hourly consumption of the appliances is plotted in Figure 5 for the minimization of electricity payment. It is obvious that all programmable appliances operate when the electricity is cheaper. According to the results, the

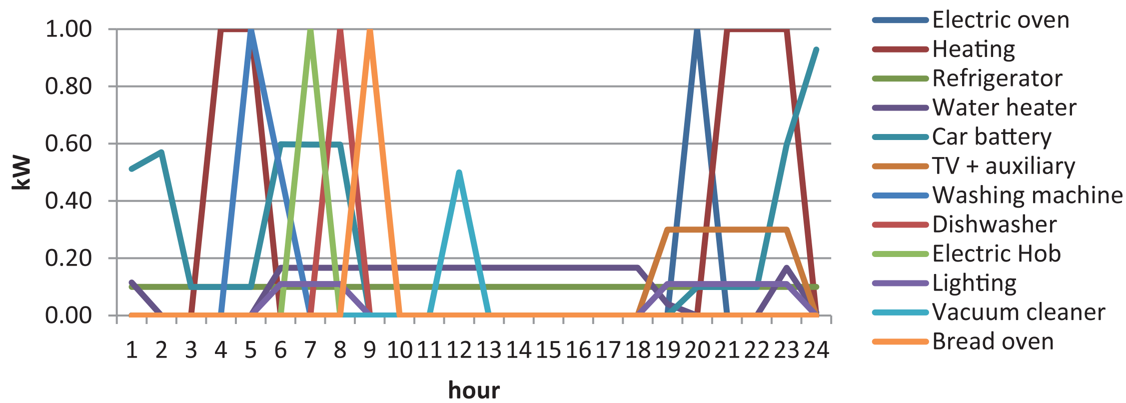

Figure 3. Hourly consumption of the appliances (reference).

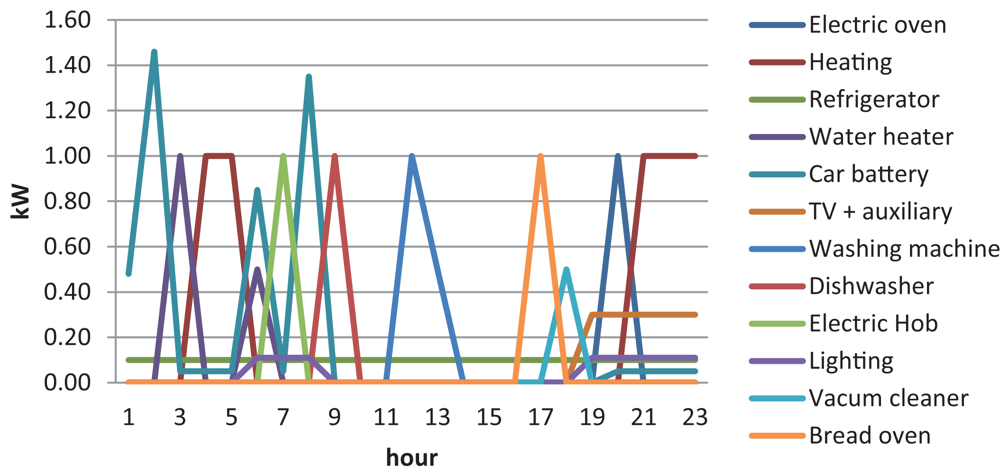

Figure 4. Daily operation curves of the appliances - peak shaving.

consumption peak is 3.00 kWh and the electricity payment is 2.86 m.u. per day. The peak is almost doubled compared to the peak shaving results. Hourly consumption profiles of a residential consumer for both scenarios (i.e. payment and peak minimization) are summarized in Table 2 and compared in Figure 6.

Table 2. Comparison of the results.

Scenarios	Peak [kWh]	Peak difference [%]	Payment [m.u.]	Payment difference [%]
Reference (no optimization)	2.27	-	3.50	-
Peak minimization	1.56	–31%	3.47	–1%
Payment minimization	3.00	32%	2.86	–18%

3.9. Calculation of the SD optimum capacity

Formulation of the problem for determining SD optimum capacity intended to be used at the residential consumer connection point in order to contribute to the peak shaving while minimizing electricity bills is illustrated in (12)–(15).

$$Min \sum_{h=1}^{24} \left[t_h \times (SV_{PS}(h) - SV_{PM}(h) + SOSD_d(h))\right]^2 \quad (12)$$

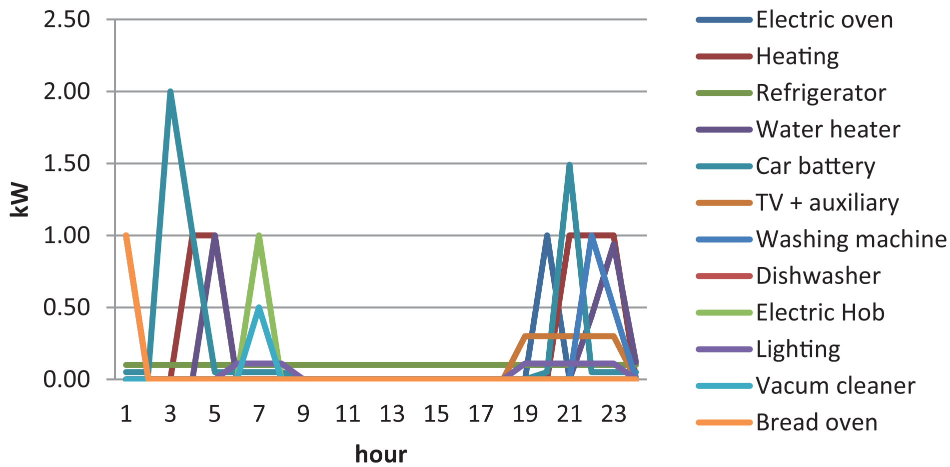

Figure 5. Daily operation curves of the appliances - electricity payment minimization.

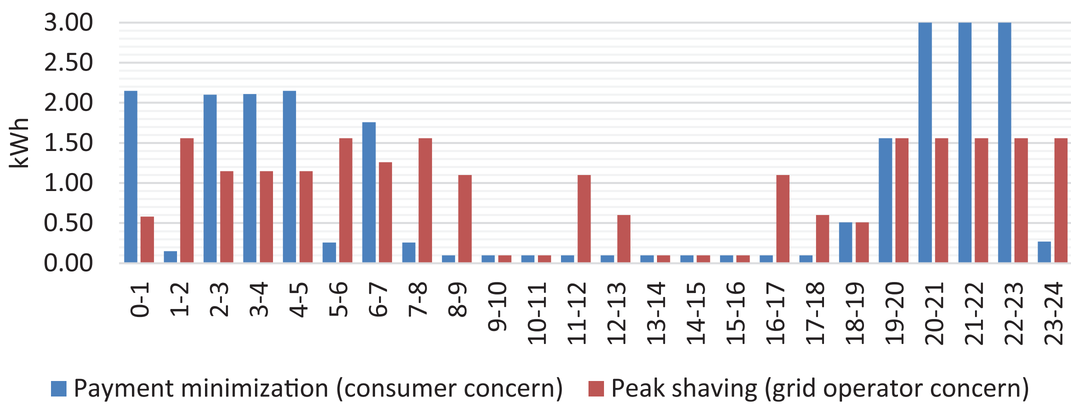

Figure 6. Payment minimization vs. peak minimization.

$$SOSD_{(d-1)}(h) = SOSD_{(d)}(h) \tag{13}$$

$$0 \leq SOSD_{(d)}\,(h) \leq SDC \tag{14}$$

$$SDDC \leq SOSD_{(d)}\,(h) \leq SDCC \tag{15}$$

t_h : Electricity tariff vector (1 $\times$ 24) for each hour h of the day (m.u./kWh);
$SV_{PS}\,(h)$: Solution vector (1 $\times$ 24) of peak shaving optimization problem (kWh);
$SV_{PM}\,(h)$: Solution vector (1 $\times$ 24) of payment minimization (kWh);
$SOSD_d(h)$: Status of SD vector (1 $\times$ 24) for day d (kWh);
$SOSD_{(d-1)}(h)$: Status of SD vector (1 $\times$ 24) for day $d-1$ (kWh);
SDC : SD capacity (kWh);
$SDCC$: SD charging capacity (kW per hour);
$SDDC$: SD discharging capacity (kW per hour).

The objective function (12) is to minimize the hourly consumption differences between the peak shaving and minimum payment solutions. $SOSD_d(h)$ is a slack variable vector that corresponds to charging/discharging status of the SD and should be the same at the end of each day as formulated by (13). Charging/discharging status of the SD is limited by its capacity (14) and satisfies the hourly charging/discharging capacity of the device (15).

The approach in formulating the SD optimum capacity is based on the assumption that the intention of the residential consumer is to minimize his/her electricity payment. That is, the more the residential consumer minimizes his/her electricity bill via shifting his/her consumption, the more benefit he/she gets from the SD. This can be practically satisfied by either scheduling or controlling the charging/discharging periods of the SD through a local or remote controller. In both cases, the objective function of the grid operator is to minimize the consumption peak in order to take advantage of both decreasing technical losses and delaying grid investments.

The hourly consumption profile of the electricity consumer, in the case of a 5 kWh total capacity of a SD with 2.5 kW per hour charging capacity, is presented in Figure 7.

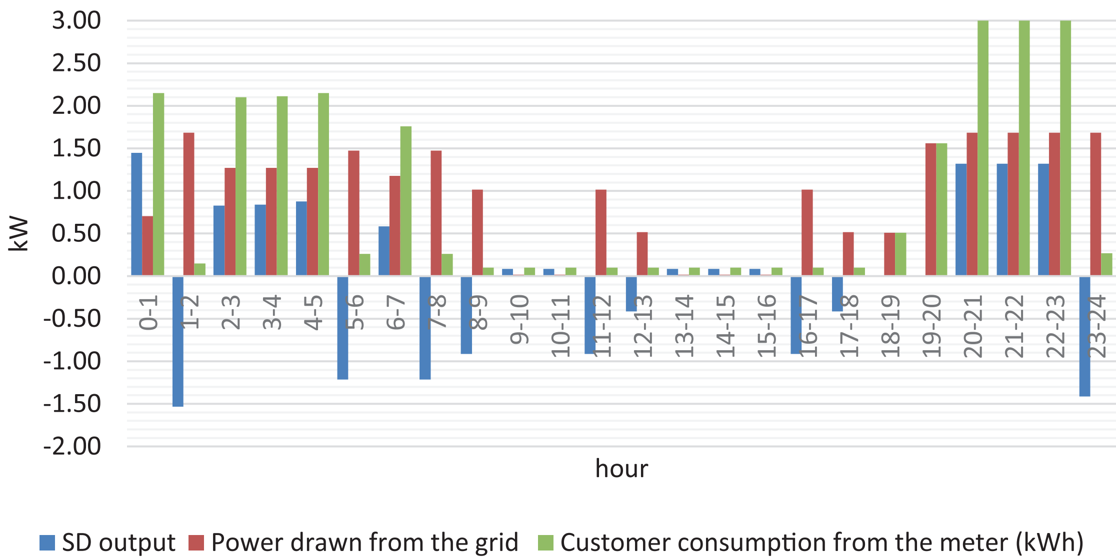

Figure 7. SD effect (positive/negative means SD is discharging/charging).

Peak power drawn from the grid (i.e. behind the SD) depends on the SD capacity as depicted in Figure 8, which illustrates that the SDs beyond 6 kWh capacity and 3 kW per hour charging/discharging capacity do not provide additional benefit. It is obvious from Figure 8 that power drawn from the grid saturates beyond 6 kWh capacity (vertical axis on the left-hand side). Such saturation is noticed beyond 3 kW per hour charging capacity (horizontal axis). In conclusion, for a typical urban residential consumer considered in this paper, the maximum capacity of the SD to be supplied by the grid operator for peak shaving purposes is limited to 6 kWh and 3 kW per hour charging/discharging for mutual benefit.

According to the results, if the consumer tries to minimize the electricity payment by shifting his/her appliances based on the ToU tariff mechanism, the SD ensures the peak shaving from the grid operator perspective. However, total consumption of the residential consumer with or without SD does not change. That is, the consumer does not get additional benefit from the SD except for savings from load shifting. Nonetheless, in the case no SD is in operation, the consumer should be aware that new peaks may occur due to the natural

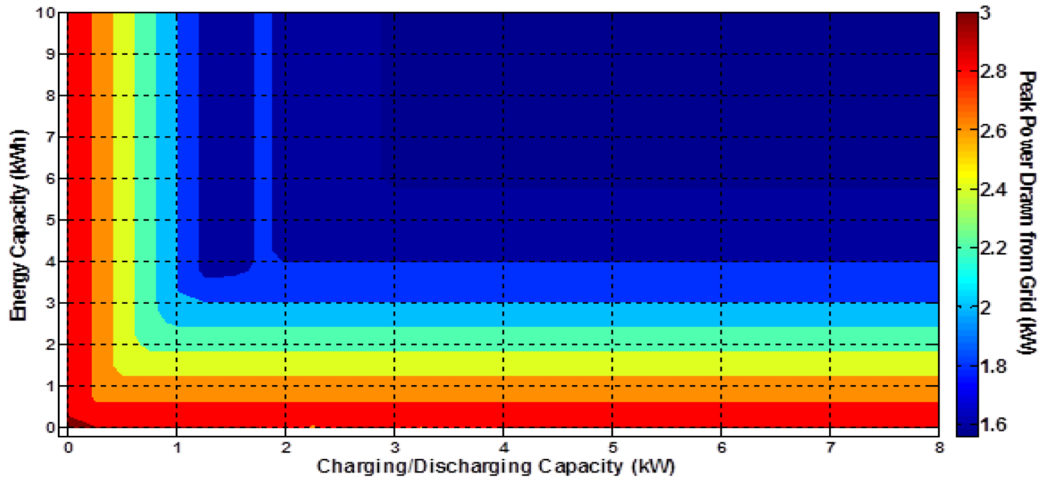

Figure 8. Peak power drawn from the grid for different SD capacities.

behavior of consumers that tend to consume at lower tariff rates. As a consequence of higher consumption, the grid operator may increase the electricity tariff due to additional investment in grid capacity. Therefore, based on the concept introduced in this paper, the SDs that could be optimized in terms of capacity might be provided by the grid operator free of charge.

The grid operator's objective function is not only to minimize the peak consumption in order to take advantage of decreasing technical losses on the grid, but also to delay grid investments. New grid capacity investments are planned considering the increase in peak consumption [13]. Therefore, the feasibility of the SD is based on economic analysis that considers savings from both technical losses and avoidance of grid capacity investments. Savings from technical losses are up to 45% at peak demand hour as illustrated in Table 3. Savings from deferring grid enforcement investments are generally higher than savings from losses [14].

Table 3. Calculation of savings from losses at peak demand hour.

	Reference	With SD
Peak power drawn from the grid	2.27 kWh	1.68 kWh
Peak power (Ip) drawn from the grid at 220 V	7.65 A	10.34 A
Loss at peak demand hour ($Ip^2 \times R_{grid}$) (R_{grid}: Equivalent resistance of the grid backward from the consumer meter)	58.47 $\times R_{grid}$	106.83 $\times R_{grid}$
Saving from loss at peak hour $\left(\frac{106.83 \times R_{grid} - 58.47 \times R_{grid}}{58.47 \times R_{grid}}\right) \times 100\%$	45%	-

3.10. Effects of photovoltaic panel on residential consumption optimization

Electricity consumers, well known as prosumers, have their own electricity sources such as PV, diesel generators, and small size wind turbines that can partially or totally cover their electricity consumption [15]. Therefore, the effects of PV on consumption are investigated in this section. It is assumed that the PV capacity of 0.2 kW is reasonable for a residential prosumer. The daily cumulative consumption curve with PV is presented in Figure 9 along with other scenarios such as: i) no SD and no PV; ii) PV only; iii) SD only; iv) SD and PV. The power generated by the PV during the daytimes, when the consumption is minimum, is injected into the grid as illustrated in Figure 9. Peak consumption occurs at night (i.e. when the PV does not generate) given the low tariff. Therefore, peak consumption is not flattened by the PV. However, the electricity payment decreased from 2.86 m.u. to 2.40 m.u., due to generation of the PV during the daytime. The results are compared in Table 4.

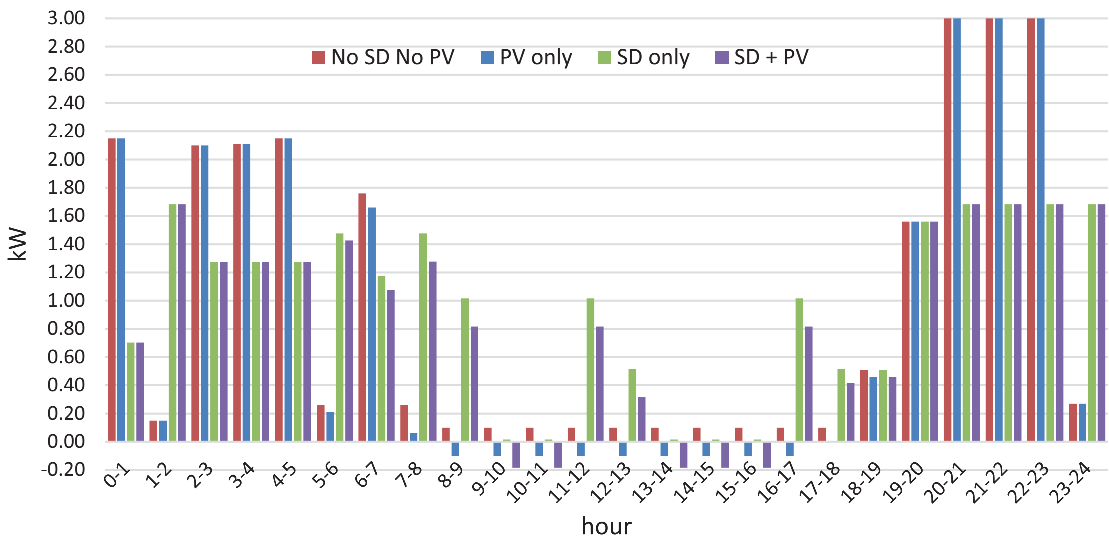

Figure 9. Cumulative consumption from the grid.

Table 4. Comparison of the results.

Scenario	Peak power drawn from the grid [kWh]	Payment [m.u.]
No SD and No PV	3.00	2.86
PV only	3.00	2.40
SD only	1.68	2.86
SD and PV	1.68	2.40

4. Conclusion

This paper proposes a method to determine the optimum capacity of a SD that significantly contributes to peak shaving of electricity consumption for residential consumers. The optimum capacity of the SD is based on the solution of two minimization problems: i) payment minimization and ii) consumption peak minimization. In order to minimize their bills, the consumers shift at night their consumption to the low tariff rates although the PV does not generate. In the case no SD is used, ToU tariff will bring new peaks that would increase the electricity tariff due to necessary investments in order to deal with the new peaks. In the case we consider the SD, we noticed that its capacity does not depend on the operation of the PV, but rather programmable appliances. According to the results, the best scenario is to use the SD to effectively contribute to peak shaving and PV to reduce the electricity payment.

Therefore, the results show that grid operators may consider SDs as an argument in promoting peak shaving of electricity consumption to minimize losses and delay grid onerous investments. The proposed approach related to acquisition of the SDs is based on several assumptions: i) acquiring SDs by the grid operator will offer proper incentives to the consumers to accept this solution; ii) the grid operator might benefit from the economy of scale by acquiring many more SDs; iii) investment cost of SDs is decreasing gradually; iv) the grid operator easily controls the SDs with similar features. Charging and discharging cycles of the SD are proposed to be programmed by the grid operator (manually or remotely) in such way that the SD charges and discharges will flatten the peak. Nevertheless, the grid operator should perform a detailed feasibility study that compares the investment and operational costs of the SDs with the benefits in terms of peak and loss reduction in the distribution grid. Therefore, the proposed method for calculating the SD optimum capacity is relevant taking into account the limit for additional benefits and the direct relation between cost and capacity.

The daily load curve of an urban residence during a typical winter weekday in Romania is considered as a reference. Given the fact that peak demand occurs in winter in Romania, it is assumed that the results span the whole year. However, the day selection over a year might slightly influence the results. Investigation of this influence could be a future study that may also include the regulatory issues regarding implementation of such a mechanism and the control of SDs in the context of smart grid applications.

Acknowledgment

This work was supported by a grant from the Romanian National Authority for Scientific Research and Innovation, CNCS/CCCDI – UEFISCDI, project number PN-III-P2-2.1-BG-2016-0286 "Informatics solutions for electricity consumption analysis and optimization in smart grids" and contract no. 77BG/2016, within PNCDI III.

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