Research Article

A Solution to Prevent a Blackout Crisis: Determining the Behavioral Potential and Capacity of Solar Power

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Increasing the power grid peak in the summer time causes power outages in industries and residential areas in Iran. The most obvious example of this issue is the power outages in the summer of 2018. Management of the demand-side is the most important strategy to reduce the grid peak due to the high cost of the development of the power plant capacity (500\$ per kilowatt). In the present study, the effect of behavioral parameters in decreasing the power grid peak was identified. The behavioral simulation was done as an agent-based model using the raw data of the time-use survey (TUS) of the Statistics Center of Iran. 4228 urban households were surveyed, and the quality of people's behavior was determined in each time step of 15 minutes during the day and night with 2 deterministic and stochastic approaches. In the stochastic approach, the Markov chain method was used. It showed that the power grid peak can only be reduced by 10% with behavioral flexibility and up to 25% by upgrading technology. In addition, based on the power deficit in 2018, 2000 megawatts of solar power capacity must be added to the network at peak times to meet grid demand.

1. Introduction

Air conditioning (AC) is capable of saving lives during warm weather and has a major contribution to peak electricity demand during summer time. Throughout exceedingly hot days or heat waves, such an elevation in energy demand results in brownouts and dimouts [1]. The electric energy and electricity industry are also key factors for the economic system's propulsion in order not to affect the economic system and public security setting [2]. In many countries with significantly demanding seasonal cooling, the role of AC in peak electricity needs is remarkably greater than overall year-round demands. For instance, AC demand in Madrid, Spain, encompassed one-third of overall peak consumption in June 2008 [3]. In such countries as Singapore or most of those in the Middle East, which have completely year-round cooling demands, the AC contribution to peak loads

can be as large as 50% or higher [3]. In the plethora of countries, a sharp elevation is predicted in contribution of space cooling to peak electricity loading, and the elevations are uppermost in hot countries, including India, in which the contribution rises from only 10% currently to 45% in 2050 [4]. As many cooling demands are fulfilled with electricity-powered fans or ACs, power systems are greatly influenced by the growing need for cooling. Elevated AC loadings particularly increase not only total electricity requirement but also peak electricity loadings. Application of ACs and electric fans for staying cool comprises approximately 20% of overall electricity, which is currently utilized in buildings worldwide [4, 5]. Such a tendency starts to develop as the focus of global economic and demographic development is toward hotter countries. Oftentimes, demand-side management (DSM) programs are primarily aimed at lowering space-cooling loadings via demand response at periods of peak electricity

FIGURE 1: Maximum production capacity and consuming demand in network peak time in Iran. Extracted from the Iran Grid Management Company (IGMC) database.

demands [6]. The overall energy requirement of a building results from both its thermic setting and its inhabitants, which have a greater complication in the assessment and quantification than the building envelope and its thermic setting [7]. Therefore, the management of energy demands in buildings requires critical consideration of the behavior of occupants [8, 9]. In this research, the amount of cooling load in the power grid peak and its reduction potential by observing behavioral issues in the form of codified scenarios are investigated by studying the behavioral details of household energy consumption using the summertime-use survey of the Statistics Center of Iran in 2015 and by agent-based modeling of the residential sector in the Tehran. The bottlenecks and important goals pursued in this study are as follows: (1) development of bottom-up modeling tools in terms of behavioral functions; (2) accuracy of estimating the effective cooling load in the peak of Tehran electricity network by different building groups; (3) investigating the effect of increasing technology efficiency, comfort temperature, and a combination of both in the peak of the electricity network; (4) determining the behavioral potentials of reducing cooling energy consumption and its impact on the peak of the electricity network; and (5) determining the share of solar electricity to manage the power grid peak. Behavioral modeling methods in the field of energy with 2 stochastic and deterministic approaches and agent-based and bottom-up modeling methods are reviewed in the literature. The following organization is presented in this study. In Section 2, the background of blackouts in Iran is reported. In Section 3, the study methodological procedure is explained. In Section 4, the results and discussion is represented. And finally, in Section 5, the main research conclusions and discussions are synthesized.

2. Background

2.1. Blackouts and Brownouts in Iran. The power supply system includes the generation, transmission, and distribution sections, and if any of these sections are disrupted, blackouts will occur [10]. The trend of demand and production capacity at the peak moment from 2007 to 2020 was increasing (from about 35000 MW in 2007 to about 58000 MW in 2020) (Figure 1). During these years, except for 2019 and 2020, the amount of power demand exceeded the production amount at the peak moment.

Table 1 shows the hours of the power grid peak in the last 10 years. It is noteworthy that in 2020, the grid peak occurred at night, which indicates that the behavior of the energy consumption is changed and also the peak hours are changed from day to night.

In 2018, the capacity to generate electricity during peak hours was about 8000 MW less than the demand due to reduced rainfall and a sharp decline in the capacity of hydropower plants. If hydropower plants are taken out of operation, the lack of capacity of the country's thermal power plants is about 8000 MW. The plan of the development of the capacity of thermal power plants in 2019 and 2020 was about 7000 MW (Table 2) of which only 1500 MW of new capacity was built.

The share of different power plants in electricity generation and different sectors in electricity consumption is as shown in Figures 2 and 3. To increase energy security, Iran must diversify its energy supply [11] and power plants. The highest electricity generation in Iran is in combined cycle power plants (36%) and the highest electricity consumption is in the industrial (36%) and residential (32%) sectors.

According to the power plant construction process in the country from 1997 to 2020 (Figure 4), the capacity of power

TABLE 1: Power grid peaks (hour and amount) in the last 10 years. Extracted from the Iran Grid Management Company (IGMC) and Tavanir Company databases.

Year	Power grid peak		Power grid peak		Day and night peak difference (GW)
	Day (GW)	Hour	Night (GW)	Hour	
July 21, 2020	58.244	12:40	58.254	21:25	0.01
July 22, 2019	57.635	16:23	56.563	21:24	1.072
July 11, 2018	57.098	16:38	54.946	22:32	2.152
July 30, 2017	55.442	14:45	52.452	21:36	2.99
July 20, 2016	52.693	14:50	50.3	21:30	2.393
July 11, 2015	50.17	15	48	22	2.17
July 26, 2014	48.527	15:24	46.3	22	2.227
July 17, 2013	45.693	14:43	44.8	22	0.893
August 14, 2012	43	16	42	22	1
August 3, 2011	42	15	41	22	1

TABLE 2: Ministry of Energy plans to increase capacity of power plants (MW). Extracted from the Thermal Power Plants Holding Company database.

Share of each section	2017	2018	2019	2020	2021
Governmental	235	42	652	938	760
Private	958	543	2099	998	555
Private buyback agreement	160	480	480	1785	640
Cumulative sum	1353	1065	3231	3721	1955

FIGURE 2: The share of various power plants in electricity generation in Iran. Extracted from the Iran Grid Management Company (IGMC) database.

plants can be increased by an average of 2000 MW per year, which cannot compensate for the lack of capacity of thermal power plants, especially in years of water shortage. There-

FIGURE 3: The share of different sectors of electricity consumption in Iran. Extracted from the Iran Grid Management Company (IGMC) database.

fore, to solve the blackout crisis, the solution must be sought along with increasing the capacity of power plants on the demand side [12].

As shown in Figure 5, the industry's electricity consumption in the peak hours of summer 2019 and 2020 is about 5000 MW, which is more than the storage power plants at this time (about 3000 MW). The high consumption of industrial electricity at the power grid peak shows the lack of a specific program in the field of the management of the load in this sector.

The peak of the power grid in most countries of the world, including Iran, is affected by the cooling load. As shown in Figure 6, the share of the cooling load from the grid peak in the United States of America is nearly 30% and in China and South Korea is more than 15% [4].

FIGURE 4: Construction of power plant trend (1995 to 2019). Extracted from Thermal Power Plants Holding Company database.

FIGURE 5: Comparison of industrial electricity consumption and power plant reserves at the peak moment in 2019 and 2020. Extracted from the Iran Grid Management Company (IGMC) database.

The temperature in the hot summer months in Tehran averages about 36 degrees Celsius, which indicates the high potential of cooling electricity consumption in this city (Figures 7 and 8).

2.2. Importance of Solar Power in Meeting the Energy Demands. The demand for solar electricity in the world is increasing, so that by 2050, the cheapest type of electricity is projected to be solar electricity. The installed capacity of

FIGURE 6: The share of cooling load from the peak of the electricity network in different countries.

solar power plants in the world by 2019 is equal to 627 thousand MW. More than 29 countries had more than a thousand megawatts of solar electricity by 2019 [13]. The price of solar panels is falling with a significant slope [14]. Solar electricity has the largest share of renewable energy types connected to the electricity grid. Some countries, such as Algeria, have paid special attention to solar power to meet the demand of the people [15]. The growth rate of the capacity of solar power plants in the world compared to last year was 28%. Iran has a high potential in the field of solar energy with 1,648,000 km² and 300 sunny days and 2200 kW/m² of radiation capacity. The distribution of solar radiation capacity in Iran is as shown in Figure 9.

3. Method: Stochastic and Agent-Based Modeling

The process of stochastic and agent-based modeling of this study is shown in Figure 10. In this research, the variable

FIGURE 7: Temperature in Tehran from June 22 to July 22.

FIGURE 8: Temperature in Tehran from July 23 to August 22.

state is simulated based on the stochastic model and the basic state is deterministic.

3.1. Agent-Based Models. In agent-based simulations that consider behavioral issues, two deterministic and stochastic approaches are used. Deterministic agent-based models follow certain schedules. Schedules include load profiles that are numerically represented between zero and 1 [16]. Stochastic agent-based models use statistical distributions for determining residents' conditions and behavior [17]. Most stochastic models are developed based on the first-order Markov chain techniques [18, 19]. Data from stochastic models are extracted from time-use surveys that describe

consumer behavior [20]. The number of stochastic agent-based studies is four times more than deterministic approaches [21]. In this research, a stochastic agent-based model is used.

3.2. Behavioral Parameters. Density, presence of residents, and their desired comfort temperature are considered as behavioral parameters of the model. An agent-based cooling simulation that takes into account the presence of individuals differs by approximately 10% from the actual state [22]. This issue shows the high performance of behavioral models to correctly detect the presence of people in the building. It should be noted that most of the behavioral

FIGURE 9: The distribution of solar radiation capacity in Iran.

FIGURE 10: The process of stochastic and agent base modeling (behavioral and bottom-up).

actions of cooling energy consumption in the building occur in the form of comfort temperature (Figure 11). For instance, Hoyt et al. [23] report that the comfort temperature of cooling and heating reflects the behavioral parameters of the household. The behavioral parameters of the research are presented in Tables 3 and 4.

3.3. Determining the Presence of People in the Building Using Time-Use Survey: A Stochastic Approach. A behavioral data-

base of people with the appropriate resolution, which is created by the government in different countries in the form of a time-use survey, is required for stochastic behavioral modeling [24]. The model of Walker and Pokoski [25] is one of the first time-use-based stochastic models. The Richardson model, developed in the United Kingdom based on the 2000 time-use survey, was the inspiration for stochastic behavioral research in this field [18]. The census of the time-use survey conducted by the Statistics Center of Iran

FIGURE 11: Influence of different behavioral characteristics of cooling energy consumption from the presence of people and comfort temperature.

in 2014 and 2015 is according to Table 5. Since our study is related to the power grid peak and this peak occurs in the summer, the census data of summer 2015 was used.

15 activity codes and their classification into 9 groups were performed according to Table 6.

The process of extracting the presence/absence statistics of individuals from the raw data of the time-use survey is shown in Figure 12.

3.4. Markov Chain. In the present study, the Markov chain method was used to understand the stochastic presence of people in the house. Most studies with a stochastic approach use the Markov chain method [26]. A Markov chain is a model for displaying a sequence of random variables in which the probability of each event occurring depends only on the previous event. So, the probability of occurrence of events in such a model depends only on the previous time, and other events do not interfere with the probability.

$$\begin{aligned} P(X_{t+1} = x \mid X_1 = x_1, X_2 = x_2, \dots, X_n = x_t) \\ = P(X_{t+1} = x \mid X_t = x_t). \end{aligned} \quad (1)$$

The Markov chain matrix was displayed as a transition probability matrix. P_{ij} indicates the probability of transition from point i to j . In this way, the transition matrix represents the values of the state space set. In the present study, the state space has 2 elements (Equation (2)). The transition probability matrix is also in accordance with Equation (3). The Markov chain matrix can be represented as a transition probability matrix. P_{ij} indicates the probability of transition from point i to j .

$$S = \{1, 2\} = \{\text{Absence in the building, presence in the building}\}, \quad (2)$$

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix}. \quad (3)$$

In this matrix, according to the principles of probability, it should be $\sum_{j=1}^K P_{ij} = 1$, which is the sum of the probabilities of each row in the matrix must be equal to 1. In general, in the Markov chain, $p_{ij}^{(n)}$ indicates the probability of reaching from state i to j in step.

$$P_{ij}^{(n)} = \sum_{r \in S} P_{ir}^{(K)} P_{rj}^{(n-K)} \cdot \forall K \cdot 0 < K < n. \quad (4)$$

The transition time step in this study is 15 minutes, and the transition probability matrix for each time step should be determined using the Markov chain. An example of a Markov chain step with and without considering the household dimension (Table 4) is shown in Tables 7 and 8.

3.5. Bottom-Up Model. Table 9 shows the specifications of the bottom-up model used to simulate cooling peak loads. According to the data of the Tehran Municipality website, there are more than 2,867,000 residential houses in eight-building groups in the capital of Iran, which in this respect has the largest share in the network peak [27]. In this simulation, the computational core of the EnergyPlus program is used through the user interface of the DesignBuilder software. The open-source and modular features of E+ facilitate the addition of new simulation modules for developers [28]. The computing core has been developed as open-source codes by the US Department of Energy [29]. The Ashrae 90.1 standard is used as the basic mode for simulating new versions of the EnergyPlus Computational Core [16]. The simulated cooling load was converted into electrical load by considering the common cooling equipment in the country according to data of the Statistics Center of Iran (Table 10). A 3-story apartment is simulated for all building groups (Figure 13). The bottom-up model is extended to all building groups with the archetype method.

3.6. Scenarios. In this section, seven scenarios about the comfort temperature and technology upgrade have been developed, and the effects of each on the electric cooling load of the power grid peak are investigated. The formulation of the scenarios is based on the main research model, namely, stochastic and agent-based model.

3.6.1. Ideal Scenario. The ideal comfort temperature in Tehran is about 27 degrees Celsius (Heidari, 2009). 23% (percentage of dispersion of gas coolers, absorption, and compression chillers; water coolers cannot adjust the temperature) of buildings with comfort temperatures of 18, 22, and 30 degrees Celsius set their comfort temperature at 27 degrees. Behavioral characteristics of people during the day and night are determined based on the results of TUS. Grid stability is considered the same during the day and night.

TABLE 3: Behavioral parameters of the model.

Specifications of the model	Parameter	Description	
Probability of the presence of people at home	Stochastic and deterministic	The cooling load is a function of the presence of people and the comfort temperature. The probability of the presence of people at home in the form of a Markov matrix and with the help of the 2015 TUS has been extracted.	
Number of occupants by building groups in Table 1	1 person	“Results of Statistics on Energy Consumption and Environmental Characteristics of Urban Households in 2016” by the Statistics Center of Iran	
	2 persons		
	3 persons		
	4 persons		
	5 persons		
	6 persons and more		
Cooling comfort temperatures by building groups in Table 1	18°C	“Results of Statistics on Energy Consumption and Environmental Characteristics of Urban Households in 2016” by the Statistics Center of Iran	
	22°C		
	27°C		
	30°C		
Population density per m ² of building based on building groups	0.065	50 m ² and less	Development by the author
	0.05	51-75 m ²	
	0.041	76-80 m ²	
	0.038	81-100 m ²	
	0.028	101-150 m ²	
	0.02	151-200 m ²	
	0.0138	201-300 m ²	
	0.0115	301 m ² and more	

TABLE 4: Number and density of people in building groups.

Building groups	Number of residents						Total	Total area (m ²)	Population density per m ²
	1 person	2 persons	3 persons	4 persons	5 persons	6 persons			
50 m ² and less	13361	50303	115762	179617	78403	33023	470471	7159486	0/065
51-75 m ²	63346	350870	852191	1039407	441192	171929	2918937	58473369	0/05
76-80 m ²	15433	108218	192606	288858	124865	74445	804429	19467276	0/041
81-100 m ²	27397	233474	502502	759694	361697	203676	2088443	54706026	0/038
101-150 m ²	30761	249616	652085	1018710	521648	285132	2757956	97432681	0/028
151-200 m ²	6830	55826	113792	183835	91073	65444	516802	25857202	0/02
201-300 m ²	4700	31812	67539	108698	43132	38353	294236	21328404	0/0138
301 m ² and more	1804	15511	23401	19116	18997	25263	104095	9045111	0/0115

TABLE 5: Characteristics of the time-use survey data in this research.

Row	Title	Description
1	Target society	People over 15 years in urban families
2	Statistical time	The statistical time of this plan, depending on the case, is last week or one continuous day and night during the census week.
3	Data collection method	In this survey, the required household information is collected through face-to-face interviews with the most informed household member and the completion of a questionnaire. Personal information is also collected in a self-reported manner by completing a questionnaire by each person aged 15 years and older in the sample household.
4	Sample size	This study was conducted in urban areas of the country for 4 seasons. The sample size in the whole statistical year (autumn and winter 2014 and spring and summer 2015) was equal to 16912 households. In summer, 8248 people belonging to 4228 households were referred.
5	Time step	Time-use of people every 15 minutes is questioned.
6	Activities	All activities that a person does during the day are divided into 15 main groups according to the ICATUS. These 15 groups eventually merge into 9 groups.
7	Place of activity	The location of the activity is given in 22 codes. Three of these 22 codes indicate the presence of people in the house, and 19 codes indicate the absence of people in the house.

TABLE 6: Code of activities and its classification into different groups.

Code	Classification ICATUS	Merged classification
01	Working for companies or quasicompanies, nonprofit organizations, and government (work in the formal sector)	Work and job activities (codes 01 to 05)
02	Working for the family in basic productive activities	
03	Working for the household in nonprimary productive activities	
04	Working for the family in construction activities	
05	Working for the family to provide services for income	
06	Providing unpaid domestic services for final consumption in your household	Household activities (codes 06 to 07)
07	Providing unpaid care services to family members	
08	Providing services to the local community and helping other households	Voluntary and charitable activities (code 08)
09	Learning	Learning activities (code 09)
10	Social participation and sociability	Social participation (code 10)
11	Going to places or visiting cultural, recreational, and sports events	Entertainment (codes 11 and 12)
12	Entertainment, games, and other recreational activities	
13	Participating in indoor and outdoor sports and related courses	Sports activities (code 13)
14	Using mass media	Use of mass media (code 14)
15	Personal maintenance and care	Personal maintenance and care (code 15)

FIGURE 12: A process model for extracting and monitoring data from a time-use survey.

TABLE 7: A step from the Markov chain regardless of the family dimension.

Resolution	Mode	Number	Deterministic probability	Next mode	Number	Probability	Stochastic probability
00:15	Presence	8191	99.3089	Presence	8186	99.9389	0.9924
				Absence	5	0.0610	
	Absence	57	0.6910	Presence	0	0	0.0075
				Absence	57	100	

TABLE 8: A step from the Markov chain considering the family dimension.

Resolution	Probability of presence at least one person at home (deterministic)	Probability of presence at least one person at home (stochastic)
00:15	0.999967	0.999357

3.6.2. Cold Room Scenario. 23% (percentage of dispersion of gas coolers, absorption, and compression chillers; water coolers cannot adjust the temperature) of buildings with comfort temperatures of 18, 27, and 30 degrees Celsius set their comfort temperature at 22 degrees. Behavioral characteristics of people during the day and night are determined

based on the results of TUS. Grid stability is considered the same during the day and night.

3.6.3. Refrigerator Scenario. 23% (percentage of dispersion of gas coolers, absorption, and compression chillers; water coolers cannot adjust the temperature) of buildings with a

TABLE 9: Specifications of the bottom-up model.

Specifications of model	Parameter	Description
Simulation site	Tehran	According to the meteorological data of Tehran in the database of DesignBuilder software
Building type	3-story apartment	The first and third floors correspond to the first and last floors of each building and the second floor as the middle floors of the buildings
Computational core	EnergyPlus	Use DesignBuilder Graphics Interface 6.1.4.00.7
Building direction	20-degree angle with north direction	The predominant orientation of Tehran buildings
Building cooling coefficient	96.1%	96.1% of buildings in Tehran are cooled.
Simulation time steps	15 minutes	
Basic simulation mode	Ashrae 90.1	According to the basic mode of DesignBuilder software
Building materials	Brick, iron, and other common materials in the interior of the building	According to the 2016 Population and Housing Census by the Statistical Centre of Iran
Cooling technology	Common technologies	“Results of Statistics on Energy Consumption and Environmental Characteristics of Urban Households in 2016” by the Statistics Center of Iran
Extension method	Archetype method	This method divides the building section into groups based on infrastructural, dimensional similarities, materials used, and more. The estimated energy for the representative of each group is developed for the whole building sector.
Building groups	50 m ² and less	Sample building: 50 m ²
	51-75 m ²	Sample building: 65 m ²
	76-80 m ²	Sample building: 80 m ²
	81-100 m ²	Sample building: 90 m ²
	101-150 m ²	Sample building: 125 m ²
	151-200 m ²	Sample building: 175 m ²
	201-300 m ²	Sample building: 250 m ²
	301 m ² and more	Sample building: 300 m ²

comfort temperature of 22, 27, and 30 degrees Celsius set their comfort temperature at 18 degrees. Behavioral characteristics of people during the day and night are determined based on the results of TUS. Grid stability is considered the same during the day and night.

3.6.4. Technology Upgrade Scenario. Considering that 65% of the country's buildings use water coolers [30] and 22% use split coolers [31], one of the ways to control the electricity peak is increasing the efficiency of these two types of widely used cooling equipment in buildings. In this scenario, the dominant grade of cooling equipment in Iran, namely, grade G, has been upgraded to grade A. Behavioral characteristics of people during the day and night are determined based on the results of TUS. Grid stability is considered the same during the day and night.

3.6.5. Combined Scenarios. A combination of the above three scenarios (idea, cold room, and refrigerator) and the technology upgrade scenario is examined. Behavioral characteristics of people during the day and night are determined based on the results of TUS. Grid stability is considered the same during the day and night.

Figure 14 shows the flowchart of the research simulation with details.

3.7. Limitations of Model. The limitations of modeling in this study are as follows:

- (i) Markov chain development of the presence of people at home with a time step of 15 minutes has been done for the first time in Iran. Refining the raw data of the Statistics Center's TUS and turning it into a Markov probability chain database is a difficult process with modeling complexities, which in turn has increased the implicit innovations in this research
- (ii) The use of behavioral modeling methods with emphasis on human identity to study the peak of the electricity network has been done for the first time in this research. Lack of data and its integration is one of the limitations of this research
- (iii) Some of the new concepts introduced in this study, such as behavioral flexibility, did not exist before. Therefore, its formulation was limited

TABLE 10: Distribution of cooling equipment used in residential buildings—"Results of Statistics on Energy Consumption and Environmental Characteristics of Urban Households in 2016" by the Statistics Center of Iran.

Cooling equipment	%	Energy grade	%
Absorption chiller	0/4	A	38.9
		B	8.2
		Not stated	52.9
Compression chiller	0.1		
Fan coil	0.2	A	19.2
		C	16.5
		E	26.7
		None	13.2
		Not stated	24.3
Refrigeration package	0.2	A	21.5
		B	35.4
		C	5
		Not stated	38
Split cooler	9.8	A	32.7
		B	13.7
		C	2.8
		D	1.3
		E	1
		F	0.1
		G	0.2
		None	15.1
		Not stated	33.1
Water cooler	56.8	A	9.4
		B	5.3
		C	4.7
		D	1.9
		E	2
		F	1.6
		G	1.3
		None	31.8
		Not stated	42
Fan	5.4		
Water cooler and split cooler	0.8		
Water cooler and split cooler and fan	0.7		
Water cooler and fan	14		
Split cooler and fan	11.5		
Other	0.1		
	100		

4. Results

4.1. Model Validation. According to Figure 15, the results of the basic state of the model showed that the electric load of the model on the peak day is 2 to 8% different from the real state, which is a good adaptation.

FIGURE 13: A sample simulated house for a building group.

4.2. Results of Basic State. The distribution of high electricity consumption hours during the day and night in the summer of 2019 and 2020 is shown in Figure 16. The distribution of peak hours of the night in summer 2019 and 2020 is similar and between 20 and 22, especially at 21:30. The peak hours of the day in the summer of 2019 were between 14:00 and 16:50. However, most of the peak hours in summer 2020 were around 12:00 and 14:30. The peak of the day in summer 2020 compared to 2019 has 2 hours back.

Figure 17 shows the stochastic and deterministic probabilities of the presence of people in the building. The maximum difference between the probabilities of at least one person at home in a stochastic state with a deterministic state is 5%, which occurs at 14:24. From 12 a.m. to 7:12 p.m., the difference between stochastic and deterministic probabilities is between 2 and 3%. Between 10 and 15 o'clock, the difference between the stochastic and deterministic probabilities is about 2%. From 16:48 to 24, the difference between the stochastic and deterministic probabilities of the presence of people decreases and goes to zero.

The most excellent behavioral flexibility in reducing the peak is 12 to 14 (Figure 18). Therefore, a strategy in peak shaving is to direct the peak time to these hours.

From 11 a.m. to 5 p.m., the behavioral flexibility potential of household cooling energy consumption is between 70 and 134 MW, which is approximately equal to 10% of the cooling peak of Tehran's electricity grid. Table 11 shows the potential for behavioral flexibility on the network peak day by building groups.

From 1:45 to 6 a.m., the behavioral flexibility potential of household cooling energy consumption is about 50 to 65 MW (Figure 19 and Table 12), which is approximately equal to 5% of the cooling peak of the Tehran power grid.

4.3. Results of the Scenario. The cooling load peaks in the refrigerator (1.48 GW) and combined (ideal temperature and technology upgrade) (0.97 GW) scenarios are the maximum and minimum cooling loads in Tehran, respectively. The distance of 500 MW of these two scenarios indicates the high potential of reducing the peak of Tehran's power

FIGURE 14: Research modeling flowchart.

FIGURE 15: Model validation, comparison of simulated electricity load, and real electricity load in Tehran.

FIGURE 16: Distribution of day and night peak times in summer 2019 and 2020.

FIGURE 17: Stochastic and deterministic probabilities of presence.

grid by adjusting the comfort temperature and technology upgrade. As the efficiency of cooling technologies increases, the average cooling load in all comfort temperature scenarios decreases between 250 and 400 MW, and up to 25% of the network peak is reduced compared to the base scenario. The maximum difference between stochastic and deterministic electric loads in the refrigerator and cold sce-

narios is 154 MW and 139 MW, respectively. This shows the flexibility of cooling energy consumption based on the presence of people in the building, in different scenarios. As productivity decreases, the potential for behavioral flexibility in energy consumption increases. The same thing happened in night peak scenarios (Figures 20–33 and Tables 13 and 14).

FIGURE 18: Basic electricity consumption and comparison of stochastic and deterministic electric load (day).

TABLE 11: Behavioral flexibility potential of cooling energy consumption by different building groups (day).

Building groups	Average potential for behavioral flexibility (MW)	Timespan	Maximum potential for behavioral flexibility (MW)	Time point
50 m ² and less	About 4.3	12 to 16:15	5.8	13:30
51-75 m ²	About 25.4	11 to 16:30	39	12
76-80 m ²	About 5.3	10:30 to 17	8.75	12
81-100 m ²	About 14	10:30 to 16:45	27	12
101-150 m ²	About 18	10:45 to 16:15	34	12
151-200 m ²	About 6.8	10:45 to 16:45	12.5	12
201-300 m ²	About 1.5	10:30 to 18	3.1	12
301 m ² and more	About 0.8	10:45 to 16:45	1.4	12

FIGURE 19: Basic electricity consumption and comparison of stochastic and deterministic electric load (night).

TABLE 12: Behavioral flexibility potential of cooling energy consumption by different building groups (night).

Building groups	Average potential for behavioral flexibility (MW)	Timespan	Maximum potential for behavioral flexibility (MW)	Time point
50 m ² and less	About 1.2	1:45 to 6	2.9	4:15
51-75 m ²	About 15.2	2 to 6	17.2	4:30
76-80 m ²	About 0.65	2 to 6	2.8	4:30
81-100 m ²	About 5	1:45 to 6	11.2	4:15
101-150 m ²	About 7	1:45 to 6	16.3	4:15
151-200 m ²	About 1.1	2 to 6	2.8	4:15
201-300 m ²	About 0.9	1:45 to 6	1.9	4:15
301 m ² and more	About 0.2	2:45 to 6	0.6	4:15

FIGURE 20: Different modes in the ideal comfort temperature scenario (day).

FIGURE 21: Different modes in the cold room scenario (day).

FIGURE 22: Different modes in the refrigerator scenario (day).

FIGURE 23: Different modes in the technology upgrade scenario (day).

FIGURE 24: Different modes in the combined scenario (ideal temperature and technology upgrade) (day).

FIGURE 25: Different modes in the combined scenario (cold room and technology upgrade) (day).

FIGURE 26: Different modes in the combined scenario (refrigerator and technology upgrade) (day).

FIGURE 27: Different modes in the ideal comfort temperature scenario (night).

FIGURE 28: Different modes in the cold room scenario (night).

FIGURE 29: Different modes in the refrigerator scenario (night).

FIGURE 30: Different modes in the technology upgrade scenario (night).

FIGURE 31: Different modes in the combined scenario (ideal temperature and technology upgrade) (night).

FIGURE 32: Different modes in the combined scenario (cold room and technology upgrade) (night).

FIGURE 33: Different modes in the combined scenario (refrigerator and technology upgrade) (night).

TABLE 13: Comparison of different scenarios (day).

Scenarios	Stochastic				Deterministic			Maximum of behavioral flexibility (MW)	Behavioral flexibility compared to base scenario (MW)
	Maximum load (GW)	Maximum difference with the base scenario (MW)	Decrease or increase compared to the base scenario in maximum load (%)	Maximum load (MW)	Maximum difference with the base scenario (MW)	Decrease or increase compared to the base scenario in maximum load (%)	Maximum difference with the base scenario (MW)		
Base scenario	1.29	—	—	1.33	—	—	—	—	134.64
Ideal scenario	1.24	-48.7	-3.75	1.28	-47.4	-3.8	-48.7	-4.94	129.7
Cold room scenario	1.33	42.27	3.00	1.37	41.12	3.1	42.27	4.28	138.92
Refrigerator scenario	1.48	195.9	14.28	1.52	190.5	14.72	195.9	19.83	154.47
Technology upgrade scenario (basic mode and technology upgrade)	1.008	-293.66	-22.03	1.037	-285.62	-21.8	-293.66	-29.71	104.93
Combined scenario (ideal temperature and technology upgrade)	0.97	-332.4	-24.96	0.998	-323.3	-24.8	-332.4	-33.63	101.01
Combined scenario (cold room and technology upgrade)	1.03	-261.53	-19.62	1.069	-254.36	-20.15	-261.53	-26.46	108.18
Combined scenario (refrigerator and technology upgrade)	1.15	-141.89	-11.27	1.18	-138	-10.85	-141.89	-14.34	120.3

TABLE 14: Comparison of different scenarios (night).

Scenarios	Deterministic			Stochastic			Maximum of behavioral flexibility (MW)	Behavioral flexibility compared to base scenario (MW)
	Maximum difference with the base scenario (MW)	Decrease or increase compared to the base scenario in maximum load (%)	Maximum load (MW)	Maximum difference with the base scenario (MW)	Decrease or increase compared to the base scenario in maximum load (%)	Maximum load (GW)		
—	57.86	—	—	0.934	—	—	0.932	Base scenario
-3.26	54.6	-53.44	-5.78	0.880	-53.44	-5.68	0.879	Ideal scenario
1.58	59.44	25.85	2.78	0.960	25.85	2.78	0.958	Cold room scenario
7.62	65.48	122.95	13.16	1.057	122.93	7.83	1.055	Refrigerator scenario
-12.77	45.09	-206.15	-22.05	0.728	-206.12	-22.10	0.726	Technology upgrade scenario (basic mode and technology upgrade)
-15.33	42.53	-248.33	-26.65	0.685	-248.30	-26.60	0.684	Combined scenario (ideal temperature and technology upgrade)
-11.58	46.28	-186.57	-20.02	0.747	-186.55	-20.06	0.745	Combined scenario (cold room and technology upgrade)
-6.87	50.99	-110.96	-11.88	0.823	-110.94	-11.80	0.822	Combined scenario (refrigerator and technology upgrade)

5. Conclusions

This study has estimated the electric cooling load of Tehran at the peak moment by stochastic and agent-based modeling. Density, presence of residents, and comfort temperature separately sorted by all building groups are considered as behavioral parameters of the model. Stochastic and deterministic presence of people based on the raw census data of the time-use survey of the Statistics Center of Iran in the summer of 2015, which was performed among 4228 households, was modeled using the Markov chain method for each time step of 15 minutes. The EnergyPlus computing core (DesignBuilder user interface) was used to develop the bottom-up model. In this study, scenarios based on household comfort temperature were developed. The results of this study showed that the most behavioral flexibility in reducing the peak is related to the 12 to 14 o'clock. So, a strategy in peak shaving is to direct the peak time to these hours. From 11 a.m. to 5 p.m., the behavioral flexibility potential of household cooling energy consumption is between 70 and 134 MW, which is approximately equal to 10% of the cooling peak of Tehran's electricity grid. The cooling load peak in the refrigerator (1.48 GW) and combined (ideal temperature and technology upgrade) (0.97 GW) scenarios are the maximum and minimum cooling loads in Tehran, respectively. The distance of 500 MW of these two scenarios indicates the high potential of reducing the peak of Tehran's power grid by adjusting the comfort temperature and technology upgrade. The maximum difference between stochastic and deterministic electric loads in the refrigerator and cold scenarios is 154 MW and 139 MW, respectively. As productivity decreases, the potential for behavioral flexibility in energy consumption increases. As the efficiency of cooling technologies increases, the average cooling load in all comfort temperature scenarios decreases between 250 and 400 MW, and up to 25% of the network peak is reduced compared to the base scenario. The same thing happened in night peak scenarios. This study, we developed possible scenarios of household comfort temperature and technology upgrade that provide a powerful tool for policymakers to manage and control the grid peak, while estimating the behavioral flexibility of reducing the power grid peak (almost 10%) and modeling energy consumption based on behavioral parameters with a resolution of 15 minutes. Based on the power deficit in 2018, 2000 megawatts of solar power capacity must be added to the network at peak times to meet grid demand.

Data Availability

The data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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