IEEE Access
Multidisciplinary ⁝ Rapid Review ⁝ Open Access Journal

Received 1 October 2023, accepted 11 December 2023, date of publication 11 January 2024, date of current version 2 February 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3353136

RESEARCH ARTICLE

Aggregator Index for 24-Hour Energy Flexibility Evaluation in an ADN Including PHEVs

ALIREZA RASHTBARYAN[1], (Student Member, IEEE), GEVORK B. GHAREHPETIAN[1], (Senior Member, IEEE), HAMID REZA BAGHAEE[2], (Member, IEEE), AND ROYA AHMADIAHANGAR[3], (Senior Member, IEEE)

[1]Department of Electrical Engineering, Amirkabir University of Technology (AUT), Tehran 15914, Iran
[2]Faculty of Electrical and Computer Engineering, Tarbiat Modares University, Tehran, Iran
[3]Department of Electrical Power Engineering and Mechatronics, Tallinn University of Technology, 19086 Tallinn, Estonia

Corresponding author: Roya Ahmadiahangar (roya.ahmadi@taltech.ee)

This work was supported by the Estonian Research Council under Grant PSG739.

ABSTRACT This paper proposes obtaining maximum and minimum daily cumulative energy curves and introduces novel hourly and daily energy flexibility indices. Also, it develops a generic methodology that quantifies and formulates energy flexibility as the possible power increase (P_in) or decrease (P_dec) within operational limits. The proposed method can be applied to derive maximum and minimum energy flexibility curves for different devices and aggregate them to extract hourly or daily energy flexibility indices based on the calculation area between daily cumulative energy curves in an hour and 24 hours. The proposed energy flexibility estimation is evaluated by doing offline digital time-domain simulations on a 100-bus home-residential active distribution network (ADN), including flexible equipment/devices (e.g., washing machines, dishwashers, domestic heat water, battery, photovoltaic (PV) panels, and plug-in hybrid electric vehicle (PHEV) charging stations) in MATLAB/Simulink software environment. Then, a price-sensitive model of every flexible equipment is introduced, and ultimately, the effect of electricity price changes on energy flexibility is evaluated. The simulations and comparisons of the energy flexibility potential of different pricing scenarios effectively prove the proposed strategy's effectiveness, accuracy, and authenticity.

INDEX TERMS Daily cumulative energy curves, energy flexibility, energy flexibility indices, plug-in hybrid electric vehicle, price-sensitive model of flexible equipment.

NOMENCLATURE

$\boldsymbol{E_c.max}$:	Daily aggregated maximum cumulative energy curve.
$\boldsymbol{E_c.nor}$:	Daily aggregated normal state cumulative energy curve.
$\boldsymbol{E_c.min}$:	Daily aggregated minimum cumulative energy curve.
$\boldsymbol{P_{inc_{[t_1.t_2]}}}$:	Power-increasing flexibility in $[t_1.t_2]$.
$\boldsymbol{P_{dec_{[t_1.t_2]}}}$:	Power-decreasing flexibility in $[t_1.t_2]$.
$\boldsymbol{m_{max.t_1}}$:	The slop of maximum cumulative energy curve in $[t_1, t_1+1]$.
$\boldsymbol{m_{nor.t_1}}$:	The slop of normal state cumulative energy curve in $[t_1, t_1+1]$.
$\boldsymbol{m_{min.t_1}}$:	The slop of minimum cumulative energy curve in $[t_1, t_1+1]$.
$\overline{(A_1, .., A_n)}$:	Average of $(\boldsymbol{A_1}.\ldots.\boldsymbol{A_n})$.
$\boldsymbol{f_{inc_{t_1}}}$:	Hourly energy flexibility index, $t_1 = 1.2.\ldots.24$.
$\boldsymbol{f_{inc_{t_1}}}$:	Hourly energy flexibility index, $t_1 = 1.2.\ldots.24$.
$\boldsymbol{F_{inc}}$:	24-hour energy flexibility index.
F_{dec} :	24-hour energy flexibility index.
FHs :	Flexibility hours provided by home appliances.
N :	Number of households that participate in a flexibility program.

The associate editor coordinating the review of this manuscript and approving it for publication was Maria Carmen Falvo.

$P_G(t, i)$:	Generation power of household i at time step t.
$P_C(t, i)$:	Consumption power of household i at time step t.
$P_{EX}(t, i)$:	Exchanged power between household i at time step t.
Pr_t :	Day-ahead price at time step t.
Pr_{av} :	The average price of the day-ahead price profile.
$SOC(t, i)$:	Battery's state of charge of household i at time step t.
SOC_{min} :	Permissible minimum state of charge.
SOC_{min} :	Permissible maximum state of charge.
P_{ch} :	Maximum power charging.
P_{disch} :	Minimum power charging.
N_{BESS} :	Total number of battery energy storage systems.

I. INTRODUCTION

A. MOTIVATION AND INCITEMENT

Flexibility has become a vital issue today for the reliability and security of the electrical energy supply. Power system flexibility is the ability of a power system to reliably and cost-effectively manage the variability and uncertainty of demand and supply across all relevant timescales. There is a growing necessity for flexibility for the following reasons:

- Increasing the share of renewable energy resources in the energy supply basket,
- Dispersion and intermittent attributes of renewable energy resources,
- Decentralized growth of energy storage systems,
- Electrical load demand increment in the transportation and heating sector because of fossil-fueled systems replacement politics with highly efficient electrical equipment like PHEVs and electrical heat waters [1], and,
- Decrement of the number of traditional controllable power plants.
- Flexibility estimation is essential for planning and managing power systems. Generally, flexibility requirements are considered holistically, both from the overall system perspective and from the more local perspectives [2]:
- From an overall system perspective, flexibility requirements are related to maintaining a stable frequency and secure energy supply.
- From a more local perspective, flexibility requirements are related to maintaining bus voltages and securing transfer capacities.

The temporary and intermittent nature of renewable energy leads to increased utilization of advanced control systems to enable the flexibility potential of the demand side by a suitable integration system [3]. Households have a vital role in energy flexibility programs on the demand side, as the home sector accounts for approximately 40% of global energy consumption [4]. Also, more than 70% of total electricity in the United States and 90% in Hong Kong is consumed by the building sector [5], [6]. Application of distributed energy resources (DER) technologies such as solar photovoltaic (PV), combined heat and power, electric vehicles (EVs), and energy storage have enabled active building loads by reducing demand and satisfying energy, capacity, and ancillary services requirements [7], [8], [9].

B. LITERATURE REVIEW

In [10], the effect of converting power to heat has been examined, various power-to-heat options have been categorized, and the authors have introduced an analytical model formulation of heat pumps and heat water storage as energy flexibility options. PHEVs can provide energy flexibility by controlling the charging process according to motivations and even act as a distributed storage system on the demand side for supplying required energy in emergencies [11].

In [12], the flexibility potential of the residential appliance has been estimated according to survey data, but it has not explained how the user behavior is modeled. In [13], the flexibility potential of residential households has been estimated according to a fixed percentage of their consumption. However, it has not mentioned how these percentages can be obtained. In [14], the flexibility estimation has been performed in detail, but this study's survey data are related to non-flexible appliances. In [15], [16], and [17], the flexibility potential of residential appliances has been estimated according to extrapolated consumption data of smart appliances. Besides, [18] has estimated the flexibility potential of households based on data from only one household with flexible appliances. In [19], the electric load shapes and demand response behavior has been characterized, and the modeling methods have been applied to evaluate demand response effectiveness. The definition of energy flexibility can be found in numerous studies and reviews [20], [21], [22]. The common view of these definitions is the ability of the grid to manage predictable or unpredictable changes. However, a more general and industrially-applicable definition is "*Power system flexibility is the ability of a power system to reliably and cost-effectively manage the variability and uncertainty of demand and supply across all relevant timescales*."

C. LITERATURE REVIEW

This paper presents a method based on the area between daily cumulative energy curves. By exploiting these curves, the value of energy flexibility potential is estimated. The main contributions of this paper are as follows:

- Formulating the energy flexibility based on maximum, minimum, and normal daily cumulative energy curves,
- Defining energy flexibility hourly and 24-hours indices,
- Comparing the energy flexibility potential between different energy management scenarios,
- Introducing the price-sensitive models of various home appliances, and

- Assessment of the effect of price changes in three-step daily price profiles on energy flexibility.

II. ENERGY FLEXIBILITY ESTIMATION METHOD

Household maximum and minimum daily cumulative energy consumption curves are determined by flexible appliances and energy generation and storage systems such as washing machines, dishwashers, domestic heat water (DHW), batteries, and solar panels. The distribution grid aggregators aggregate daily averages of cumulative household energy consumption in a specific area. The total maximum and minimum cumulative energy curves determine power-increasing and power-decreasing flexibility over a certain period.

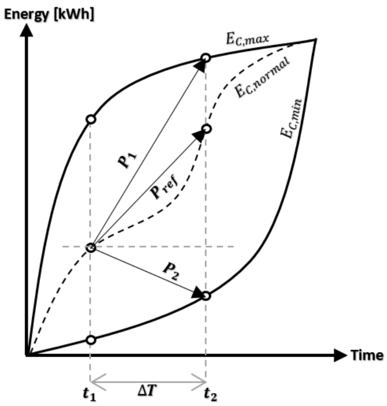


FIGURE 1. Daily aggregated cumulative energy curves.

In this paper, energy flexibility is defined as the ability to increase or decrease the consumption power of a particular area in a given period, referred to as power-increasing flexibility and power-decreasing flexibility, respectively. (see Fig. 1) [20].

$$\begin{aligned}
P_{inc}[t_1,t_2] &= P_1 - P_{ref}\\
&= \left\{\left(\frac{E_{c,max}(t_2)-E_{c,normal}(t_1)}{t_2-t_1}\right)\right.\\
&\quad \left.-\left(\frac{E_{c,normal}(t_2)-E_{c,normal}(t_1)}{t_2-t_1}\right)\right\}\\
&= \left(\frac{E_{c,max}(t_2)-E_{c,normal}(t_2)}{\Delta T}\right)\\
P_{dec}[t_1,t_2] &= P_2 - P_{ref}\\
&= \left\{\left(\frac{E_{c,min}(t_2)-E_{c,normal}(t_1)}{t_2-t_1}\right)\right.\\
&\quad \left.-\left(\frac{E_{c,normal}(t_2)-E_{c,normal}(t_1)}{t_2-t_1}\right)\right\}\\
&= \left(\frac{E_{c,min}(t_2)-E_{c,normal}(t_2)}{\Delta T}\right) \qquad (1)
\end{aligned}$$

III. ENERGY FLEXIBILITY INDICES

In this paper, hourly and 24-hours indices compare numerous more flexible scenarios. As shown in Fig. 2, to calculate the hourly maximum/minimum energy flexibility index, the

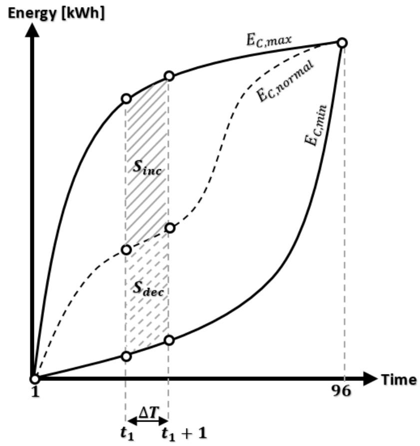


FIGURE 2. The area between aggregated cumulative energy curves.

area between the maximum/minimum aggregated cumulative energy curve and the normal aggregated cumulative energy curve every hour is calculated. It is divided into the total area between the maximum aggregated cumulative energy curve and the minimum aggregated cumulative energy curve every hour (sampling rate of cumulative energy curves: 4 samples per hour).

$$\begin{aligned}
m_{max,t_1} &= \frac{E_{c,max}(t_1+1)-E_{c,max}(t_1)}{(t_1+1)-(t_1)}\\
&= E_{c,max}(t_1+1)-E_{c,max}(t_1)\\
m_{nor,t_1} &= \frac{E_{c,nor}(t_1+1)-E_{c,nor}(t_1)}{(t_1+1)-(t_1)}\\
&= E_{c,nor}(t_1+1)-E_{c,nor}(t_1)\\
m_{min,t_1} &= \frac{E_{c,min}(t_1+1)-E_{c,min}(t_1)}{(t_1+1)-(t_1)}\\
&= E_{c,min}(t_1+1)-E_{c,min}(t_1) \qquad (2)
\end{aligned}$$

$$\begin{aligned}
E_{c,max}(t)-E_{c,max}(t_1) &= m_{max,t_1}\times(t-t_1)\\
E_{c,max}(t) &= \left(m_{max,t_1}\right)\times t\\
&\quad + \left[E_{c,max}(t_1)-\left(m_{max,t_1}\times t_1\right)\right]\\
E_{c,max}(t) &= [A(t_1)\times t]+B(t_1)\\
E_{c,nor}(t)-E_{c,nor}(t_1) &= m_{nor,t_1}\times(t-t_1)\\
E_{c,nor}(t) &= \left(m_{nor,t_1}\right)\times t\\
&\quad + \left[E_{c,nor}(t_1)-\left(m_{nor,t_1}\times t_1\right)\right]\\
E_{c,nor}(t) &= [C(t_1)\times t]+D(t_1)\\
E_{c,min}(t)-E_{c,min}(t_1) &= m_{min,t_1}\times(t-t_1)\\
E_{c,min}(t) &= \left(m_{min,t_1}\right)\times t\\
&\quad + \left[E_{c,min}(t_1)-\left(m_{min,t_1}\times t_1\right)\right]\\
E_{c,min}(t) &= [E(t_1)\times t]+F(t_1) \qquad (3)
\end{aligned}$$

$$\begin{aligned}
S_{inc,t_1} &= \sum_{i=(4\times t_1-3)}^{(4\times t_1-1)} \int_i^{i+1}\int_{E_{c,nor}(t)}^{E_{c,max}(t)} dE\times dt\\
&= \sum_{i=(4\times t_1-3)}^{(4\times t_1-1)} \frac{(A(t_1)-C(t_1))}{2}
\end{aligned}$$

$$\times [2i+1] + (\mathrm{B}(t_1) - \mathrm{D}(t_1))$$

$$\mathrm{S}_{\mathrm{dec},t_1} = \sum_{i=(4\times t_1-3)}^{(4\times t_1-1)} \int_{i}^{i+1} \int_{\mathrm{E}_{c,\min}(t)}^{\mathrm{E}_{c,\mathrm{nor}}(t)} \mathrm{dE}\cdot \mathrm{dt}$$
$$= \sum_{i=(4\times t_1-3)}^{(4\times t_1-1)} \frac{(\mathrm{C}(t_1) - \mathrm{E}(t_1))}{2} \times [2i+1] + (\mathrm{D}(t_1) - \mathrm{D}(t_1)) \quad (4)$$

$$\mathrm{f}_{\mathrm{inc},t_1} = \frac{\mathrm{S}_{\mathrm{inc},t_1}}{\mathrm{S}_{\mathrm{total},t_1}} = \frac{\mathrm{S}_{\mathrm{inc},t_1}}{\mathrm{S}_{\mathrm{inc},t_1} + \mathrm{S}_{\mathrm{dec},t_1}} \quad \left(0 \leq \mathrm{f}_{\mathrm{inc},t_1} \leq 1\right)$$
$$\mathrm{f}_{\mathrm{dec},t_1} = \frac{\mathrm{S}_{\mathrm{dec},t_1}}{\mathrm{S}_{\mathrm{total},t_1}} = \frac{\mathrm{S}_{\mathrm{dec},t_1}}{\mathrm{S}_{\mathrm{inc},t_1} + \mathrm{S}_{\mathrm{dec},t_1}} \quad \left(0 \leq \mathrm{f}_{\mathrm{dec},t_1} \leq 1\right) \quad (5)$$

$$\mathrm{F}_{\mathrm{inc}} = \frac{\sum_{t_1=1}^{24} \mathrm{f}_{\mathrm{inc},t_1}}{24} = \left(\mathrm{f}_{\mathrm{inc},1}, \mathrm{f}_{\mathrm{inc},2}, \ldots, \mathrm{f}_{\mathrm{inc},24}\right)$$
$$\mathrm{F}_{\mathrm{dec}} = \frac{\sum_{t_1=1}^{24} \mathrm{f}_{\mathrm{dec},t_1}}{24} = \left(\mathrm{f}_{\mathrm{dec},1}, \mathrm{f}_{\mathrm{dec},2}, \ldots, \mathrm{f}_{\mathrm{dec},24}\right) \quad (6)$$

IV. PRICE-SENSITIVE MODEL OF LOADS EQUIPMENT

This paper estimates the energy flexibility provided by home appliances and storage units. A price-sensitive load model must be defined to examine the effect of price variation on energy flexibility in the day-ahead electricity price profile. The following presents a price-sensitive model of home appliances like washing machines, dishwashers, domestic heat water, and lighting load. Also, batteries' charging and discharging algorithms belong to buildings equipped with photovoltaic panels and plug-in hybrid electric vehicles (PHEVs) batteries.

TABLE 1. TOU and Fhs information on washing machines and dishwashers.

Appliance	TOU Data	FHs Data
Washing Machines	Normal Distribution $\mu = 12{:}00$ $\sigma = 06{:}00$	Randomly selecting between [00:00 – 12:00]
Dishwashers	Normal Distribution $\mu = 12{:}00$ $\sigma = 07{:}00$	Randomly selecting between [00:00 – 12:00]

A. WASHING MACHINE AND DISHWASHER PRICE-SENSITIVE MODEL

Time of use (TOU) and hours of participation in flexibility programs (FHs) have been shown in Table 1. In [23], the consumption profile of washing machines and dishwashers has been presented. Also, owners are given a day-ahead electricity price profile, and they can select the optimum TOU of every appliance according to its TOU, FHs, and cost of energy consumption based on the day-ahead electricity price profile in the range of [*TOU-FHs*, *TOU-FHs*].

In this price-sensitive model, the starting point is moved in the time steps in the range of [*TOU-FHs*, *TOU-FHs*]. In every step, the cost of energy consumption is calculated according to the consumption power profile and day-ahead electricity price profile. Finally, the optimum time of use (TOU_{opti}) of the appliance is obtained with the object of minimum cost of energy consumption.

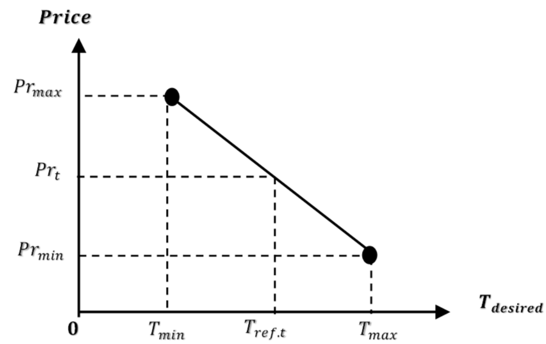


FIGURE 3. Calculating reference temperature in time step *t*.

B. DOMESTIC HEAT WATER (DHW) PRICE-SENSITIVE MODEL

In this model, to consider the prosperity of households, the temperature of water in the storage tank should be kept within [T_{min}, T_{max}] which are selected by the households.

For simplification of this model, T_{min} *and* T_{max} is considered the same for all households. According to Fig.3, in every time step, the reference temperature (T_{ref}) of DHW is obtained according to T_{min}, T_{max} Maximum and minimum price in the day-ahead electricity price profile and electricity price in that time-step. If in time step t, the water temperature of the tank of DHW is higher than $T_{ref.t}$; the DHW heater turns off; otherwise, the heater will be turned on.

$$\mathrm{T}_{\mathrm{ref},t} = \mathrm{T}_{\min} + \left\{ (\mathrm{Pr}_t - \mathrm{Pr}_{\max}) \times \frac{\mathrm{T}_{\max} - \mathrm{T}_{\min}}{\mathrm{Pr}_{\min} - \mathrm{Pr}_{\max}} \right\} \quad t = 1, 2, \ldots, 96 \quad (7)$$

TABLE 2. Random distribution of households' heat water consumption.

Period	Random Distribution Specification	
	The permissible range of consumption (Litr)	Number of samples
[1-28]	[0-3]	*N*
[29-76]	[0-5]	*N*
[77-96]	[0-4]	*N*

The daily power consumption profile of households' DHW is needed to derive the price-sensitive daily cumulative energy curve. Table 2 considers three random distributions to gather households' daily hot water consumption.

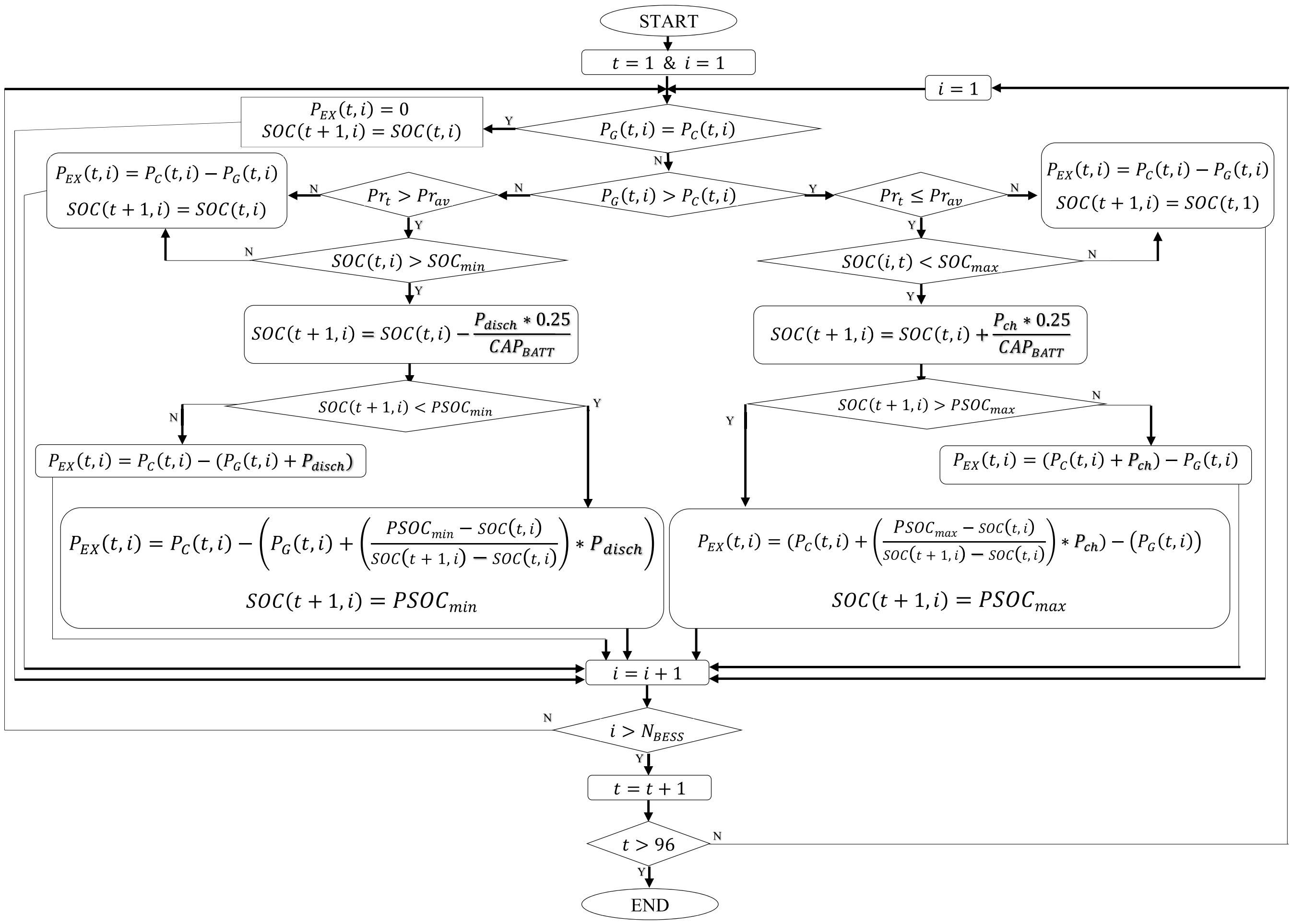


FIGURE 4. The charging and dischrging algoritm for battry energy storage systems.

In every time step, the equilibrium temperature of DHW_i ($T_{eq}(t, i)$) is calculated according to the hot water consumption of DHW_i (HWC_i), the temperature of residual water in the DHW's tank ($T_{res,w}(t, i)$), total volume of DHW_i (V_i), and the temperature of the water, which is replaced with consumed hot water (T_w).

$$\mathrm{T_{eq}(t, i)} = \left(\frac{\mathrm{HWC(t, i)}}{\mathrm{V_i}} \times \mathrm{T_w}\right) + \left(\frac{\mathrm{V_i} - \mathrm{HWC(t, i)}}{\mathrm{V_i}} \times \mathrm{T_{res,w}(t, i)}\right) \quad \mathrm{t} = 1, 2, \ldots, 96 \quad \& \quad \mathrm{i} = 1, 2, \ldots, \mathrm{N} \tag{8}$$

In this paper, the volume of DHW's tank in all households and the temperature of cold water (T_w), is considered 100 Litr and 18°, respectively, for simplification. Comparison between $T_{eq}(t, i)$ and $T_{ref.t}$ in every time step is specified whether the DHW_i should be turned on or not. If $T_{eq}(t, i)$ be less than $T_{ref.t}$, then the DHW_i in the time step, t will be turned on; otherwise, it will be turned off. The energy consumption of DHW in a time step when it is turned on is calculated by the below relation.

$$\mathrm{E_{DHW}(t, i)^{kWh}} = \mathrm{P^{kW}_{DHW_i}} \times 0.25^{\mathrm{h}} \tag{9}$$

For simplification, P_{DHW} is considered 1kW for all of DHWs.

C. CHARGING AND DISCHARGING ALGORITHM OF THE BUILDING'S BATTERY

This paper considers the battery storage system for households with a PV system. The charging and discharging strategy of a building's battery has been designed in Fig. 4 based on every household's total generation and consumption and the day-ahead price profile. The maximum and minimum state of charge (SOC_{max}, SOC_{min}) and the maximum power of the Charger in charging mode (G2V) and discharging mode (V2G) are considered the limiting factors in this planning. Finally, the energy consumption and generation of the batteries in every time step are calculated by the below relation.

$$\mathrm{E_{BATT}(t, i)} = [\mathrm{SOC(t+1, i)} - \mathrm{SOC(t, i)}] \times \mathrm{CAP_{BATT}} \quad \forall \mathrm{t} \in 1, 2, \ldots, 96 \tag{10}$$

The specification of the energy storage system of buildings is shown in Table 3.

TABLE 3. The specification of the energy storage system of buildings.

The capacity of the battery (CAP_{BATT})	2kWh
Efficiency of charging	90%
Efficiency of discharging	90%
Maximum power of charging	0.8kW
Maximum power of discharging	0.8kW

D. CHARGING AND DISCHARGING ALGORITHM OF PHEVS' BATTERY

This paper supposed that 50% of households possess PHEVs inclined to contribute flexibility programs and exchange power from the battery to the grid (V2G) or conversely (G2V). In the other word, according to the day-ahead price profile, the minimum and maximum permissible state of charge ($PSOC_{min}, PSOC_{max}$) specified by PHEV owners, the charging and discharging strategy are designed. In this study, it is supposed that 20% of PHEVs contribute flexibility programs only at parking lots of buildings, and 30% contribute flexibility programs only at stations nearby the workplace. The others contribute flexibility programs at both places. Table 4 shows information such as arrival time, departure time, initial SOC, and location of the PHEVs.

TABLE 4. The information of the PHEVs in the flexibility program.

Number of PHEVs	Location	Arrival Time (a_t)	Departure Time (d_t)	Initial SOC (SOC_0)
Type_1: 20% of n_PHEVs	parking lots of buildings	00:00	24:00	Randomly between [0.3-0.7]
Type_2: 30% of n_PHEVs	Charging and discharging station	a_{t_2}	d_{t_2}	Randomly between [0.3-0.7]
Type_3: 50% of n_PHEVs	parking lots of buildings	$a_{t_{3-1}}$: 00:00	$d_{t_{3-1}}$	Randomly between [0.3-0.7]
	Charging and discharging station	$a_{t_{3-2}}$	$d_{t_{3-2}}$	Depends on Previous step
	parking lots of buildings	$a_{t_{3-3}}$	$d_{t_{3-3}}$: 24:00	Depends on Previous step

a_{t_2}= [6: 00 < Nor(9: 00,1: 30) < 12: 00]
d_{t_2} = a_{t_2} +[6: 00 < Nor(9: 00,1: 00) < 12: 00]
$d_{t_{3-1}}$ = $a_{t_{3-1}}$+ [4: 00 < Nor(6: 00,1: 00) < 8: 00]
$a_{t_{3-2}}$ = $d_{t_{3-1}}$+ Randomly between [1-8]
$d_{t_{3-2}}$ = $a_{t_{3-2}}$+ [7: 00 < Nor(9: 00,1: 00) < 11: 00]
$a_{t_{3-3}}$ = $d_{t_{3-2}}$+ Randomly between [1-8]

In the proposed charging and discharging strategy, the PHEVs are charged when the hourly electricity price be less than the average price of the day-ahead price profile, and the SOC of the battery must not be higher than $PSOC_{max}$. On the other hand, the PHEVs are discharged when the hourly electricity price is higher than the average price of the day-ahead price profile, and the SOC of the battery must not be less than $PSOC_{min}$. Finally, the energy consumption and generation of every PHEV's battery in every time step is calculated by the below relation.

$$\mathrm{E}_{\mathrm{BATT}}^{\mathrm{PHEV}}(\mathrm{t}\,,\mathrm{i}) = [\mathrm{SOC}(\mathrm{t}+1\,,\ \mathrm{i})\ -\ \mathrm{SOC}(\mathrm{t}\,,\ \mathrm{i})] \times \mathrm{CAP}_{\mathrm{BATT}}^{\mathrm{PHEV}} \quad \forall \mathrm{t} \in 1, 2, \ldots, 96 \tag{11}$$

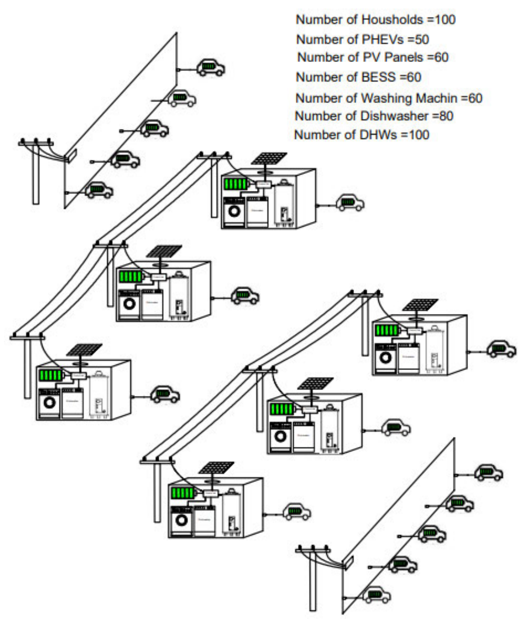


FIGURE 5. The outline of the sample microgrid.

V. CASE STUDY

In this section, a microgrid with 100 households is considered. Some of those have home appliances such as a Washing- machine, dishwasher, and DHW participating in flexibility programs. Also, some households have equipment such as PV panels, Battery Energy Storage Systems, and PHEVs participating in flexibility programs. In Fig. 5, the outline of the sample microgrid is shown. The final goal of this study is the collection of generation or consumption energy data of the different sections of the study case and estimating the energy flexibility of a sample microgrid due to the information gathered from households and the microgrid's components. The day-ahead electricity price information of two various price scenarios is shown in Table 5. Pricing criteria are based on low, medium, and full load times.

VI. SIMULATION RESULTS

Two scenarios are provided in this paper to validate the proposed method for estimating energy flexibility potential.

TABLE 5. The day- ahead electricity price information.

-	Light Load	Heavy Load	Medium Load
Time (hour: minute)	00:00 - 08:00	08:00 - 16:00	16:00 - 24:00
Electricity Price_1 ($/kWh)	0.07	0.1	0.09
Electricity Price_2 ($/kWh)	0.07	0.1	0.06

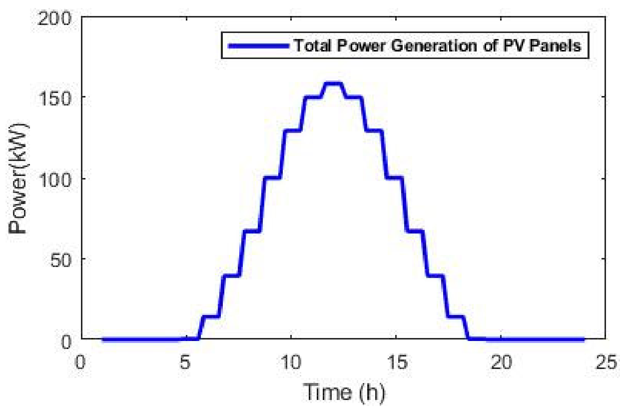


FIGURE 6. Total power generation of PV panels [25].

A. SCENARIO 1: EVALUATION OF ENERGY FLEXIBILITY POTENTIAL OF PROPOSED MICROGRID IN SECTION (V)

In this study case, 60 PV units were considered randomly for distributed generation of the houses. The total daily power generation of PV panels has been illustrated in Fig. 6. In Figs. 7 and 8 illustrate the washing machine and dishwasher's maximum, minimum, and daily cumulative energy curves. Also, in Figs, normal daily cumulative energy by applying price-sensitive models. 7 and 8.

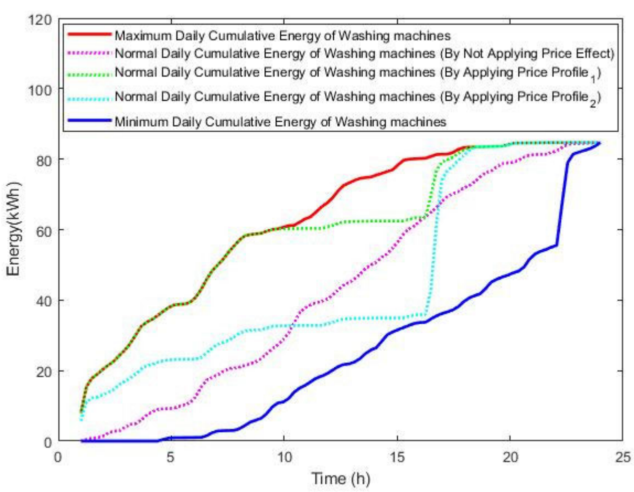


FIGURE 7. Daily cumulative energy profiles of washing machines.

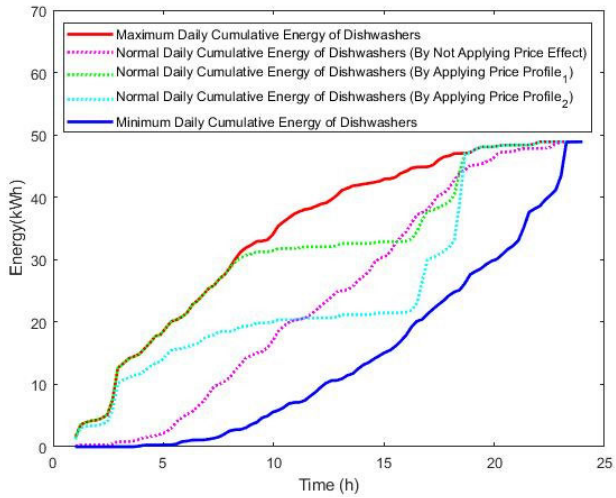


FIGURE 8. Daily cumulative energy profiles of dishwashers.

The impact of electricity price on displacement TOU of the washing machines and dishwashers is evident in Figs. 7 and 8, respectively. As expected, because of the low electricity price in the time range of 00:00 to 08:00 in price profile 1, some of the washing machines and dishwashers, which are allowed to start during this period according to parameters like TOU and FHs, set earlier to decrease total cost of energy consumption. Whereas due to price profile 2, the minimum price is related to the range of 16:00 to 24:00.According to Figs. 7 and 8, as much as the electricity price is approached at the minimum price of the day-ahead prices, the normal cumulative energy of washing machines and dishwashers is approached to maximum daily cumulative energy curves.

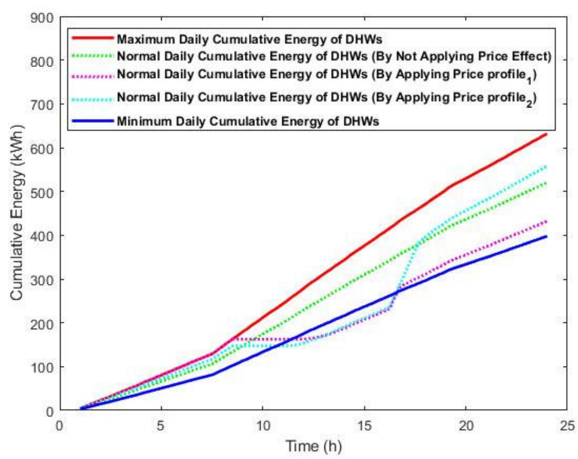


FIGURE 9. Daily cumulative energy consumption of DHWs.

On the other hand, the normal cumulative energy of washing machines and dishwashers is approached to minimum daily cumulative energy curves when the electricity price is approached to the maximum price of the day-ahead prices, provided that the displacement of TOU of the objective appliance is possible. Fig. 9 shows the maximum and minimum daily cumulative Energy profiles of DHWs. Also, the normal daily cumulative energy by considering the daily price impact on the energy consumption of DHWs has been calculated. For this purpose, two operation mode has been designed below.

• ***Operation Mode 1***: Calculating normal daily cumulative energy by applying price impact on consumption energy of DHWs, so that According to section II-B, the reference temperature of DHWs in every time step is specified based on Fig. 3.

• ***Operation Mode 2***: Calculating normal daily cumulative energy by not applying price impact on consumption energy of DHWs so that the reference temperature of DHWs in every time step is selected randomly within $[T_{min}, T_{max}]$.

As illustrated in Fig. 9, in the range of 00:00 to 08:00, the reference temperature OM1 is higher than the reference temperature OM2. Therefore, the energy consumption of the DHWs, in OM1 is more than in OM2. In the range of 08:00 to 16:00, the electricity price has been maximum, and the reference temperature has been T_{min} Furthermore, the heater of the DHW s sets off. The equilibrium temperature of DHWs' storage tank is decreasing by heat water consumption of households until the equilibrium temperature of DHWs' storage tank equals T_{min}. At this moment, the DHW sets on. Finally, in the range of 16:00 to 24:00, the price of electricity is decreased, and the reference temperature becomes more than T_{min} and energy consumption of DHWs is increased. In Fig. 10, the maximum and minimum daily cumulative energy curves have been achieved by charging and discharging all BESSs at the beginning of the day. The normal daily cumulative energy has been calculated due to factors used in the BESSs charging and discharging flowchart in Fig. 4. These factors are SOC of BESSs, hourly electricity price, generation power, and consumption power of every household.

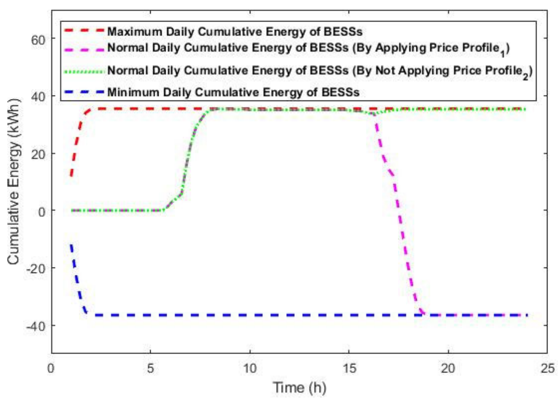


FIGURE 10. Daily cumulative energy profiles of BESSs.

Considering three types of PHEVs' owners' contribution in this study case that is mentioned in Table 3, and due to the day-ahead electricity price information in Table 4, the daily cumulative energy profiles of three groups of PHEVs are calculated (Fig. 11). In this study case, the average daily electricity price is equal to 0.086667 $/kWh according to the day-ahead electricity price. All PHEVs are expected to be in charging mode within [00:00-08:00], as the electricity price in this period is less than the average electricity price of the day-ahead electricity price profile. Due to the absence of PHEVs that belong to the type2 within [00:00-06:00], despite the proper condition for PHEVs charging, the cumulative energy of this group has been equal to zero.

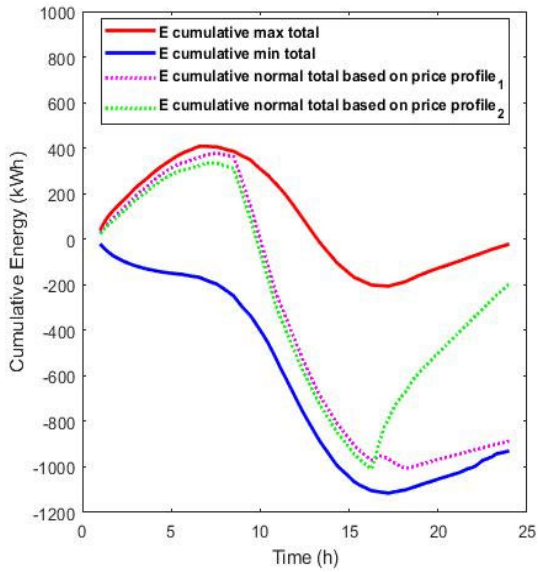


FIGURE 11. Daily cumulative energy profiles of PHEVs.

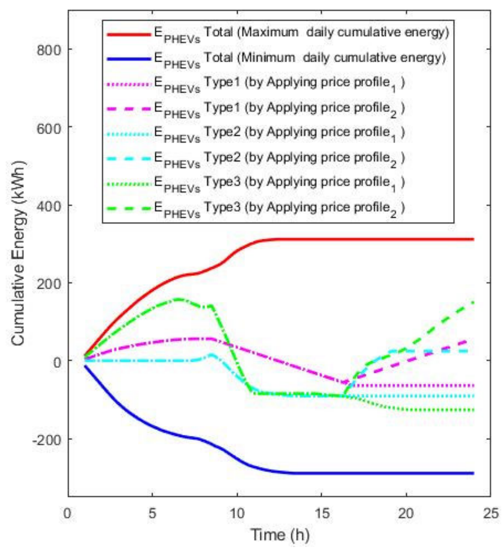


FIGURE 12. Total daily cumulative energy profiles.

Finally, as seen in Fig. 12, the total daily cumulative energy curves related to the objective zone are achieved by summing all the maximum, minimum, and normal curves of various sectors contributing to the flexibility program. According to the provided strategy in Section II, the hourly power-increasing flexibility and hourly power-decreasing flexibility

FIGURE 13. Hourly power increasing flexibility.

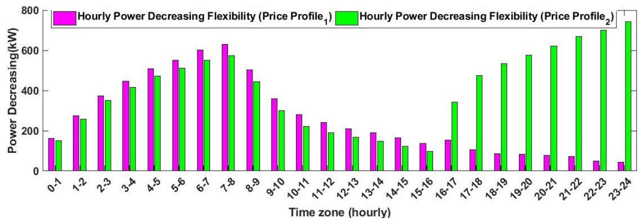


FIGURE 14. Hourly power decreasing flexibility.

are calculated, which is mentioned in Figs. 13 and 14, respectively. By comparison of electricity prices information in Table 4, it is expected that the total consumption power related to price profile 2, in the range of [16:00,24:00], will be increased. Consequently, in the range of [16:00,24:00], hourly power-increasing flexibility in price profile 2 is less than in price profile 1. In other words, the hourly power-decreasing flexibility in price profile 2 is more than the hourly power-decreasing flexibility in price profile 1. All the above results are evident in Figs. 12-14.

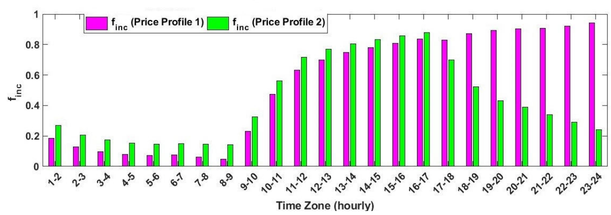


FIGURE 15. Hourly increased energy flexibility indexes profile.

According to the relations presented in Section III, hourly increased and decreased energy flexibility indices are calculated for price profiles 1 and 2. Hourly energy flexibility rate is described with the help of hourly increased and decreased energy flexibility indices. When the energy flexibility index is approached 1, energy flexibility is increased. Due to the hourly increase and decreased energy flexibility indices profile in Figures 15 and 16, in the range of [17:00,24:00], the tendency to increase power in price profile 1 is higher than in price profile 2. On the contrary, the tendency to power decrease in price profile 2 is more than in price profile 1. For daily increasing and decreasing energy flexibility assessment, daily increased and decreased energy flexibility are presented by indices that realize the daily energy flexibility potential comparison possibility between diverse scenarios. According to Fig. 17, daily increased and decreased energy flexibility

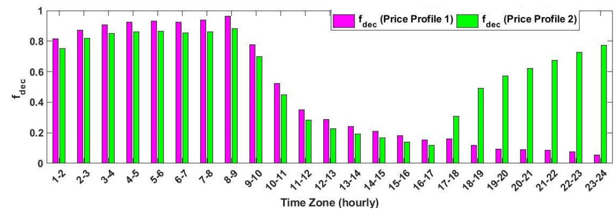


FIGURE 16. Hourly decreased energy flexibility indexes profile.

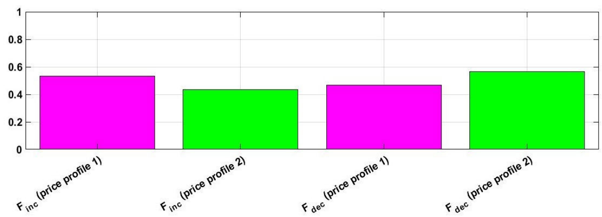


FIGURE 17. Daily increased and decreased energy flexibility indexes.

indices are achieved by calculating the average of the hourly increased and decreased energy flexibility indices, respectively. Generally, the daily increased energy flexibility index in price profile 1 is more than the daily increased energy flexibility index in price profile 2. On the contrary, the daily decreased energy flexibility index in price profile 2 is more than the daily decreased energy flexibility index in price profile 1.

TABLE 6. EV charger (I) schedule.

EV_j	EV_1	EV_4	EV_7	EV_9	EV_{11}
$\widehat{SoC}_{j,r,j}$	28.0	13.0	22.0	24.0	30.0
$SoC_{j,a,j}$	8.4	7.6	3.4	6.6	21.5
$\tilde{a}_j$	3:30	7:30	11:30	15:30	20:30
a_j	3:40	7:20	11:20	15:30	20:20
d_j	5:30	10:30	14:50	19:30	23:30

B. SCENARIO 2: COMPARISON WITH A PREVIOUSLY-REPORTED FLEXIBILITY EVALUATION TECHNIQUE [24]

In [24], three EV charging strategies have been presented, and their energy flexibility potential has been evaluated. Minimum Time (MT), economic Model Predictive Control (eMPC), and Optimal Control with Minimum Cost and Maximum Flexibility (OCCF) have been considered for each Charger in the charging station. Maximum charging power in fast mode has been considered 50kW, and the battery capacity of an EV is 80kWh. To analyze the proposed charging strategies, the EV charger schedule for one charging station has been reported in Table 6. The power profile of EV charger (I) with the different strategies has represented in Fig. 18. The proposed strategy of this paper determines the maximum and minimum cumulative energy curves of this scenario. All the cumulative energy curves have represented in Fig. 19.

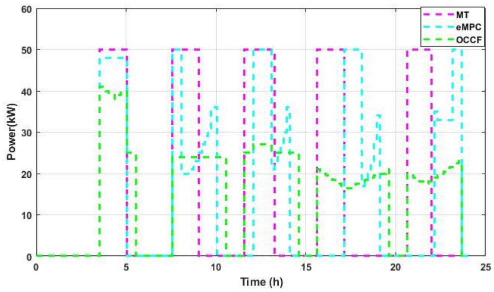


FIGURE 18. Power profiles of EV Charger (I) with the different strategies.

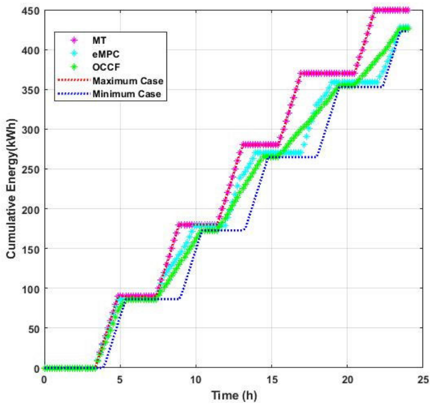


FIGURE 19. Cumulative energy curves of EV Charger (I).

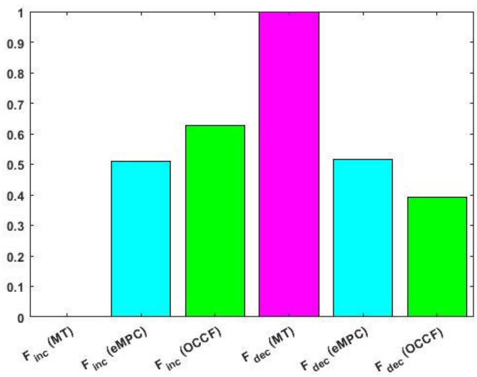


FIGURE 20. Daily increasing and decreasing energy flexibility indexes of EV Charger (I) with the different strategies.

According to Fig. 19 and the proposed energy flexibility estimation strategy, daily increasing and decreasing energy flexibility indices are calculated (Fig. 20). According to Fig. 20 and Table 4 in [24], the OCCF strategy is more flexible than the eMPC strategy and eMPC strategy is more flexible than MT strategy from increasing power potential prospective. Also, the MT strategy is more flexible than the eMPC strategy, and the eMPC strategy is more flexible than the OCCF strategy from decreasing power potential perspective. The results effectively prove the accuracy and authenticity of the method presented in this paper.

VII. CONCLUSION

This paper presents and formulates a novel approach to estimating energy flexibility. We propose a generic methodology that quantifies and formulates energy flexibility as possible power increases and decreases within operational limits. Utilizing this formulation, energy flexibility indices were introduced that allow comparisons between various pricing scenarios. The maximum and minimum cumulative energy curves for a day were obtained, along with indices of energy flexibility created hourly and daily. We derived maximum and minimum energy flexibility curves for different types of devices. We extracted hourly or daily energy flexibility indices using the calculation areas between daily cumulative energy curves recorded in one hour and one day. Additionally, the price-sensitive models corresponding to each load were introduced to apply the reaction of loads to pricing politics. This makes it possible to change energy flexibility by changing electricity prices over a specific period. The proposed energy flexibility estimation strategy was evaluated using offline digital time-domain simulations in MATLAB/Simulink software on a home-residential grid. The simulation results and comparisons of the presented energy flexibility potential of different pricing scenarios revealed that the proposed strategy is effective, accurate, and authentic.

REFERENCES

[1] F. Birol, L. Cozzi, A. Bromhead, T. Gould, and M. Baroni, "Global energy trends to 2040," in *World Energy Outlook 2014*. Paris, France: OECD iLibrary, 2014, doi: 10.1787/weo-2014-4-en.

[2] E. Hillberg et al., "Flexibility needsin the future power system," Tech. Rep., 2019.

[3] R. Halvgaard, P. Bacher, B. Perers, E. Andersen, S. Furbo, J. B. Jørgensen, N. K. Poulsen, and H. Madsen, "Model predictive control for a smart solar tank based on weather and consumption forecasts," *Energy Proc.*, vol. 30, pp. 270–278, Jan. 2012, doi: 10.1016/j.egypro.2012.11.032.

[4] K. B. Lindberg, "Impact of zero energy buildings on the power system: A study of load profiles, flexibility and system investments," Tech. Rep., 2017.

[5] X. Cao, X. Dai, and J. Liu, "Building energy-consumption status worldwide and the state-of-the-art technologies for zero-energy buildings during the past decade," *Energy Buildings*, vol. 128, pp. 198–213, Sep. 2016, doi: 10.1016/j.enbuild.2016.06.089.

[6] *Hong Kong Energy End-Use Data 2018*, The Energy Efficiency Office, Hong Kong, 2018.

[7] D. Fischer, A. Surmann, W. Biener, and O. Selinger-Lutz, "From residential electric load profiles to flexibility profiles—A stochastic bottom-up approach," *Energy Buildings*, vol. 224, Oct. 2020, Art. no. 110133, doi: 10.1016/j.enbuild.2020.110133.

[8] J. Huber, D. Dann, and C. Weinhardt, "Probabilistic forecasts of time and energy flexibility in battery electric vehicle charging," *Appl. Energy*, vol. 262, Mar. 2020, Art. no. 114525, doi: 10.1016/j.apenergy.2020.114525.

[9] E. Mollenhauer, A. Christidis, and G. Tsatsaronis, "Increasing the flexibility of combined heat and power plants with heat pumps and thermal energy storage," *J. Energy Resour. Technol.*, vol. 140, no. 2, Feb. 2018, Art. no. 020907, doi: 10.1115/1.4038461.

[10] A. Bloess, W.-P. Schill, and A. Zerrahn, "Power-to-heat for renewable energy integration: A review of technologies, modeling approaches, and flexibility potentials," *Appl. Energy*, vol. 212, pp. 1611–1626, Feb. 2018, doi: 10.1016/j.apenergy.2017.12.073.

[11] F. G. Venegas, M. Petit, and Y. Perez, "Electric vehicles as flexibility providers for distribution systems. A techno-economic review." in *Proc. 25th Int. Conf. Electr. Distrib. (CIRED)*, Jun. 2019, pp. 3–6.

[12] R. Dugan, in *Proc. CIRED 22nd Int. Conf. Electr. Distrib.*, vol. 664, 2013, pp. 10–13.

[13] N. Prüggler, "Economic potential of demand response at household level—Are central-European market conditions sufficient?" *Energy Policy*, vol. 60, pp. 487–498, Sep. 2013, doi: 10.1016/j.enpol.2013.04.044.

[14] S. Nistor, J. Wu, M. Sooriyabandara, and J. Ekanayake, "Capability of smart appliances to provide reserve services," *Appl. Energy*, vol. 138, pp. 590–597, Jan. 2015.

[15] B. Drysdale, J. Wu, and N. Jenkins, "Flexible demand in the GB domestic electricity sector in 2030," *Appl. Energy*, vol. 139, pp. 281–290, Feb. 2015, doi: 10.1016/j.apenergy.2014.11.013.

[16] P. S. Kwon and P. Østergaard, "Assessment and evaluation of flexible demand in a Danish future energy scenario," *Appl. Energy*, vol. 134, pp. 309–320, Dec. 2014, doi: 10.1016/j.apenergy.2014.08.044.

[17] M. E. H. Dyson, S. D. Borgeson, M. D. Tabone, and D. S. Callaway, "Using smart meter data to estimate demand response potential, with application to solar energy integration," *Energy Policy*, vol. 73, pp. 607–619, Oct. 2014.

[18] K. Kouzelis, I. D. de Cerio Mendaza, and B. Bak-Jensen, "Probabilistic quantification of potentially flexible residential demand," in *Proc. IEEE PES Gen. Meeting*, Jul. 2014, pp. 1–5, doi: 10.1109/PESGM.2014.6938836.

[19] J. L. Mathieu, P. N. Price, S. Kiliccote, and M. A. Piette, "Quantifying changes in building electricity use, with application to demand response," *IEEE Trans. Smart Grid*, vol. 2, no. 3, pp. 507–518, Sep. 2011, doi: 10.1109/TSG.2011.2145010.

[20] G. Reynders, R. A. Lopes, A. Marszal-Pomianowska, D. Aelenei, J. Martins, and D. Saelens, "Energy flexible buildings: An evaluation of definitions and quantification methodologies applied to thermal storage," *Energy Buildings*, vol. 166, pp. 372–390, May 2018, doi: 10.1016/j.enbuild.2018.02.040.

[21] A. Bampoulas, M. Saffari, F. Pallonetto, E. Mangina, and D. P. Finn, "A fundamental unified framework to quantify and characterise energy flexibility of residential buildings with multiple electrical and thermal energy systems," *Appl. Energy*, vol. 282, Jan. 2021, Art. no. 116096, doi: 10.1016/j.apenergy.2020.116096.

[22] R. Luthander, J. Widén, D. Nilsson, and J. Palm, "Photovoltaic self-consumption in buildings: A review," *Appl. Energy*, vol. 142, pp. 80–94, Mar. 2015, doi: 10.1016/j.apenergy.2014.12.028.

[23] F. Issi and O. Kaplan, "The determination of load profiles and power consumptions of home appliances," *Energies*, vol. 11, no. 3, p. 607, Mar. 2018.

[24] C. Diaz-Londono, L. Colangelo, F. Ruiz, D. Patino, C. Novara, and G. Chicco, "Optimal strategy to exploit the flexibility of an electric vehicle charging station," *Energies*, vol. 12, no. 20, p. 3834, Oct. 2019, doi: 10.3390/en12203834.

[25] H. R. Baghaee, M. Mirsalim, G. B. Gharehpetian, and H. A. Talebi, "Reliability/cost-based multi-objective Pareto optimal design of stand-alone wind/PV/FC generation microgrid system," *Energy*, vol. 115, pp. 1022–1041, Nov. 2016, doi: 10.1016/j.energy.2016.09.007.

ALIREZA RASHTBARYAN (Student Member, IEEE) received the B.Sc. and M.Sc. degrees in electrical engineering from the Amirkabir University of Technology, Tehran, Iran, in 2018 and 2021, respectively. His research interests include power system flexibility, microgrids, and renewable energies.

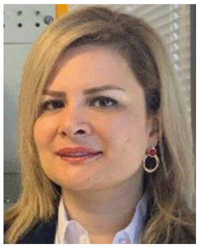
GEVORK B. GHAREHPETIAN (Senior Member, IEEE) received the B.S. degree (Hons.) in electrical engineering from Tabriz University, Tabriz, Iran, in 1987, the M.S. degree (Hons.) in electrical engineering from the Amirkabir University of Technology (AUT), Tehran, Iran, in 1989, and the Ph.D. degree (Hons.) in electrical engineering from Tehran University, Tehran, in 1996.

He was with the High Voltage Institute, RWTH Aachen, Aachen, Germany. He was also an Assistant Professor, from 1997 to 2003, an Associate Professor, from 2004 to 2007, and has been a Professor, since 2007, with AUT. He is the author of more than 1300 journals and conference papers. His teaching and research interests include smart grids, microgrids, FACTS and HVdc systems, and monitoring of power transformers and its transients.

Prof. Gharehpetian is a Distinguished Member of CIGRE and IAEEE. He was selected by the Ministry of Science Research and Technology (MSRT) as a Distinguished Professor of Iran, by the Iranian Association of Electrical and Electronics Engineers (IAEEE) as a Distinguished Researcher of Iran, by the Iran Energy Association (IEA) as the Best Researcher of Iran in the field of energy, by the MSRT as a Distinguished Researcher of Iran, by the Academy of Science of the Islamic Republic of Iran as a Distinguished Professor of electrical engineering, by the National Elites Foundation as a Laureates of Alameh Tabatabaei Award, and was awarded the National Prize in 2008, 2010, 2018, 2018, 2019, and 2019, respectively. As a Ph.D. Student, he has received scholarship from the German Academic Exchange Service (DAAD), from 1993 to 1996. Since 2004, he has been the Editor-in-Chief of the *Journal of Iranian Association of Electrical and Electronics Engineers*. Based on the Web of Science database (2005–2019), he is among the world's top 1% elite scientists according to Essential Science Indicators (ESI) ranking systems.

HAMID REZA BAGHAEE (Member, IEEE) received the Ph.D. degree in electrical engineering from the Center of Excellence in Power Engineering, Amirkabir University of Technology (AUT) (the most prestigious university of Iran in electrical power engineering), in 2017.

From 2007 to 2017, he was a Teaching and Research Assistant with the Department of Electrical Engineering, AUT. In August 2019, he joined AUT as an Associate Research Professor with the Department of Electrical Engineering. In 2022, he joined the Faculty of Electrical and Computer Engineering (ECE), Tarbiat Moadares University, Tehran, Iran, where he is currently an Assistant Professor. He was a short-term scientist with CERN and ABB Switzerland. He is a Project Coordinator of the AUT Pilot Microgrid Project, one of the sub-projects of the Iran Grand (National) Smart Grid Project. Since 2017, he has been a co-supervisor and a consulting professor of more than 13 Ph.D. and 15 M.Sc. students. He is the author of three books, three published book chapters, 85 ISI-ranked journal articles (mostly published in IEEE, IET, and Elsevier journals), 60 conference papers, and the owner of one registered patent. His book titled *Microgrids and Methods of Analysis* was selected as the "Best Book of the Year in the Power and Energy Industry of Iran" by the Technical Committee of the Iran Ministry of Energy (MOE), in November 2021, and the Winner of the "Distinguished Author of the International Books" Award in the AUT, in December 2021. He has many hot and highly-cited papers in his journal and conference papers, based on SciVal and Web of Science (WoS) statistics. His research interests include micro- and smart grids, cyber-physical power systems, power system cybersecurity and cyber-resiliency, application of artificial intelligence (AI) and machine learning (ML), big data analytics in power systems, real-time simulation of power systems, distributed generation and renewable energy resources, FACTS, HVdc and custom power devices, power electronics applications in power systems, power electronics-dominated grids (PEDGs), power quality, real-time simulation of power systems, and power system operation, control, monitoring, and protection. He is a member and the Secretary Chair of the IEEE Iran Section Communication Committee, from 2020 to 2023, and a member of the IEEE Smart Grid Community, the IEEE Internet of Things Technical Community, the IEEE Big Data Community, the IEEE Smart Cities Community, and the IEEE Sensors Council. He is the Winner of four national and international prizes, as the Best Dissertation Award from the Iran Scientific Organization of Smart Grids (ISOSG), in December 2017; the Iranian Energy Association (IEA), in February 2018; the AUT Award, in December 2018; and the IEEE Iran Section, in May 2019, for the Ph.D. dissertation. Since August 2021, he has been an elected member of the board and the Chairman of the committee on publication and conferences at the ISOSG and a member of the IEE Transmission and Distribution (TD) Committee, the IEEE PES Transmission Subcommittee, and its working groups of reliability impacts of inverter-based resources, generation and energy storage integration, voltage optimization, and transmission power system switching. Besides, he has been a member and the Vice Chairman of the IEEE Iran Section Power Chapter, since 2022. He was also the IEEE PES Subcommittee on Big Data Analytics for Power Systems, the IEEE PES Task Force on Application of Big Data Analytics on Transmission System Dynamic Security Assessment, the IEEE PES Task Force on Resilient and Secure large-Scale Energy Internet Systems (RSEI), and the IEEE Task Force on Microgrid Design. He is a reviewer of several IEEE, IET, and Elsevier journals, a guest editor of several special issues in IEEE, IET, Elsevier, and MDPI, and a scientific program committee member of several IEEE conferences. Since December 2020, he has been an Associate Editor and an Energy Section Editor of the *IET Journal of Engineering*. He has also been selected as the Best and Outstanding Reviewer of several journals, such as IEEE Transactions on Power Systems (Top 0.66 of reviewers, among more than 8000 reviewers, in 2020), *Control Engineering Practice* (Elsevier), in 2018, 2019, and 2020, *International Transaction on Electrical Energy Systems* (Wiley), in 2020, and the Pablon best and listed among top 1 of the reviewers in engineering, in 2018, and both engineering and cross-field, in 2019. He was selected as a Star Reviewer of the IEEE JESTPE and IEEE Power Electronics Society (PELS), in 2020, commemorated and presented during the IEEE ECCE 2021 Conference in Vancouver, Canada. He has also been listed in 2020, 2021, and 2022 editions of the top 2 scientists in the field of energy, electrical engineering, and enabling and strategic technologies according to the Science-Wide Citation Indicators, (reported by Stanford University, USA), and mentioned among Worlds top 1 of elite scientists according to WoS and Essential Science Indicators (ESI) ranking, since 2020. He has presented 15 worships and ten invited talks at national and international conferences and scientific events. After pursuing the Postdoctoral Fellowship with AUT, from October 2017 to August 2019.



ROYA AHMADIAHANGAR (Senior Member, IEEE) received the M.Sc. and Ph.D. degrees in power system engineering from the Babol University of Technology (Ranked 1st, 2017–2019, Times Magazine), Babol, Iran, in 2009 and 2014, respectively. Since 2018, she has been a Postdoctoral Researcher with the Department of Electrical Power Engineering and Mechatronics, Tallinn University of Technology, Estonia, Tallinn. She has authored or coauthored one book, five book chapters, and more than 60 published papers on the power system and smart grids. Her research interests include the integration of DER in smart grids, demand response, demand-side flexibility, AI applied to smart grids and planning, and management of power systems. She was a recipient of the Iranian Ministry of Science Scholarship for Ph.D. studies (Merit Scholarship) and Ranked first in the Ph.D. program.