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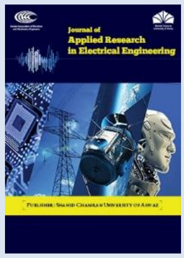

Research Article

Energy Management in Distribution Systems Considering Consumer Behavior and Internet of Things

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Abstract: Internet of Things (IoT)-based energy management systems (EMSs) are considered a new technology in which consumers can manage their electricity payments according to their preferences, such as reducing costs or increasing satisfaction. Each consumer has its own program for communicating with a central control unit. In addition, the central control unit that is responsible for energy pricing can access consumer information and network performance status through the IoT infrastructure. Therefore, technical analysis can be performed using big data to determine the optimal price in order to make a compromise between the buyer and the goals of the distribution system operators. This paper presents a model to accurately assess the impact of pricing on the behavior of IoT-based energy systems. Then, according to the load specifications of each item and the technical limitations of the distribution network, the best time to use pricing is determined. The results show that the higher the price variance, the more discomfort the consumer and the lower the daily payment. Therefore, in this paper, the main goal of energy management is to minimize the total weight of the costs paid and their discomfort level. The paper could facilitate further penetration of IoT-based EMSs into smart grids. The study was performed on an IEEE standard 33-bus network. Optimization was implemented using YALMIP and MOSEK toolboxes. Therefore, it can be concluded that IoT technology allows consumers to enjoy the benefits of the network and makes optimal consumption management possible.

Keywords: Internet of things, distribution networks, energy management, smart grids, consumer discomfort.

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NOMENCLATURE

Symbol	Description
Variables	
c_t^{DG}	Generation price of DG
$c_{t,wholesale}^{DG}$	Wholesale rate of DG generation
c_t^{TOU}	Retail rate with ther term of use
c_{nl}^{TOU}	Term of use rate of the no-load
c_{ml}^{TOU}	Term of use rate of the mid-load
c_{pl}^{TOU}	Term of use rate of the peak-load
$c_t^{TOU,wholesale}$	Wholesale rate market with a term of use
$c_{min}^{TOU,wholesale}$	Min wholesale rate market with a term of use
$c_{max}^{TOU,wholesale}$	Max wholesale rate market with a term of use
c_{min}^{TOU}	Min retail sell rate market with a term of use
c_{max}^{TOU}	Max retail sell rate market with a term of use
$\underline{C}$	The minimum amount of rate market with a term of use
$\overline{C}$	The maximum amount of rate market with a term of use
E_t^S	The energy level of the storage system
$\underline{E}_t^S, \overline{E}_t^S$	The min/max energy level of the storage system

$E^S_{t_{ini}}, E^S_{t_{final}}$	Initial/final mode of charging the storage system
$MUT^{\mathcal{L}}$	Minimum loading time
$N(\varepsilon^i_1)$	Number of consumers with the ε^i_1 coefficient
$\mathcal{P}^{base}_n$	The node basis electricity of n
$\mathcal{P}^{DG}_t$	Retail electricity purchase from DG
$\mathcal{P}^{DG}_{t,wholesale}$	Wholesale electricity purchase from DG
$\underline{\mathcal{P}}^{DG}_t, \overline{\mathcal{P}}^{DG}_t$	Min/max range of DG
$\mathcal{P}^{Grid}_t$	Electricity purchase of the net
$\mathcal{P}^{Grid}_{i,t}$	Electricity purchase of the net by consumer i
$\underline{\mathcal{P}}^{Grid}_t, \overline{\mathcal{P}}^{Grid}_t$	Min/max range of the net power
$\mathcal{P}^{UpGrid}_t$	Electricity purchase of the upstream net
$\mathcal{P}^{\mathcal{L}}_t$	Electric power of load
$\breve{\mathcal{P}}^{\mathcal{L}}_t$	Ideal electric power of load
$\hat{\mathcal{P}}^{\mathcal{L}}_t$	Nominal electric power of load
$\mathcal{P}^S_t$	Electric storage charging
$\underline{\mathcal{P}}^S_t, \overline{\mathcal{P}}^S_t$	Min/max electric storage charging
$t, \Delta t$	Time distance and its duration
t_{ini}, t_{final}	Initial and final time
$t^{\mathcal{L}}_{operation}$	Operating time for each load
$t^{\mathcal{L}}_{des}$	Desired time to start the time flexible load
$\gamma^{\mathcal{L}}_t$	Discomfort rate of the load
$\xi^{\mathcal{L}}_t$	Changing load situation
$\tau^{\mathcal{L}}_t$	Binary for turn on/turn off situation of the load
σ^2_{TOU}	Rate amount with a term of use
$\sigma^2_{TOU,desired}$	Desired rate amount with a term of use
h_{nl}	No load factor
h_{md}	Medium load factor
h_{Peak}	Peak load factor
Parameters	
$Pr^{new}(\chi)$	New Possibility related to the χ
$\mathcal{T}$	Collection of time parts
$\delta^{\mathcal{L}}_t$	A hypothetical vector that shows the effect of time delay on time flexible loads
$\varepsilon_1, \varepsilon_2$	Coefficients Weighting of the consumer cost
ε^i_1	Weight Coefficient of the i^th consumer cost
$\Omega^{Bus}, \Omega^{DG}, \Omega^{Line}$	Collection of DGs , lines , nodes
$\Omega^{TFL}, \Omega^{PFL}, \Omega^{NFL}$	Collection of time flex, power flex, and non-flex loads
$\Omega^{Load}, \Omega^{customers}$	Collection of loads, consumers
$\Omega^{storage}$	Collection of batteries
d_{KL}	Kullback Leibler distance
$f_{customer}$	The fitness function of consumer
$f_{discomfort}$	Discomfort cost
$f_{Payment}$	Electricity payment cost
L^{Total}_t	Total load; considering normal consumer behavior
PD^{total}_t	The total power demand of the net
PD^t_n	Node load of n
$\mathcal{P}^{\mathrm{base}}_{\mathrm{Total}}$	The general basis power of the net
$\mathrm{Pr}(\varepsilon^{\mathrm{i}}_1)$	Possibility related to the $\varepsilon^{\mathrm{i}}_1$
$\mathrm{Pr}(\chi)$	Possibility related to the χ

1. INTRODUCTION

The Internet of Things (IoT) has transformed traditional energy management systems into responsive embedded systems that reflect consumer preferences in their energy supply process [1]. The concept of IoT is somehow simple while its practical implementation requires several infrastructures such as communication systems, instruments, sensors, actuators, control, and protection systems [2-3]. Bilateral communication of costumers with smart grid operators will have several technical and economic benefits for various components of the system including consumers, distribution system operators, and central control units (e.g., government entities) [4]. The IoT technology is a technology similar to smartphone architectures but it is more complex since data is shared among several sensors and actuator interfaces simultaneously. Each home utility can share its data via the Internet and contribute to distribution system management with or without the presence of smart meters. IoT application in smart homes has been reviewed in [5] in view of technical challenges in the communication protocol and interoperability. The potential of the US electricity grid for the implementation of the IoT system has been investigated in [6]. A review of smart cities operating with IoT has been presented in [7]. Several merits of IoT-based systems have been investigated in [8]. Distribution operation cost minimization, loss minimization, encouragement of renewable energy resource utilization, end-user payment minimization, and customer satisfaction improvement have been enumerated as the main economic benefits of IoT development [9]. Moreover, some technical benefits such as load profile flattening, peak shaving, loss minimization, and voltage deviation optimization can be achieved by this technology. Here, we concentrate on how these benefits can be achieved by properly modeling IoT-based energy management systems (EMSs). An IoT-based framework has been introduced in [10] for the integration of energy storage and renewable energy resources in distribution systems. An autonomous energy management cost reduction solution has been proposed in [11] using the home energy management system (HEMS). IoT has found its way into smart grids, especially in distribution systems. Demand-side management can be more efficient in the presence of IoT. IoT-based EMSs can have bidirectional communication with smart grids and decide according to their preferences, time-of-use pricing, and flexible devices. Therefore, customers would consume electricity more interactively [12].

The future of IoT does not seem to be unforeseen. Various legal projects are running recently to practically implement IoT in smart grids. A smart IoT-based substation has been designed by the cooperation of Siemens and Glitre Energi Nett (a Norwegian distribution system operator (DSO)) as a pilot project to improve reliability through earlier fault and risk detection, continuous monitoring, cloud-based operating system, and maintaining cybersecurity [13]. CyberSANE is another innovative dynamic security system for continuous learning of cyber attacks of IoT-based environments with a budget of over six million EUR. Several capabilities of these systems are threat prevention and detection, security exploitation, risk information analysis, and protection [14]. A comprehensive centralized structure for microgrid operations, including active and reactive power sources, is presented in this paper. In this method, distributed generation (DGs), energy storage systems (ESS), response demand program (DR), load change scheme, changeable capacitor banks, and plug-in hybrid electric vehicles are considered simultaneously [15]. This paper deals with the optimal energy management and performance of network microgrids by considering different types of portable units such as fuel cells and microturbines and inseparable units such as wind turbines and solar units. To change the role of vehicle-only consumption to an active role with the potential for profitability, vehicle network (V2G) technology is presented in [16].

In recent years, with the rapid development of the battery energy storage industry, its technology has demonstrated the features and processes of large-scale integration and distributed multi-objective applications. As a grid-level application, EMS, a real-time battery energy storage system, was deployed in instrument control centers as an important component of grid management. Based on the analysis of the development status of a BESS. This paper introduced practical scenarios such as reducing output power fluctuations, agreeing with the output plan on the side of renewable energy production, regulating the frequency of the power grid, and optimizing the current flow in power transmission [17]. This paper provides presentation, deployment, and validation of an IoT-based SEMS strategy and its related benefits to overcome challenges of energy management on the consumer side. The presented SEMS incorporates various communication interfaces and protocols to integrate with any software-based smart solution [18]. A two-layer in-depth secured management architecture has been proposed in [19] for the optimal operation of energy Internet in hybrid microgrids. In the cyber layer of the proposed architecture, a two-level intrusion detection system is proposed to detect various cyber-attacks (i.e., Sybil attacks, spoofing attacks, false data injection attacks) on wireless-based advanced metering infrastructures [19].

In previous research, demand response has been used to manage the energy of distribution networks. So far, the analysis of the issue of energy management with IoT has not been considered. Also, most studies have not considered the issue of changing consumer behavior as an essential parameter in energy management. Distribution energy resources are modeled based on the traffic flow of computer network principles. This paper quantitatively analyzes an IoT-based EMS in a distribution system. A practical and straightforward framework is presented to facilitate the control of this system. This framework considers the benefits of both customers and DSOs simultaneously. Several analyses are presented to show the effect of time of use (ToU) variance and customer satisfaction factor on either economic (e.g., total payment and discomfort cost of customers) or technical parameters (such as peak load, average load, and load factors). The results show that this framework can provide more benefits from the IoT infrastructure of smart grids.

The innovations of the paper are as follows:

1. Performing an EMS in the presence of the IoT
2. Using the Kohlberg convergence distance to show the difference between the general consumer distribution function and the normal distribution function
3. Considering the effect of changes in consumer behavior on energy management in the presence of IoT
4. Considering the effect of consumer discomfort on energy management in the presence of IoT

The rest of the paper is organized as follows. Section 2 describes the model of the problem and the governing relationships that will be extracted. Section 3 presents the simulation data and its results. Section 4 provides some conclusions.

2. Model Description

The case study is a radial distribution network that has several residential loads connected via IoT technology. Each home in the network has a renewable energy resource (photovoltaic, in this paper), an energy storage unit, nonflexible load, time flexible load, and power flexible one. Each consumer has his/her preference to select the weight of payment and discomfort. The IoT-based EMS receives the day ahead of the ToU tariff from the central control unit, schedules all flexible or nonflexible loads according to user preferences, and sends this information to the central unit for more analysis. Then, the aggregated load is calculated by the central control unit and sent to the power system operators to be used for distribution system studies. The operators use this information for optimal power flow (according to its benefits) and extract any technical or economic violations and communicate the results to the central unit. Again, the price is adjusted by the central unit to provide the optimal solution. It is assumed that the DSO is just concerned about peak load level. No optimal power flow or security constraints are considered for the power system operator. Just load level is selected as a limitation for simplicity. So, at first, the IoT-based EMS model is presented.

The mathematical model of the problem optimization is fully described here. The control system type is a combination of decentralized and centralized control. The home energy management department is managed locally based on its interests and the information transmitted to it from the central server. The necessary analyses are performed on it, and the results are sent back to the central server. Based on the information received by the central server, a decision is made on changing or not changing the price of electricity based on the interests of the central server, these changes are sent to the home energy management units, the results are sent intermittently until the best decision is made, and the information is provided on the web and sent to the consumer program so that they can consume electricity accordingly. IoT offers a structure for communicating and managing different parts of the distribution system. There are many benefits to using IoT for consumers, DSO, and the power market. Decisions can be made based on the limitations, benefits, information received from the Internet of Things Central Unit, and new information sent to each unit. Data analysis is then performed in the center to gather the final optimization decision. Fig. 1 shows the structure of IoT. In this structure, consumers, DSOs, and the power market connect to the center through communications.

Electricity consumers take the time-based tariff price from the center and return the load profile to the center (power purchased from the grid) for extensive data analysis. The electricity procured from the upstream network gets even to

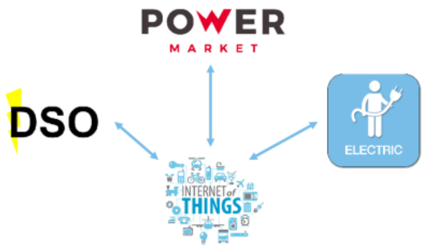

Fig. 1: The schematic of the proposed IoT-based infrastructure.

the center. Then, to achieve the optimal time consumption and wholesale tariff, the amount of power purchased from the wholesale and consumer markets is sent to the electricity market. These prices are then sent to the center. This process is repeated until the best price is reached.

2.1. MILP Model of Consumers Behavior

The HEMS finds information about the home's electrical equipment and the number of typical desires. It optimizes domestic electricity consumption based on the electricity received from the central server. In general, loads of a home can be divided into three categories: nonflexible loads (NFLs), time flexible loads (TFLs), and power flexible loads (PFLs). NFLs are unchangeable and are operated at the desired time and with a specific power. TFLs can shift time, and the consumer can change the operating time according to his/her interests. The third category is flexible loads with a specific working time but can be increased or decreased depending on the conditions. It is also assumed that each home is equipped with renewable resources and storage. The use of renewable resources is also included in the cost. The user can choose to supply a few percent of his energy from renewable sources and a few percent from upstream network electricity depending on the cost of using renewable products or the price of electricity. In this study, the purpose of EMS is to minimize the weight of the costs paid and the amount of their discomfort. Therefore, the objective function of EMS will be equal to

$$fcustomer = \varepsilon_1\, fpayment + \varepsilon_2\, \mathrm{fdiscomfort} \tag{1}$$

in which the first term is related to the costs paid by consumers, which includes two costs: (a) the cost of electricity purchased from the network and the cost of electricity provided by DG, which is calculated by (4). The second term is also related to the cost of consumer welfare or discomfort, which is due to the difference between the electricity consumed and the desired consumption pattern being predetermined according to (5). There is a predetermined pattern of electricity consumption. If electricity consumption conforms to this pattern, there will be no discomfort. Otherwise, a cost of discomfort will be added to the objective function. The ε_1 and ε_2 weighting coefficients indicate the consumer's desire to pay or discomfort. According to (2), the sum of these coefficients must be equal to 1 and have positive values where ε_1 and ε_2 are constant coefficients selected as:

$$\begin{aligned} &\varepsilon_1 + \varepsilon_2 = 1 \\ &\varepsilon_1 , \varepsilon_2 \geq 0 \end{aligned} \tag{2}$$

The selection of these coefficients is entirely on the consumer's basis, and based on their selection, the analysis and studies are performed for domestic energy management. Therefore, each consumer has complete control over the choice of their interests. It should be noted that the vector of domestic energy management decision variables is equal to :

$$\begin{aligned} &\mathrm{X}=[P_t^L, \tau^L ,\ldots\ldots, P_t^S, E_t^S, \ldots\ldots, P_t^{DG}], \\ &\mathrm{L} \in \Omega^{Load}, \mathrm{DG} \in \Omega^{DG}, \mathrm{S} \in \Omega^{Strg}, \mathrm{t} \in T \end{aligned} \tag{3}$$

which includes the power of each load, their time delay, the power of energy storage, the management of DG sources, and the energy level of the storage. All variables in this program are real numbers. Equation (1) can be rewritten as (4) and (5). In (4), $f_{payment}$ consists of two terms. The first term shows the amount paid by consumers to the upstream network, and the second term shows the amount paid by consumers to DG. In (5), $f_{discomfort}$ also consists of two terms; the first term shows the degree of discomfort with PFLs, and the second term shows the degree of discomfort with TFLs. In the first term, when the power consumption is equal to the desired power of the network, there will be no discomfort. Still, if the power consumption is more than the desired power, discomfort is caused by PFLs, which are multiplied by the price of electricity. In the second term, fines are imposed for TFLs. This penalty is considered when the consumption of these loads is more than the allowable limit. Otherwise, there will be no discomfort.

$$f_{payment} = \sum_{t\in T} (C_t^{TOU}\, P_t^{Grid} + C_t^{DG} P_t^{DG}) \tag{4}$$

$$\begin{aligned} f_{discomfort} = &\sum_{t\in T} \sum_{\mathrm{L}\in\Omega^{PFL}} \gamma_t^L \,(P_t^{\sim L}\_P_t^L\ ) \\ &+ \sum_{t\in T} \sum_{\mathrm{L}\in\Omega^{TFL}} \gamma_t^L \delta_t^L \tau_t^L \end{aligned} \tag{5}$$

In (6), δ_t^L is a hypothetical vector that shows the effect of time delay on TFLs and is expressed as follows:

$$\delta_t^L = \begin{cases} 0 & t \leq t_{des}^L \\ t - t_{des}^L & t > t_{des}^L \end{cases} \tag{6}$$

Also, $\tau_t^{\mathcal{L}}$ is a fixed fine for any kind of load, γ_t^L is the price of electricity, and $\breve{\mathcal{P}}_t^{\mathcal{L}}$ is the shape of the desired load for each PFL. It can be determined as follows as per the consumers' desire:

$$\breve{\mathcal{P}}_t^{\mathcal{L}} = \begin{cases} \breve{\mathcal{P}}_t^{\mathcal{L}} & t \in t_{operational}^L \\ 0 & t \notin t_{operational}^L \end{cases} \tag{7}$$

Equation (7) states that ideal PFLs must operate at rated power at the allowable period distance and be OFF at other times. Assuming (1) to (7), the priorities of the consumer objective function can be called linear. Also, the electricity consumption of PFLs is a continuous variable, and the execution time of TFLs are binary variables. Domestic energy management should be done so that the boundary conditions of the problem are observed. To achieve an acceptable method, which is listed below, various boundary constraints shall be met.

$$\sum_{L\in\Omega^{Load}} P_t^L + \sum_{S\in\Omega^{Storage}} P_t^S = \sum_{DG\in\Omega^{DG}} P_t^{DG} + P_t^{Grid} \tag{8}$$

$$\sum_{L\in\Omega^{Load}} P_t^L = \sum_{L\in\Omega^{PFL}} P_t^L + \sum_{L\in\Omega^{TFL}} P_t^L + \sum_{L\in\Omega^{NFL}} P_t^L \tag{9}$$

$$0 \le P_t^L \le \breve{\mathcal{P}}_t^{\mathcal{L}}, \quad \forall L \in \Omega^{PFL}, t \in T \tag{10}$$

$$P_t^L = \tau_t^L \breve{\mathcal{P}}_t^{\mathcal{L}}, \forall L \in \Omega^{TFL}, \ t \in T \tag{11}$$

$$P_t^L = \breve{\mathcal{P}}_t^{\mathcal{L}}, \forall L \in \Omega^{NFL}, \ t \in T \tag{12}$$

$$E_{t+1}^S = E_t^S + P_t^S \Delta t, \forall S \in \Omega^{Strg}, \ t \in T \tag{13}$$

$$P_{-t}^S \le P_t^S \le P_t^{-S}, \ \forall S \in \Omega^{Strg}, \ t \in T \tag{14}$$

$$E_{-t}^S \le E_t^S \le E_t^{-S}, \quad \forall S \in \Omega^{Strg}, t \in T \tag{15}$$

$$E_{tfinal}^S = E_{tini}^S, t_{final}, t_{ini} \in T, \forall S \in \Omega^{Strg} \tag{16}$$

$$P_{-t}^{DG} \le P_t^{DG} \le P_t^{-DG}, \quad \forall DG \in \Omega^{Strg}, t \in T \tag{17}$$

$$P_{-t}^{Grid} \le P_t^{Grid} \le P_t^{-Grid}, \quad t \in T \tag{18}$$

$$\tau_t^L \in \{0,1\}, \forall L \in \Omega^{FTL}, \ t \in T \tag{19}$$

$$\xi_t^L = \tau_t^L - \tau_{t-1}^L, \forall L \in \Omega^{FTL}, \ t \in T \tag{20}$$

$$\tau_{ti}^L \ge \xi_t^L, \forall L \in \Omega^{FTL}, ti \in [t, t + MUT^L - 1] \tag{21}$$

Equation (8) shows the total power distributed generation and electricity procurement from the network, which should be equal to the power consumption of the load and the charging power of the energy storage. Equation (9) shows that the sum of three load types equals the total network load. PFLs turn on and off at certain times that cannot be changed, and only their rated power in this range can change between zero (off) to their ideal level. According to Equation (10), other types of loads are flexible so that their on and off times can be moved, but no change can be made in the value, and only the entire ideal customer curve can be shifted in the time domain only according to (11). Given that neither time nor consumer power can be changed and shifted in nonflexible loads, the power and energy level of energy storage devices should always be within their minimum and maximum range according to (14) and (15). Also, the relationship between charging power and storage energy level is determined by (13). The battery energy level at the beginning and end of the study period should also be calculated by (16). The power level harvested from each of the DGs should be in a range from minimum (usually zero) to maximum (available renewable power), and the electricity purchase from the upstream network must be within the minimum and full capacity according to (17) and (18). Equation (19) shows the constraints of a binary variable. Equations (20) and (21) mean that when a TFL is on, that is $\xi_t^{\mathcal{L}} \ge 1$, they cannot be turned off in the time interval $[t, t + MUT^{\mathcal{L}} - 1]$ due to $\tau_{t_i}^{\mathcal{L}} \ge \xi_t^{\mathcal{L}} \ge 1$ constraints. Upon receipt of ToU price data from the center, each consumer proceeds to plan the load according to their interest. Customers can choose the weight of ε1 to show their demands between reducing electricity payment and discomfort costs. Also, energy storage provides the option to preserve energy at charge and discharge energy at higher price distances. NFLs can overstep their defined values acceptably. Still, TFLs can vary their operative time, and PFLs can regulate their electrical power at work to provide favorable cost and discomfort. After planning, the total net hourly consumption information of each consumer is sent to the center to be utilized in data analysis [12].

2.2. Impact of Price Tariff at Time of Use on Consumer Behavior

First, the role of pricing tariffs in various parameters of a smart home is evaluated. It is assumed that the price of electricity follows the tariff of consumption time, and the hours of the day are divided into three parts: no-load, medium load, and high load as shown in Table 1.

To investigate the effect of price variations on the subject, different scenarios have been considered. In these scenarios, it is assumed that the average consumption time tariff is equal to the unit value of a per unit (PU) to create a competitive environment between renewable products and the electricity distribution network. If the average price of electricity tariff is higher than a renewable generation, the consumer will have an intense desire for DG, and if the average price of this tariff is less than DG, the consumer will prefer to consume all its consumption from the supply network. Therefore, to balance, it is assumed that the average tariff is equal to the price of DG, i.e., PU. But, to model price variations, a parameter called the standard deviation of price standard had been used. The typical (consumer) reaction to price changes is essential. Undoubtedly, changing the price variance can affect consumer behavior. Therefore, a model for determining the consumption hour tariff based on the standard deviation and the average tariff is formed as follows, the purpose of which is to find the tariff related to each hour of the day and night. The times of no-load, medium load, and peak load are pretty clear. The mean and standard deviation of the price is also considered a particular input parameter of the problem, the allowable limits of which are based on Table 1. The price of electricity is related to the periods of no-load, medium load, and peak load as to be unknown. Therefore, the equation system is formed as follows:

$$h_{nl} C_{nl}^{TOU} + h_{md} C_{md}^{TOU} + h_{Peak} C_{Peak}^{TOU} = \mathrm{T}\mu \tag{22}$$

$$h_{nl}(C_{nl}^{TOU} - \mu)^2 + h_{md}(C_{md}^{TOU} - \mu)^2 + h_{Peak}(C_{Peak}^{TOU} - \mu)^2 = \mathrm{T}\mu \tag{23}$$

$$C_{nl}^{TOU} \le C_{md}^{TOU} \ge C_{Peak}^{TOU} \tag{24}$$

$$\underline{C} \le C_{nl}^{TOU} \ge \overline{C} \tag{25}$$

$$\underline{C} \le C_{md}^{TOU} \ge \overline{C} \tag{26}$$

$$\underline{C} \le C_{Peak}^{TOU} \ge \overline{C} \tag{27}$$

To better understand the answers to the problem, a drawing method has been used to display the answers. Equation (23) represents an ellipse in three-dimensional space. Equation (22) corresponds to a plane in space, and Equations (24) to (27) also represent the ranges that divide space by a similar plane into two parts. The answer to the problem is obtained by sharing the answers of all these

Table 1: Network electricity consumption hours [12].

	No load	Mid load	Peak load
Time	11pm-7am(8 hr)	7am-19pm(12hr)	19pm-2pm(4hr)
Price	0-3pu	0-3pu	0-3pu

subspaces according to Fig. 3. There are various ways to solve this problem where it can be converted into a conical optimization form and solved using MOSEK and YALMIP toolboxes. The standard form of optimization is as follows:

$$Min\ abs(\sum_i hi(xi-\mu)2\ \_T\,\sigma 2) \tag{28}$$

$$\sum_i hixi = T\mu \tag{29}$$

$$x_{i-1} \leq x_i \ \geq x_{i+1} \tag{30}$$

$$\underline{x} \ \leq x_i \ \geq \overline{x} \tag{31}$$

In (28) and (31), the values of μ , $\sigma 2$, T , hi , $\overline{x}$ and, $\underline{x}$ represent the average price, price variance, period of study, length of the period such as price, upper and lower acceptable price, which is all known data of the problem coming, respectively.

2.3. Data Solving for Load Collecting

By calculating the load of each consumer, data solving is executed in the center to compute the total load profile in the distribution network. To further simplify computations, the load profiles of all distribution systems are obtained only by adding the information of each consumer (according to (32)). Then, the load accumulated on all buses is distributed according to the load of the nominal basis of each bus (according to (33) and (34)). It is as follows:

$$PD_t^{TOtal} = \sum_{i\in\Omega^{customers}} P_{i,t}^{Grid}(\,\varepsilon 1, C_t^{TOU}) \tag{32}$$

$$PD_n^t = \frac{P_n^{base}}{P_{Total}^{base}} PD_t^{Total} \tag{33}$$

$$P_{Total}^{base} = \sum_{n\in\Omega^{bus}} P_n^{base} \tag{34}$$

where $\mathcal{P}_{i,t}^{Grid}$ refers to the electricity purchased by the consumer i from the net. In this paper, to show the relationship of $\mathcal{P}_{i,t}^{Grid}$ between the effect of two parameters ε_1 and c_t^{TOU} without considering the total losses, several valuable curves have been extracted. Also, a probability distribution function has been evaluated to select all consumers with the parameter ε_1 Therefore, Equation (35) is:

$$L_t^{Total} = \sum_{\varepsilon_1^i} N(\,\varepsilon_1^i) Pr(\varepsilon_1^i) P_t^{Grid}(\varepsilon_1^i, C_t^{TOU}) \tag{35}$$

Considering the law of probability for each density function as follows:

$$\sum_{\varepsilon_1^i} Pr(\varepsilon_1^i) = 1 \tag{36}$$

The paper aims to achieve the whole distribution system's load profile for each price by the standard normal probability density function and accordingly evaluate the impact of the distribution function changes. The parameter KL is applied as a convergence to display the interval by the probability distribution function to $Pr(\chi)$, which is as follows:

$$d_{KL} = \sum_\chi (Pr(\chi)\, log\, \frac{Pr(\chi)}{Pr^{new}(\chi)}) \tag{37}$$

Thus, the different effects of the normal distribution function can be shown for each parameter. The outcome displays that a more significant distance from the standard normal distribution function will cause more maximum and minimum peaks in the load profile curve [12].

2.4. Market Preferences

Electricity market decisions are usually adjusted according to ToU prices to maximize total profile supply. The profile of the distribution system is obtained from the difference between the cost of supplying electrical energy from the upstream network and the income from the sale of electricity to consumers and is expressed as follows:

$$max\ benefit = \sum_{t\in\tau}(\,C_{t,wholesale}^{TOU}\ \ P_t^{UPGRID} - C_t^{TOU} PD_t^{TOTAL}) \tag{38}$$

Some of the boundary constraints should be considered to support the competition between DGs.

1. The average price should be equivalent to the average price (DG) units (according to (39) and (40)).
2. The prices should be within their prescribed range (according to (41) and (42)).
3. Price variance can be selective to show the effect of price changes on consumer behavior (according to (43) and (44)).

$$\sum_{t\in T} C_t^{TOU} = \sum_{t\in T} C_t^{DG} \tag{39}$$

$$\sum_{t\in T} C_{t,wholesale}^{TOU} = \sum_{t\in T} C_{t,wholesale}^{DG} \tag{40}$$

$$C_{min}^{TOU} \leq C_t^{TOU} \geq C_{max}^{TOU} \tag{41}$$

$$C_{min}^{TOU,wholesale} \leq C_t^{TOU,wholesale} \geq C_{max}^{TOU,wholesale} \tag{42}$$

$$\mathrm{Var}(\sum_{t\in T} C_t^{TOU}) = \sigma_{TOU,desired}^2 \tag{43}$$

$$\mathrm{Var}(\sum_{t\in T} C_t^{TOU}) = \sigma_{TOU,wholesale,desired}^2 \tag{44}$$

The flowchart of the proposed method is shown in Fig.2 .

3. Simulation Results

In this section, the EMS of a home is examined. Then, the role of network consumers in the load profile of each home and their purchased electricity is reviewed. Then, assuming that the network consumers criterion follows the normal distribution function, the network load profile is obtained. It, then, looks at how electricity pricing can affect grid load profiles and electricity costs. Finally, network load profiles are displayed in different pricing. Assuming that the load profile distribution in the network buses follows a uniform function, the load of each network bus is obtained. This paper includes a standard 33 bus network (IEEE) with 2000 consumers with the same features as classified in Table 2. Every consumer uses a 1kW/3 kWh battery, and also, a 2kW ceiling photovoltaic system is provided for each consumer.

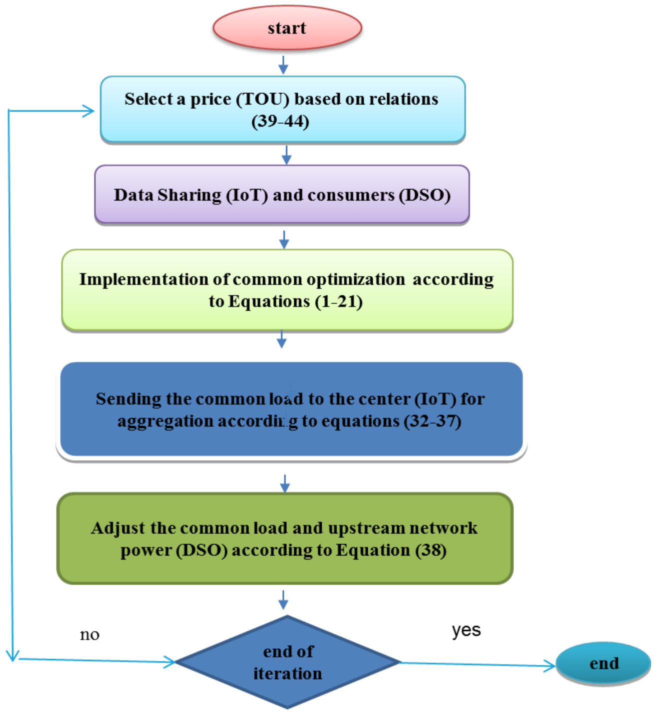

Fig. 2: The flowchart of the proposed method.

Table 2: Consumer load data [12].

Type	Name	Time (h)	kW	$\gamma_t^{\mathcal{L}}$ ($/kWh)
Time Flex	Wash-machine	2hr working duration	0.7	1
Power Flex	Light	11-17	0-0.8	0.8
	Air conditioner	Full time	0-1.4	1.4
Non Flex	Kettle	8-9,17-18, 20-21	0.3	0
	Toaster	8-9	0.2	0
	Refrigerator	Full time	0.2	0

Table 3: Technical and economic data of the net [12].

Item	Value	Item	Value
DG unit location	Bus 6, 7, 13, 18, 28, 33	$c_{t,min}^{TOU}$	0 pu
DG unit capacity	500, 1200, 1350, 1350, 1200, 500kW	$c_{t,max}^{TOU}$	3 pu
DG power factor	1, 0.8, 0.9, 0.9, 0.8, 1	No Load interval	0-7
Voltage Limits	0.95-1.05 pu	Mid interval	7-19
$c_{t,wholesale}^{DG}$, c_t^{DG}	1 pu	Peak interval	19-24

The studied intervals are 24 hours. The difference between consumers is based only on their benefit factors. Some technical and economic data of the distribution network are presented in Table 3.

Energy storage is a 1kW/3-kWh battery charged or discharged without wasting energy. The cost of TFL and PFLS is considered 0.001 per unit per hour and 1 per unit per kilowatt-hour, respectively. The results of IoT-based EMS optimization are displayed in Fig. 4. This indicates a situation where the customer tends to minimize his/her discomfort regardless of the cost. Therefore, PFLs at their maximum rating and TFLs are launched precisely at the desired time and without delay.

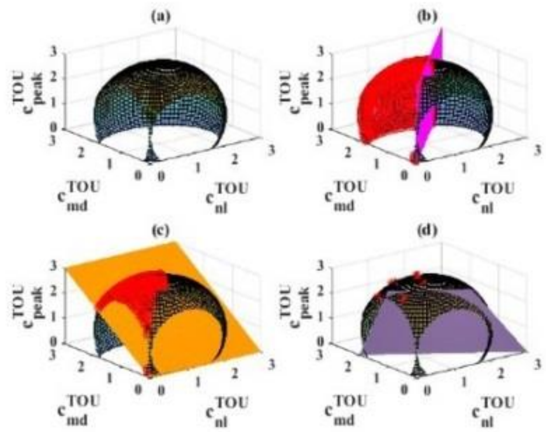

Fig. 3: Procedure for finding the solution space of TOU tariffs for $\sigma^2 = 1$, (a) Solution of (23), and (25)-(27), (b) Adding constraint $c_{nl}^{TOU} \le c_{md}^{TOU}$, (c) Adding constraint $c_{md}^{TOU} \le c_{peak}^{TOU}$, and (d) Adding constraint (23).

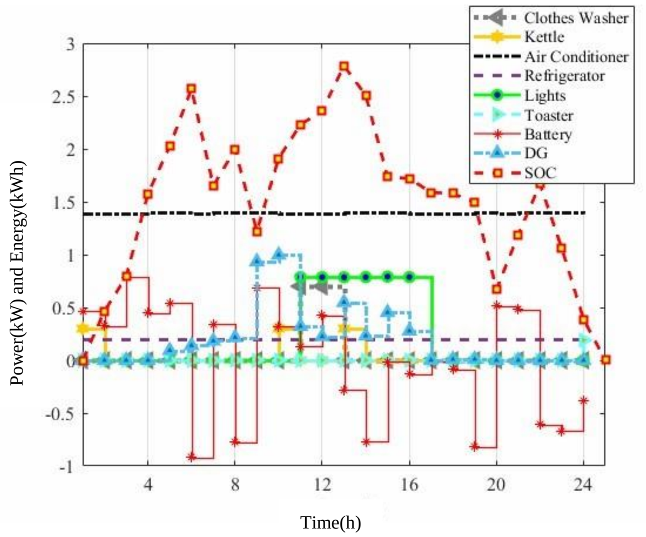

Fig. 4: Energy management system results for $\sigma^2 = 1$ and $\varepsilon = 0$.

3.1. Impact of ε_1 and σ_{TOU}^2 on Network Technical Parameters

In Table 4, the total payment is obtained simultaneously with the changes in ε_1, σ_{TOU}^2. Table 5 shows that market benefit is obtained from the difference between retail and wholesale prices. Table 6 shows that considering several cases, with increasing standard deviation, the cost of payment decreases, and discomfort, peak load, and average load increase. Table 7 shows that with increasing consumer weight ε_1, the cost of payment decreases and discomfort increases, as well as peak load and average load decrease.

3.2. Data Analysis to Calculate the Total Network Load

To show the effect of approximate error, several standard normal distribution functions have been considered to investigate the mutual satisfaction behavior. Fig. 5 shows that

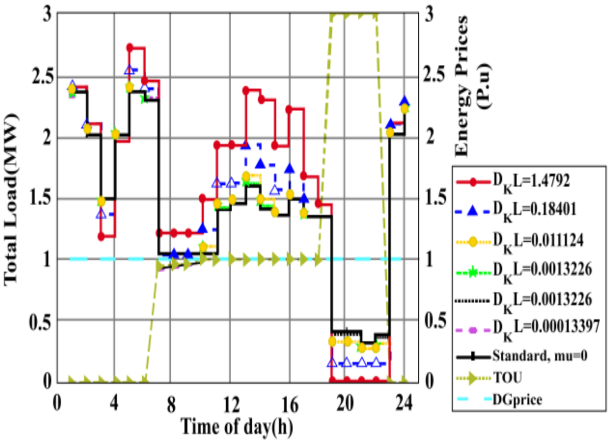

Fig. 5: The whole load in various standard probability density functions (pdf) of ε_1.

Table 4: Impact of changes of ε_1 and σ_{TOU}^2 on the total cost.

ε_1 / σ_{TOU}^2	0	0.1	0.2	0.3	0.4	0.5
0	45.1201	44.1113	42.0398	39.3618	35.7096	30.8990
0.1	45.1904	43.3885	40.7477	37.9936	34.1628	29.2118
0.2	45.1392	41.7038	39.9498	36.7433	32.7051	28.7185
0.3	44.9410	41.0773	38.3843	35.0943	31.1537	25.7690
0.4	44.5359	39.5955	37.2538	33.7937	29.8272	24.6544
0.5	44.3943	38.2162	35.6013	31.6939	27.5399	21.3524
0.6	45.0616	37.5760	33.3571	30.1942	25.6445	18.9922
0.7	46.2372	35.1883	32.5725	28.7632	23.1035	15.4657
0.8	42.3949	34.8915	31.0184	27.3300	21.5086	13.1245
0.9	44.8860	33.8534	31.0236	26.0376	19.7878	12.5736
1	42.0014	31.9110	28.4341	25.1953	17.3905	10.2588

Table 5: Results of different pricing methods using electricity market decisions.

σ_{TOU}^2 wholesale	σ_{TOU}^2 retail	Total cost (p.u)	Total income (p.u)	Benefit (p.u)	PDG%
0	1	22.019	28.508	6.489	20.47
0.1	1	13.676	25.572	11.896	19.37
0.2	1	11.931	25.633	13.702	25.95
0.3	1	13.993	26.807	12.814	17.41
0.4	1	11.761	27.035	15.273	24.47
0	0.5	14.476	28.508	14.032	41.62
0.1	0.5	11.883	25.572	13.689	33.56
0.2	0.5	11.828	25.633	13.805	33.72
0.3	0.5	12.435	26.807	14.371	31.80
0.4	0.5	12.435	27.035	14.599	31.80
0	0	21.022	28.508	7.486	26.26
0.1	0	18.513	25.572	7.059	30.20
0.2	0	20.717	25.633	4.916	21.90
0.3	0	20.472	26.807	6.335	26.06
0.4	0	20.537	27.035	6.498	25.82

Table 6: Impact of electricity price variations on technical and economic parameters of consumers.

ε_1	Cost	Discomfort	Peak load	Mid load
0	45.1201	0.0174	3.0317	1.7164
0.1	44.1113	0.0873	3.7532	1.7481
0.2	42.0398	0.4483	2.4608	1.5929
0.3	39.3618	1.3417	2.4699	1.5098
0.4	35.7096	3.3390	2.5572	1.2913
0.5	30.8990	7.3074	1.9115	1.0849
0.6	24.3335	15.3327	1.6400	0.8631
0.7	14.2211	34.3327	1.5844	0.4125
0.8	9.1808	47.4616	1.7644	0.2308
0.9	9.1333	47.4851	1.0729	0.2125
1	9.2647	47.214	1.4466	0.1943

Table 7: The results of changing consumers' interests in their behavior.

Item	Standard deviation	Cost	Discomfort	Peak load	Mid load
1	0	30.6999	7.4912	2.3842	1.0600
2	0.1	29.0947	7.7809	2.5964	0.9612
3	0.1	29.2460	7.6795	2.3985	0.9652
4	0.1	29.4847	7.5922	2.7519	1.1822
5	0.1	29.6018	7.5130	2.5932	1.2818
6	0.2	27.2362	8.1549	2.8855	0.9538
7	0.2	27.5776	7.9302	2.8807	0.9624
8	0.2	28.0290	7.7758	2.4379	1.0540
9	0.2	28.2538	7.6124	2.5905	1.2853
10	0.3	25.1129	8.6651	2.9706	0.9461
11	0.3	25.6328	8.3360	2.4153	0.9582
12	0.3	26.3439	8.0758	2.7296	1.1461
13	0.3	26.6610	7.8343	2.3017	1.2888
14	0.4	22.8845	9.1535	2.6606	0.9437
15	0.4	23.4480	8.8475	3.0342	0.9548
16	0.4	24.4065	8.8457	2.8479	1.1158
17	0.4	24.8286	8.1785	2.9332	1.2923
18	0.5	20.4807	9.6939	2.7226	0.9437
19	0.5	20.7654	9.6061	2.8821	0.9468
20	0.5	21.1511	9.4810	3.0985	0.9512
21	0.5	22.2355	9.0356	2.5160	1.1022
22	0.5	22.7540	8.6448	2.8317	1.2958
23	0.5	22.9575	8.5538	2.6165	1.3003

the load profile can be plotted using different normal distribution functions with a constant mean of 0.5 and variable variance $\sigma^2 = 0.2, 0.4, 0.6, 0.8, 1$ (according to (37)).

Here, the distance from the normal distribution function (*Kl*) for each distribution function is equal to (0.0001, 0.0013, 0.0111, 0.1840, 1.4792). Therefore, the total network load under these distribution functions is shown in Fig. 5.

It is evident from Fig. 5 that the distance (*Kl*) causes more deviation of the load profile from its mean value than the normal distribution function and will also cause peaks (MIN, MAX) in the load profile curve. Therefore, the standard normal distribution function assumed for consumer behavior was considered a clear idea of problem-solving and the high cost of network operation as a pessimistic idea.

3.3. Comparison Based on the Total Cost

To evaluate the IoT method with other methods, four types of load profiles named LS1, LS2, LS3, and LS4 are first considered, and their required data such as residential load profiles and their desired schedule are extracted from reference [11]. According to reference [11], the number of household appliances (M = 10) in different time slots (N = 8) have been considered. Therefore, each time slot represents 3 hours of continuous work of each piece of equipment to obtain (8 * 3) 24 hours a day. The details of different load scenarios and their demand are given in [11].

The 24-hour loads including four load profiles LS1, LS2, LS3, and LS4 are equal to 63kW, 57kW, 44.5kW, 44.5kW, respectively. To analyze performance, the total cost of consumption per day is calculated by demand response (DR), DijCosMin Algorithm (PRDSol), Low Complexity Algorithm (LCSol), Optimum Solution (OPTSol), and Pmanuscript Swarm Optimization (PSO). Table 8 shows the results of this comparison. To clarify the subject, these results are plotted in Fig. 6. According to Fig. 6, it is clear that the total cost of IoT analysis is much lower than other algorithms. Therefore, according to this comparison, it can be concluded that the IoT method reduces the total cost of consumption per day and night.

3.4. Comparison Based on the Time Response

IoT time response is compared with existing algorithms, and its results are given in Table 9. According to Table 9, the time response of the IoT method is 0.047 seconds, which is the lowest time compared to the time response of other algorithms. In practical applications, time response parameters include communication time, the distance between the central system and home appliances, Internet speed, etc.

3.5. Comparison Based on the Peak Load Demand

To test the capability of the IoT method in managing peak load demand and reducing the peak to average load ratio, a case study of peak load demand has been performed by considering IoT and other existing algorithms for LS1. To clarify the issue, the IoT method is compared with different existing algorithms to reduce the peak load demand for LS1. The results are shown in Fig. 7. In general, the cost of electricity consumption increases during peak hours and decreases during off-peak hours. Therefore, peak demand can be reduced by shifting the load from a high-cost time slot (peak load hours) to a low-cost time slot (non-peak load hours). In Fig. 7, cost-based time slots are arranged in ascending order. The highest cost time slot is related to T6, and the lowest cost time slot is associated with T7. According to Fig. 7, it can be seen that the amount of IoT loading in the time slot T6 is low and increases for subsequent time slots. Also, the highest demand for IoT is in the time slot T7. Therefore, the effect of the IoT method in reducing peak load demand and reducing the peak to average load ratio compared to other algorithms is very clear.

Table 8: A comparison based on the total cost.

	Cost (Pu)					
LS	IoT	DR	LCsol	OPTsol	PRDsol	Pso
LS1	29.7	36	33.5	30,4	32.8	32.7
LS2	29.4	36.5	30.8	27.2	28.7	31.8
LS3	23.1	29.7	26.9	24.2	25.5	26.3
LS4	24.5	30.1	26.7	25.3	26.8	28.7

Table 9: A comparison based on time response.

Type of method	Simulation time (s)
IoT	0.047
DR	0.534
LCsol	0483
OPTsol	8.599
PRDsol	179
Pso	18.58

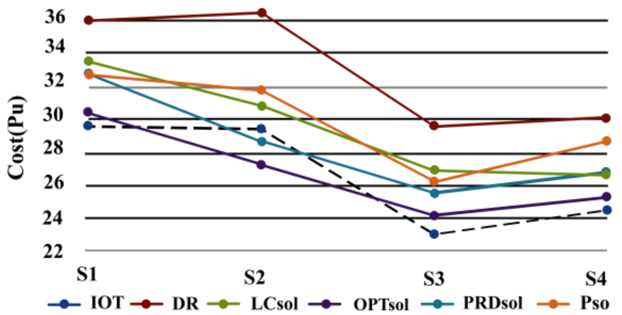

Fig. 6: A comparison based on the total cost.

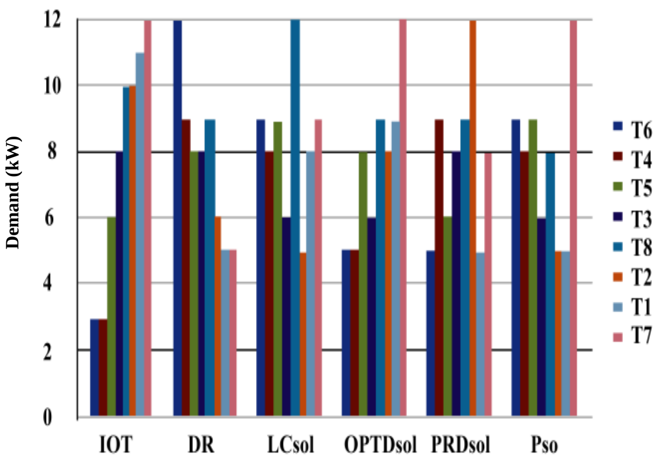

Fig. 7: A comparison based on peak load reduction.

4. CONCLUSION

This paper presents a conceptual and straightforward framework for energy-efficient management in IoT-based distribution systems, including IoT-based residences, power system operators, and central control units. End-user preferences are considered according to the definition of customer satisfaction factor. In addition, the central unit changes the usage time of prices to trade between the DSO and consumers. Several detailed analyzes have been performed to ascertain the impact of energy pricing and customer preferences on technical parameters, e.g., the load index of distribution systems and economic indicators such as daily payment or the cost of discomfort to end-users. This data provides a good framework for the central unit to manage the IoT-based system efficiently. As such, both the benefits of the DSO and consumer expectations are met. Distribution network energy management by comparing changes in IoT-based consumer behavior has been compared with previous works regarding cost, time response, and peak load demand. The results show that the IoT method will reduce the total cost and lower the system response time and ultimately reduce the peak load demand.

Credit Authorship Contribution Statement

Moaiad Mohseni: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Roles/Writing - original draft, Writing - review & editing. **Mahmood Joorabian:** Data curation, Investigation, Software, Visualization, Writing - review & editing. **Afshin Lashkar Ara:** Investigation, Project administration, Visualization.

Declaration Of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

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