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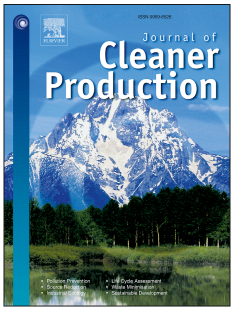

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Internet-of-Things-Based Optimal Smart City Energy Management Considering Shiftable Loads and Energy Storage

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Abstract:

Formulating a novel mixed integer linear programing problem, this paper introduces an optimal Internet-of-Things-based Energy Management (EM) framework for general distribution networks in Smart Cities (SCs), in the presence of shiftable loads. The system's decisions are optimally shared between its two main designed layers; a "core cloud" and the "edge clouds". The EM of a Microgrid (MG), covered by an edge cloud, is directly done by its operator and the Distributor System Operator (DSO) is responsible for optimising the EM of the core cloud. Changing the load consumption pattern, based on market energy prices, for the edge clouds and their peak load hours, the framework results in decreasing the total operation cost of the edge clouds. Using the optimal trading power of the MGs aggregators as the input parameters of the core cloud optimisation problem, the DSO optimises the network's total operation cost addressing the optimal scheduling of the energy storages. The energy storages are charged in low energy prices through the purchasing power from the market and discharged in high energy prices to meet the demand of the network and to satisfy the energy required by the edge clouds. As a result,

the shiftable loads and the energy storages are used by the DSO and the MGs to meet the energy balance with the minimum cost.

Key Words: Energy management, Internet-of-Things, Microgrids, Optimal scheduling, Renewable energy sources.

Nomenclature

Acronyms:		P_t^{F,in^*}	Purchased power from the market (kW)
EM	Energy management	P_t^{F,out^*}	Sold power to the market (kW)
DBN	Deep belief network	$P_{f,i,t}^{L}$	Power demand of MGs (kW)
DR	Demand response	$P_{f,t}^{L}$	Power demand of feeders (kW)
Disco	Distribution company	$P_{f,i}^{MG,max}$	Maximum capacity of transformers (kW)
DG	Distributed generation	$P_{f}^{F,max}$	Maximum capacity of feeders (kW)
DSO	Distribution system operator	$P_{f,i,t}^{MG,in^*}$	Purchased power by the MGs (kW)
GIS	Geographical information systems	$P_{f,i,t}^{MG,out^*}$	Sold power by the MGs (kW)
IoT	Internet-of-things	$P_{f,t}^{MG,in^*}$	Purchased power from the edge clouds (kW)
MG	Microgrid	$P_{f,t}^{MG,out^*}$	Sold power to the edge clouds (kW)
MGA	Microgrid aggregator	$P_{f,i,t}^{PV}$	Power generation of PVs (kW)
PAR	Peak to average ratio	$P_{f,t}^{WT}$	Power generation of wind farm (kW)
PV	Photovoltaic	α	The percentage of load shifting capacity
RESs	Renewable energy sources	$\eta_{f,i}^{MG}$	Efficiency of transformers
SG	Smart grid	$\eta_{f,j}^{discharge}/\eta_{f,j}^{charge}$	Efficiency of discharging/charging
SC	Smart city	**Variables:**	
WT	Wind turbine	$E_{f,j,t}^{batt}$	Stored energy in energy storage (kWh)
Sets/Indices:		$P_{f,j,t}^{charge}$	Power charging of energy storage

			(kW)
f	Index of feeders	$P_{f,j,t}^{discharge}$	Power discharging of energy storage (kW)
i	Index of MGs	$P_{f,t}^{F,in}$	Purchased power for each feeder (kW)
j	Index of energy storages	$P_{f,t}^{F,out}$	Sold power from each feeder (kW)
t	Index of time	$P_{f,i,t}^{MG,in}$	Purchased power by the MGs (kW)
Parameters:		$P_{f,i,t}^{MG,out}$	Sold power by the MGs (kW)
C_t	The energy market prices (€/kWh)	$P_{f,i,t}^{SL\_DN}$	The amount of shift down load (kW)
$E_{f,j}^{batt,max}$	Maximum capacity of energy storage (kWh)	$P_{f,i,t}^{SL\_UP}$	The amount of shift up load (kW)
$E_{f,j}^{batt,min}$	Minimum capacity of energy storage (kWh)	$X_{f,j,t}^{batt}$	The binary variable used for power charging/discharging of energy storage
$E_{f,j}^{batt,ini}$	Initial capacity of energy storage (kWh)	$X_{f,t}^{F}$	The binary variable used in power trading with the market
$P_{f,j}^{batt,max}$	Maximum power of energy storage (kW)	$X_{f,i,t}^{MG}$	The binary variable used in power trading of the MGs with the grid

1 Introduction

The traditional power systems face problems such as fossil fuel reduction, low energy efficiency, and environmental pollution. There is also a rapid increase in electricity consumption. High penetration of renewable energy sources (RESs), especially in the distribution networks, along with on-site energy storage systems is a key solution to these problems (Ray et al., 2011). The annual installed capacity of photovoltaic (PVs) arrays is forecasted to reach 100.6 GW and 232.6 GW in low and high scenarios respectively in 2022, due to an increase in investment on RESs around the world (Watson and Schmela, 2018). The share of the Rooftop PVs reaches 40.2 GW and 83.7 GW in low and high scenarios, respectively (Watson and Schmela, 2018). Installing a large number of smart metres around the world facilitates the implementation of the demand response (DR) programmes such as shifting loads. For instance, there were 25.7 M electricity metres operated by large energy suppliers in domestic properties across Great Britain until March 2019, from which 7,325,300 of which were smart metres (Deaprtment for Business, 2019). Integration of RESs-based distributed generations (DGs), the energy storages, and the responsive loads along with an efficient energy management (EM) scheme supported by a high-level communication and information system to control them refers to the concept of Microgrid (MG) (Marvasti et al., 2014), which may be connected to the distribution network (Golpîra et al., 2019).

In present and future electrical energy systems, it's possible to have MGs with shiftable loads and PVs in distribution networks. However, there are some challenges and difficulties in implementing such frameworks, including the problems of the existing grid in accepting the RESs, cyber security problems, energy storage concerns, data management, communication issues, and the stability concerns. Implementing such systems in the distribution networks requires high investment costs from the governments and the consumers. Governments should pay two types of costs for such systems; 1) costs for preparing the grid in different aspects for the high penetration rate of RESs as well as for smart consumers and 2) costs of having the support scheme policies for the consumers and investors to invest in these energy sources and to participate in the DR programmes. Such an active distribution grid needs a smart optimal interconnection among its autonomous individuals, to operate in a secure and economic manner (Mohammadi et al., 2019). Since the implementation of such systems has benefits for the government, it will be willing to pay the investment costs if it is optimal. For example, in the smart city (SC) of Queensland, Australia, the peak demand and the electricity consumption have both reduced up to 46% by June 2012.

Smart Grids (SGs) can control the production, transmission, distribution, and consumption equipment by gathering information from individuals in a two-way scheme (Bahramara and Golpîra, 2018). They can also use Internet-of-Things (IoT) technology to create several additional intelligent services (Liu et al., 2011), particularly in the SC since the SGs play an essential role in data evolution (Seema and Sushma, 2019) in order to connect the physical objects with the Internet and make them smarter (Babar et al., 2019b). Cloud-based control and management is consequently an emerging field of research (Mital et al., 2015). Developing the IoT technology in the SC makes it possible to transfer the customer's power demand information to the edge cloud and provide a demand side EM programme to schedule the customer's appliances centrally. The bank of information is also optimised in a cloud-based server, and the whole electricity production-distribution network can be controlled by an IoT cyber-physical network technology (Das et al., 2020). Using such a cloud-based technology can also enable a dynamic DR optimisation and provide a high level of scalability and reliability at a lower cost while improving the power grid performance (Yaghmaee Moghaddam et al., 2016). Therefore, given the intense growth and acceptance of the IoT (Babar et al., 2019a), most research works in recent years have focused on the applications of the IoT (Safaeipour and Golpîra, 2018), especially in the field of the SC (Scuotto et al., 2016).

More like real-life situation, this paper proposes a cloud-based electrical energy scheduling programme of a SC that controls the power supply and the demand of the clustered consumers with a feeder considered for each region. The feeders are provided to improve the performance of any individual MG (Patrao et al., 2015). In other words, customers who live in different areas, with their own feeders, are equipped with their own MGs to optimise individually. They are further optimised regarding their interrelationship with the distribution company (Disco) as the system's core cloud through the concept of service layer abstraction. The top core cloud is responsible for performing a centralised load optimal scheduling at such a multi-region structure. Therefore, the IoT communication technology is performed in this paper using an optimal cloud-based hybrid centralised-decentralised approach. Since applying such an advanced communication infrastructure for the self-healing grids may enhance power reliability and quality (Haidar et al., 2015), the optimal structure presented in this paper can be attractive not only to the academicians, but also to the practitioners. Besides, since many future communications systems will follow hybrid centralised-decentralised models (Fabiano, 2017), as introduced in this paper, the suitability and practicability of the framework presented in the paper are further demonstrated. The information of the system's demand-side, including the consumption demands and the MGs generation data are fully forwarded to a smart edge cloud. The edge cloud makes optimal decisions about power consumption schedule for the appliances. Afterwards, the optimal load scheduling data of all the regions are forwarded to the system's core cloud to obtain final centralised decision-making based on the information obtained from the Disco to provide a minimum multi-region cost. Thus, the proposed framework allows centralised and decentralised decision-making mechanisms, wherein multiple decision makers independently solve their optimisation problems. The main motivations of the paper are as follows. a) Proposing a centralised-decentralised decision-making among the district MGs, feeders, and the component units by applying an optimal cloud-based decision-making mechanism, as a new system-wide optimal decision-making approach, is done in this paper for the first time. b) Recognising the issue that literature reveals that it is still a challenging issue to cover the concept of the IoT while optimising the EM under a multi-stage problem in the SC context. c) Providing the optimal energy balance of the core cloud as the central energy manager of the system as its significant decision. In such systems, the operator can use the stored energy in the storages or the energy supplied by the Disco in each feeder to decrease the operation costs, while meeting the demands. d) Obtaining the energy balance for each edge cloud as a major concern regarding the separated regions and their own managerial concerns. This means that using the approach introduced in this paper, the operator of each MG optimises its own objective function based on the market prices and the available resources. Such a decision is made, optimally, upon shifting up and down the loads based on the amounts of hourly energy demand and supply. e) Analysing the effect of shiftable load consideration mathematically in a near real-world application as a significant performance evaluation of not only the operators of the MGs, but also the core cloud as the other major concern of the SC optimal EM.

The rest of the paper is as follows. Reviewing the most relevant research is done in Section II. The problem is described in Section III, and the model formulation is developed in Section IV. Solution results and sensitivity analysis are provided in Section V, and the conclusion and some future research directions are presented in Section VI.

2 Literature Review

Integrating the decisions of different functions in a single optimisation model is an efficient approach to deal with the EM problem (Ling et al., 2015), especially for the SC. Some recent research papers have been published to tackle the problem of electrical energy production-consumption in SCs through such an approach. More recently, a comprehensive overview of the SG with its general features, functionalities related technologies, and characteristics was presented by Tuballa and Abundo (2016). They concluded that, nowadays, the traditional grid has become limited and it needs more features. There are also opportunities for research in the areas of power flow optimisation, battery systems, cloud computing, and practical large scale RESs integration. Morvaj et al. (2011) gave a good overview over the features and paradigms to evaluate the existing cities in line with their opportunity of becoming SCs. Classifying the planning and operation scopes within the SC, Calvillo et al. (2016) proposed a methodology for developing an improved energy model in this context along with some additional final recommendations. In their research, it has been recommended to follow some forms of optimisation algorithm with clearly defined and prioritised objective functions because it is shown that using such approaches may significantly improve the expected benefits of the systems under optimisation. Bulkeley et al. (2016) examined the ways in which the SC is being put to work for different ends and through different means. Emphasising on the importance of the SG and the IoT contexts in any SC, Kim et al. (2017) and Tanwar et al. (2018) summarised the role of the IoT for the development of the SC as one of its applications. There exist a few mathematical frameworks for using the IoT, especially in SCs and the related areas, where its most recent applications are well-summarised by Safaeipour and Golpîra (2018). Laying stress on the importance of the waste collection optimisation in SCs, Oralhan et al. (2017) introduced a waste management software-based IoT technology to optimise waste collection to reduce both the cost of collection and the pollution effect on the environment. Based on the real-time IoT and the geographical information systems (GIS) data, Yang et al. (2017) optimised the dynamic transportation network assignment for an IoT-based SC. Their proposed system is processed by the deep belief network (DBN) model and K-means to meet the requirements of high-performance computing and economic costs. The model is particularly useful for optimising traffic network planning in real-time, high-data, low-cost conditions, as well as promoting the SC's construction and development. Developing a lightweight analytical model, Baz (2018) proposed a new routing metric for the energy-efficient IoT network over the SCs enabling each node to estimate the energy consumption of each possible path and to select the lowest energy path. Hu et al. (2019) proposed the architecting, implementation, and optimisation of an air quality sensing system for a SC, which provides the real-time and the fine-grained air quality map of the area. To do the optimisation, they simultaneously studied the problems of power control and location selection of the sensing system to minimise the joint error of the real-time and the fine-grained air quality map.

More specifically, in line with using the IoT technology for the SCs, Yaghmaee Moghaddam et al. (2016) formulated a two-tier cloud-based demand-side management to control the residential load equipped with the local power generation and energy storages. The aim of the mathematical modelling (Yaghmaee Moghaddam et al., 2016) is to minimise the total purchased energy from the main grid using demand-side management. For this purpose, the consumers' energy consumption is optimised in the edge clouds and then their required energy is supplied by several MGs in the core cloud. The objective of the core cloud is to minimise the peak to average ratio (PAR). In other words, the main objective of this study (Yaghmaee Moghaddam et al., 2016) can be simply summarised as optimally decreasing the purchased power from the main grid. In the proposed model, presented in this paper, the EM of a SC is modelled considering the distribution system operator (DSO) as the core cloud operator and the microgrid aggregator (MGA) as the edge clouds one. The objective of the MGA is to meet the energy balance of the network through optimal load shifting and trading power with the main grid. Moreover, the energy balance of the distribution network is supplied by the DSO in the core cloud using the energy storages' optimal scheduling. In this paper, the EM of the distribution network is optimised so that the DSO can purchase more energy from the grid in low energy prices to meet the shifted loads and to charge the energy storages.

3 Problem Description

In this paper, the EM problem of an active distribution network in a SC is modelled based on the IoT concept. The proposed EM framework is shown in Fig. 1. The distribution network includes several feeders, each of which consists of different loads, energy storages, wind turbines (WTs), and several MGs. The MGs are equipped with PV arrays and the percentage of their loads equipped with smart metres has the capability of shifting their consumptions regarding the market energy prices.

The distribution network has a hierarchical framework to trade energy and information from the wholesale energy market to the consumers and vice versa as shown in Fig. 2. All the MGs (i) in each feeder are operated by the MGA in the edge cloud problem. The MGs meet their energy balance regarding the energy market prices, the demand of the consumers, and the power generation of the PVs and decide on the amount of shifting up and down the loads as well as power trading with the distribution network. All the information of the MGs is sent to the DSO via the MGA. The EM problem of the distribution network with several feeders (*f*) is optimised by the DSO as a core cloud. Regarding the wholesale market prices, power trading with the MGAs, the output power of wind turbines, and the demand of the feeders, the DSO decides about charging/discharging the energy storages optimally in each feeder regarding which it determines the power trading with the wholesale markets. The DSO announces the market operator about the trading power. In this framework, it is assumed that the measurement sensors are reliable and it is beyond the scope of this paper to consider the probability of their failures.

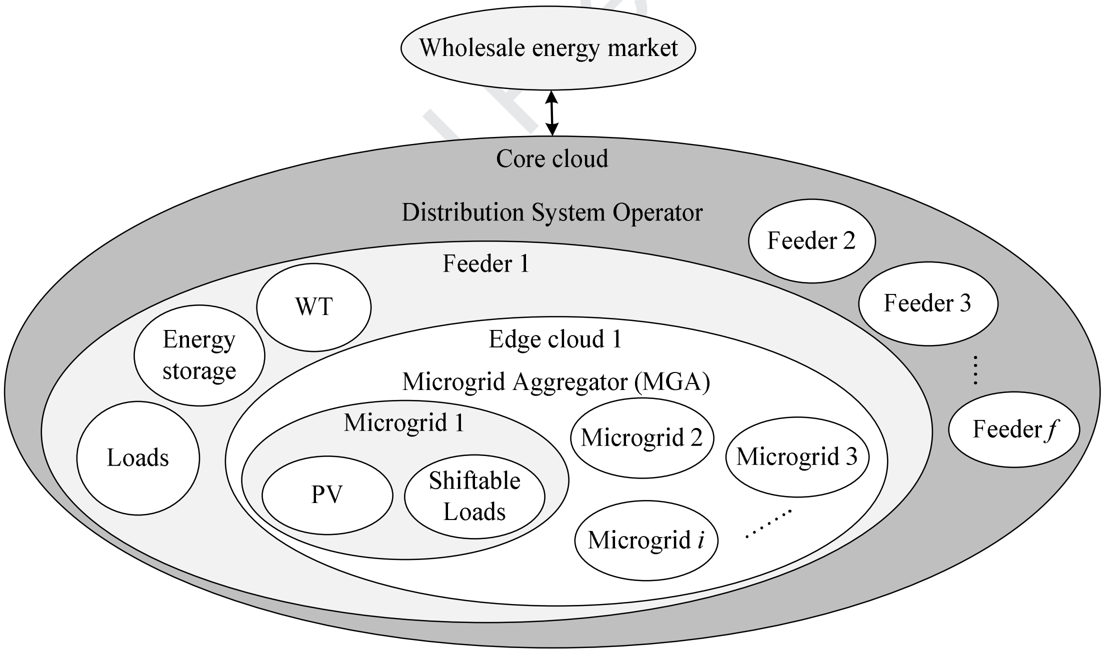

Fig. 1. The proposed EM framework based on the IoT concept

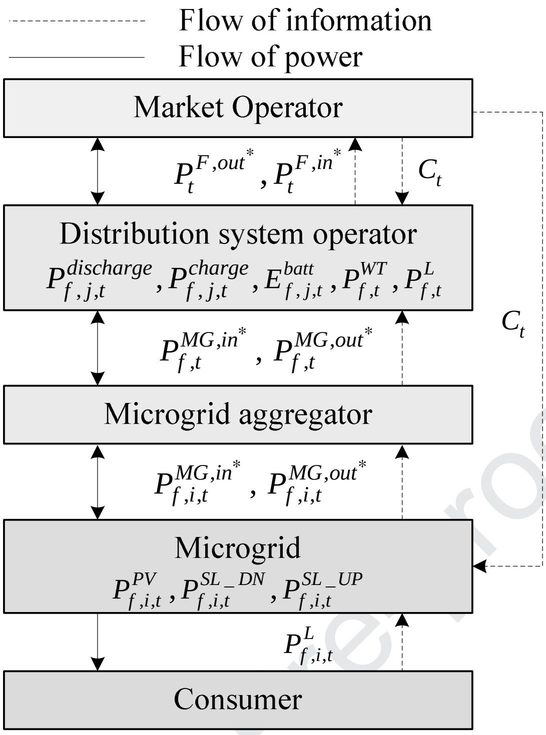

Fig. 2. Flows of power and information in the proposed EM framework

4 Mathematical Modeling

The proposed framework in Fig. 1 is mathematically formulated in this section. For this purpose, at first, the problem of the edge clouds is formulated to determine the energy balance for each MG regarding the power generation of PVs considering the shiftable loads. This problem is solved by the MGA in each edge cloud. As further illustrated in Figure 2, the optimal power trading of the MGs with the main grid is considered as the output decision variable of this stage, which will be considered as a parameter in the next step in the EM problem of the core cloud. The problem of the core cloud is solved by the DSO to meet the energy balance of the distribution network with the output power of WTs, optimal scheduling of energy storages, and power trading with the wholesale market regarding the energy prices. The details of this modelling approach are described in the following sub-sections.

4.1 The problem of each edge cloud

The operation problem of each edge cloud, which should be solved by the MGA, is modeled as (1)-(6).

$$\text{Minimise} \quad OF^{edge} = \sum_{i}\sum_{t} C_t (P_{f,i,t}^{MG,in} - P_{f,i,t}^{MG,out}) \tag{1}$$

The objective function of each MG is described as (1) to model the cost of trading power with the Disco, where C_t is the energy market price (€/kWh), $P_{f,i,t}^{MG,in}$ is the purchased power by the MGs (kW), and $P_{f,i,t}^{MG,out}$ is the sold power by the MGs (kW). The indices of f, i, and t are used to model the feeders, MGs, and time, respectively.

$$P_{f,i,t}^{PV} + P_{f,i,t}^{MG,in}\eta_{f,i}^{MG} + P_{f,i,t}^{SL\_DN} = \frac{P_{f,i,t}^{MG,out}}{\eta_{f,i}^{MG}} + P_{f,i,t}^{SL\_UP} + P_{f,i,t}^{L} \qquad \forall f,i,t \tag{2}$$

Power balance for each MG in each feeder in each time step is modeled as (2) where the sum of the power generation of the PV ($P_{f,i,t}^{PV}$), the purchased power by the MG from the Disco, and the amount of shift down load ($P_{f,i,t}^{SL\_DN}$) is equal to the sum of the sold power by the MG, the amount of shift up load ($P_{f,i,t}^{SL\_UP}$), and the load of the MG ($P_{f,i,t}^{L}$). In this equation, $\eta_{f,i}^{MG}$ is used to model the efficiency of the MGs' transformers.

$$0 \le P_{f,i,t}^{MG,in} \le P_{f,i}^{MG,max} X_{f,i,t}^{MG} \quad \forall f,i,t \tag{3}$$

$$0 \le P_{f,i,t}^{MG,out} \le P_{f,i}^{MG,max}(1 - X_{f,i,t}^{MG}) \quad \forall f,i,t \tag{4}$$

Power trading with the grid is limited by (3) and (4) regarding the capacity of the transformer of each MG ($P_{f,i}^{MG,max}$). Since the MG cannot purchase/sell energy from/to the main grid simultaneously, a binary variable ($X_{f,i,t}^{MG}$) is used in this equation. When the value of this variable is 1, it means that the MG cannot sold power to the grid and it can only purchase power from the grid. On the other hand, when $X_{f,i,t}^{MG} = 0$ it means that the MG cannot purchase power from the grid and it can only sell power to the grid.

$$0 \le P_{f,i,t}^{SL\_DN} \le \alpha P_{f,i,t}^{L} \;,\; 0 \le P_{f,i,t}^{SL\_UP} \le \alpha P_{f,i,t}^{L} \quad \forall f,i,t \tag{5}$$

$$\sum_{t} P_{f,i,t}^{SL\_DN} = \sum_{t} P_{f,i,t}^{SL\_UP} \quad \forall f,i \tag{6}$$

In each MG, the percentage of the load with the capability of shifting the load is modelled as (5), and equation (6) is used to model the fact that the sum of the shift down and shift up loads in the operation period must be equal. In fact, the shiftable loads consume the fixed energy in the operation period. In equation (5), α is the percentage of load shifting capacity.

$$\text{Output: } P_{f,i,t}^{MG,in^*} \;,\; P_{f,i,t}^{MG,out^*}$$

The amount of purchased power by the MGs from the Disco ($P_{f,i,t}^{MG,in^*}$) and the amount of the sold power by the MGs to the Disco ($P_{f,i,t}^{MG,out^*}$) are considered as the output decision variables of the edge cloud problem optimisation. These variables are considered as the parameters in the optimisation problem of the core cloud.

4.2 The problem of the core cloud

The operation problem of the DSO, as the core cloud, is modeled as (7)-(16).

$$\text{Minimise } OF^{core} = \sum_{f}\sum_{t} C_t \left[P_{f,t}^{F,in} - P_{f,t}^{F,out} + P_{f,t}^{MG,out^*} - P_{f,t}^{MG,in^*} \right] \tag{7}$$

The objective function of this problem is modeled as (7) where the sum of the costs of the purchased power from the market and the edge clouds and the sum of the revenue from the power sold to them is minimised. In this equation, $P_{f,t}^{F,in}$ is the purchased power for each feeder (kW) and $P_{f,t}^{F,out}$ is the sold power from each feeder (kW). As shown in the equation, the core cloud objective function is defined as a function of two main terms as: net power transfer to the feeders $\left(P_{f,t}^{F,in} - P_{f,t}^{F,out}\right)$ and optimal net power transfer to the MGs $\left(P_{f,t}^{MG,in^*} - P_{f,t}^{MG,out^*}\right)$, which are obtained from the first level of the optimisation problem, considering the monetary cost of energy per hour $\left(C_t\right)$. Given equation (2), the first-level optimal objective value should be provided considering the limitation of the power balance, whereas the optimisation of the core cloud is not required in this level. So, given the convexity of the problem, the optimal value obtained from solving the first-level optimisation problem is guaranteed. This motivates the edge clouds, i.e. the decentralized edge clouds, become willing to operate under the management of a central core cloud through the IoT approach, because in such a system the optimality of every single edge cloud will not be negatively affected. Each of these clouds are solely responsible for the feeders which are located only within the clouds' coverage. From the viewpoint of the core cloud and its objective function, provided by (7), it is logical that the core cloud's optimal value is completely related to the optimal values obtained from the first level optimisation problem since the edge clouds are included within the core cloud. By this means, given the convexity of the second level optimisation problem, the final solution value obtained from the core cloud is also guaranteed, but with respect to the optimal values provided by the first level one. This guarantees that there will be no better response to the second level problem, given the optimal input of the first level problem, which is inevitable. The reason is that the core cloud is mainly responsible for the collection of extracting information from the edge clouds (Kasnesis et al., 2019) to manage and monitor the use of the resources and services in every single edge cloud (Jun et al., 2020). In this way, the core cloud cannot be optimised unless it receives data from the edge clouds, which is completely provided in the framework proposed in this paper. The basic idea is to tackle a complex problem through solving a sequence of the easier ones, which can be solved using standard methods. Such a proposed cloud-based architecture is an effective solution that leverages data-centric communication for scalable and flexible communication between utility and the consumers (Fang et al., 2012).

$$\sum_{j} P_{f,j,t}^{discharge} \eta_{f,j}^{discharge} + P_{f,t}^{F,in} + P_{f,t}^{WT} + P_{f,t}^{MG,out^*} = \sum_{j} \frac{P_{f,j,t}^{charge}}{\eta_{f,j}^{charge}} + P_{f,t}^{F,out} + P_{f,t}^{MG,in^*} + P_{f,t}^{L} \quad \forall f,t \tag{8}$$

$$P_{f,t}^{MG,out^*} = \sum_{i} P_{f,i,t}^{MG,out^*}, \; P_{f,t}^{MG,in^*} = \sum_{i} P_{f,i,t}^{MG,in^*} \quad \forall f,t \tag{9}$$

The power balance of the core cloud for each feeder in each time step is modelled as (8) where the sum of the discharging power of energy storages ($P_{f,j,t}^{discharge}$), the purchased power from the market, the output power of the wind farm in each feeder ($P_{f,t}^{WT}$) and the purchasing power from the edge clouds ($P_{f,t}^{MG,out^*}$) is equal to the sum of the charging power by energy storages ($P_{f,j,t}^{charge}$), the selling power to the market, the sold power to the edge clouds ($P_{f,t}^{MG,in^*}$), and the demand of each feeder ($P_{f,t}^{L}$). The purchased/sold power by each edge cloud from/to the core cloud equals the sum of the power trading of the MGs in that edge cloud with the grid (i.e. the output decision variables of the previous optimisation problem) as modeled in (9). In equation 8, the Index of energy storage is $\boldsymbol{j}$.

$$0 \le P_{f,t}^{F,in} \le P_f^{F,max} X_{f,t}^F \quad \forall f,t \tag{10}$$

$$0 \le P_{f,t}^{F,out} \le P_f^{F,max} (1 - X_{f,t}^F) \quad \forall f,t \tag{11}$$

For each feeder trading power with the market is limited as (11) and (12) regarding the capacity of each feeder $P_f^{F,max}$. In these equations, $X_{f,t}^F$ is used as a binary variable to avoid simultaneous occurrence of the purchased/sold power from/to the market for each feeder.

$$0 \le P_{f,j,t}^{charge} \le P_{f,j}^{batt,max} (1 - X_{f,j,t}^{batt}) \quad \forall f,j,t \tag{12}$$

$$0 \le P_{f,j,t}^{discharge} \le P_{f,j}^{batt,max} X_{f,j,t}^{batt} \quad \forall f,j,t \tag{13}$$

The power charging/discharging of energy storages are modelled as (12) and (13) where in each time step the energy storages can only be charged or discharged in the optimisation process as modelled using the binary variable ($X_{f,j,t}^{batt}$). In these equations, $P_{f,j}^{batt,max}$ is the maximum power of each energy storage (kW).

$$E_{f,j}^{batt,min} \le E_{f,j,t}^{batt} \le E_{f,j}^{batt,max} \quad \forall f,j,t \tag{14}$$

$$E_{f,j,t}^{batt} = E_{f,j,t-1}^{batt} + P_{f,j,t}^{charge} - P_{f,j,t}^{discharge} \quad \forall f,j,t > 1 \tag{15}$$

$$E_{f,j,t}^{batt} = E_{f,j}^{batt,ini} + P_{f,j,t}^{charge} - P_{f,j,t}^{discharge} \quad \forall f,j,t = 1 \tag{16}$$

The stored energy in the energy storages ($E_{f,j,t}^{batt}$) is limited to storages' minimum ($E_{f,j}^{batt,min}$) and maximum ($E_{f,j}^{batt,max}$) values as (14). The dynamic behaviour of the energy storages in the operation period is modeled as (15) and (16) regarding which they can be charged in low energy prices of the market and they can be discharged in high energy prices to minimise the operation costs of the core cloud. In these equations, $E_{f,j}^{batt,ini}$ is the initial capacity of the energy storage (kWh) and $\eta_{f,j}^{discharge}/\eta_{f,j}^{charge}$ are the efficiency of discharging/charging, respectively.

$$\text{Output: } P_t^{F,out^*} = \sum_f P_{f,t}^{F,out^*} \quad , \quad P_t^{F,in^*} = \sum_f P_{f,t}^{F,in^*} \quad \forall t$$

The amount of purchased power by the DSO from the market (P_t^{F,in^*}) and the amount of the sold power to the market (P_t^{F,out^*}) are considered as the final decision variables of the system.

The model of the edge clouds consists of 13453 single equations, 9073 single variables, and 2880 discrete variables and the model of the core cloud consists of 1513 single equations, 1153 single variables, and 144 discrete variables. The models are both solved by CPLEX solver with GAMS 24.1.2 software. A personal computer with 6GB RAM running on Intel Core i-5 with a CPU speed of 2.60GHz, 64bits operating system is used to solve the model. Using this system, the computational time to solve the model of the edge clouds and the core cloud is 10.266 sec and 3.188 sec, respectively. Therefore, the obtained computational time for the model is acceptable for the energy management problems since these problems are solved in two main time scales consisting of day-ahead (24 hours) for the day-ahead energy scheduling problems and real-time (usually 5 minutes) for the real-time energy management ones.

5 Simulation Results

To investigate the effectiveness of the proposed method and its solution methodology, it is applied on a distribution network with three main feeders. The demand of each feeder is extracted from (Bahramara et al., 2015). Each feeder consists of 20 MGs which supplies 30 percent of the load of the feeder. The sum of the energy storages capacity in each feeder is equal to 1,500MWh. The energy storages have the maximum power charging and discharging equal 800kW. The initial and the minimum stored energy equal 300kWh, 240kWh, and 150 kWh for feeders 1, 2, and 3, respectively. It is assumed that there is a wind farm with the capacity of 5MW, i.e. 50 wind turbines with the capacity of 100kW, in feeders 1 and 2. The output power of the wind farm is shown in Fig. 3. This output is minimum in hours 1-3 and 22-24 and its maximum output power occurrs in hours 7-9, and 13-17.

The demand of each MG is equipped with smart metres and has the potential to shift that 30 percent of its consumption in response to the market prices. There are 100 kW PV arrays in each MG. To obtain the power generation of the PV arrays, the location of the assumed region, including its latitude and longitude, are entered to the HOMER software (Bahramara et al., 2016) regarding which the solar radiation and the clearness index of the region are determined by the software. Then, HOMER calculates the output power of the PV arrays, which is shown in Fig. 4, regarding the mentioned input data. As shown in this figure, the output power of the PV arrays is zero in hours 1-7 and 20-24 and their maximum output power is in hours 11-15. The energy price is collected from the Nordpool energy market in 02 May 2019 as illustrated in Fig. 5 and Table 1 (Nordpool, 2019). The market price is low in hours 1-6 and 13-19 and it's high in the other hours. The maximum capacity and the efficiency of the distribution transformer of the MGs to trade power with the main grid are 500 kW and 0.98, respectively.

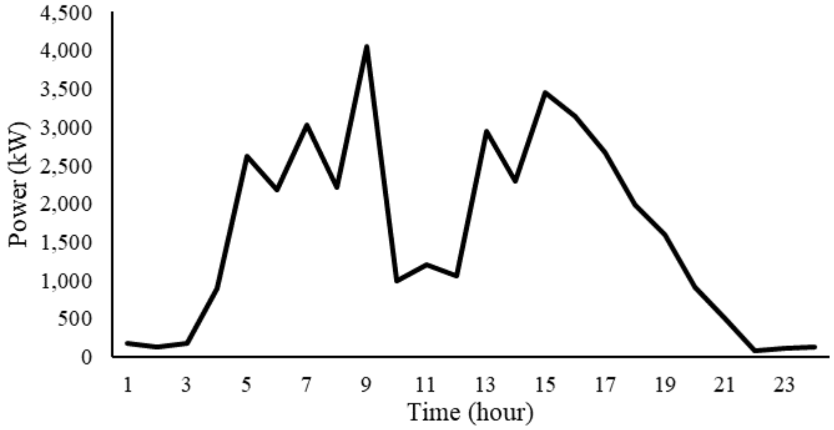

Fig. 3. The output power wind farm in each feeder

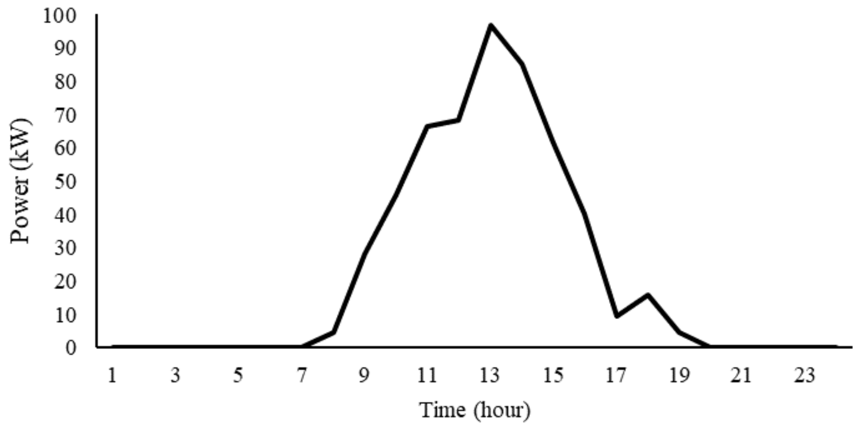

Fig. 4. The power generation of PV arrays in each MG

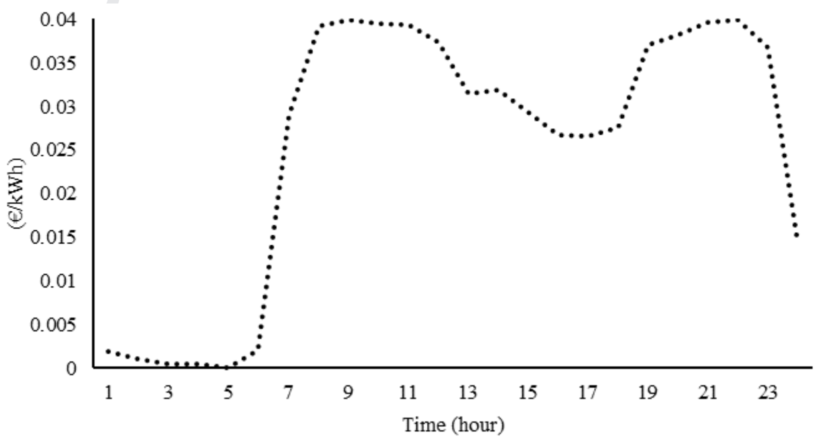

Fig. 5. The energy market prices

Table 1: The hourly energy market prices

Time (hour)	Energy price (€/kWh)	Time (hour)	Energy price (€/kWh)	Time (hour)	Energy price (€/kWh)	Time (hour)	Energy price (€/kWh)
1	0.00192	7	0.02896	13	0.03142	19	0.03701
2	0.00103	8	0.03916	14	0.0319	20	0.03826
3	0.00055	9	0.03999	15	0.0293	21	0.03971
4	0.00047	10	0.03948	16	0.0268	22	0.03991
5	0.00012	11	0.03936	17	0.02655	23	0.03676
6	0.0021	12	0.03732	18	0.02766	24	0.01441

5.1 Results

The energy balance for the edge clouds is shown in Figs. 6-8. The operation problem of the MGs is optimised regarding the market prices and its resources. As shown in Figs. 6-8, the demand of the MGs shifts up in hours 1-7, 13-18, and 24 for the first edge cloud, in hours 1-7, 12-18, and 24 for the second edge cloud, and in hours 1-7, 13, 15-18, and 24 for the third edge cloud regarding the low energy prices of the market in these hours. This decision increases the purchased power from the grid by the MGAs to meet the new energy consumption. In the other hours for each edge cloud, the MGAs decide to decrease their demand regarding the high energy prices of the market. Therefore, the purchased power by the MGAs from the market decreases in these hours. In hours 8-19, the power generation of the PV arrays have significant impacts on the energy balance of each edge cloud. Regarding the generated power of the PV arrays and the shifting down of the loads in hours 11 and 12 for the first edge cloud, in hours 10-13 for the second, and in hour 12 for the third, the behaviour of the trading power with the grid changes. In these hours, most of the MGs sell power to the main grid and the minimum purchased power from the grid by the MGs is obtained.

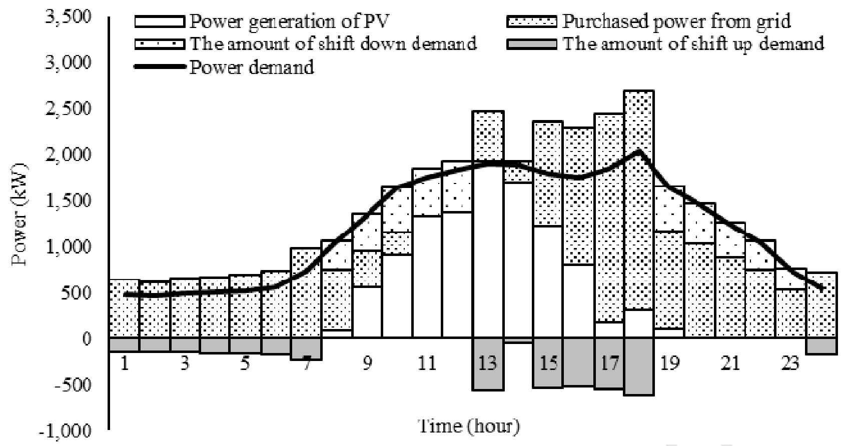

Fig. 6. The energy balance of the first edge cloud

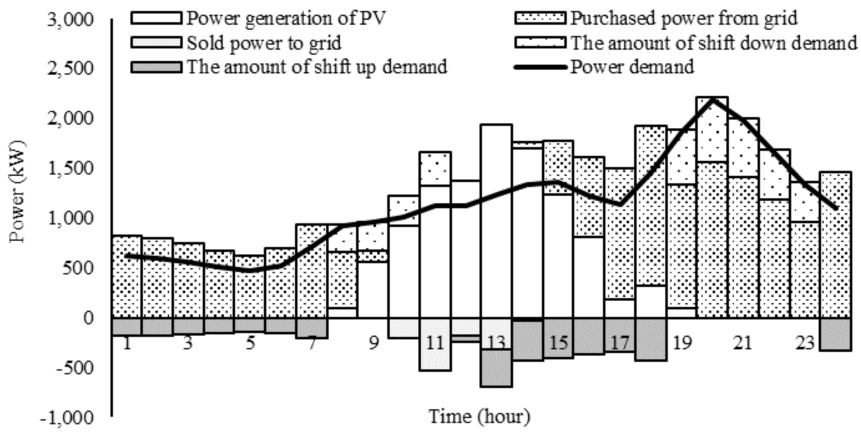

Fig. 7. The energy balance of the second edge cloud

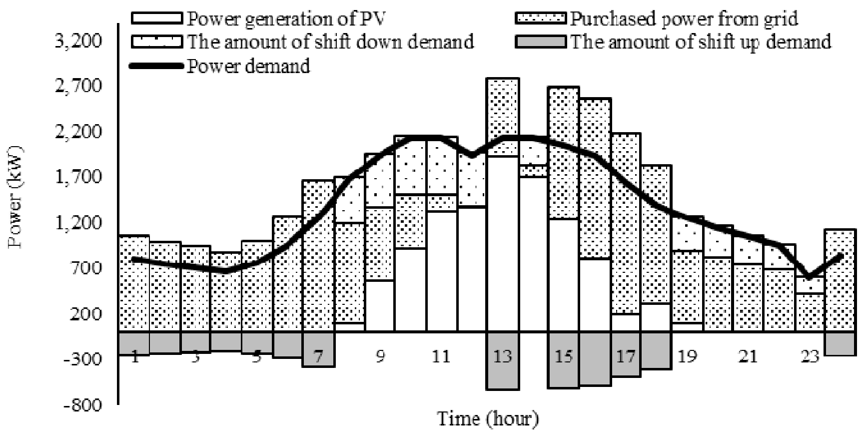

Fig. 8. The energy balance of the third edge cloud

The optimised load consumption, applying the load shifting for each edge cloud, is shown in Figs. 9-11 and Tables 2-4. As shown in these figures and tables, the load consumption patterns change regarding the market energy prices. For the first edge cloud, the load consumption increases in hours 1-7, 13-18, and 24 regarding the low amount of the energy prices and it decreases in other hours with the high amount of energy prices. Therefore, the main reason for the sudden increase in load consumption at hour 13 is its low energy price in comparison with the energy prices in the previous hours (hours 8-12) regarding which the MGA decides to shift the demand from hours 8-12 to the hours 13-18. For the second edge cloud, the load consumption shifts from hours 1-7, 12-18, and 24 to hours 8-11 and 19-23 regarding the energy market prices. As presented in Table 3, for the same amount of load consumption in hours 11 and 12, regarding the lower amount of the energy price in hour 12 in comparison with 11, the load consumption decreases in hour 11 and it increases in hour 12. For the third edge cloud, the load consumption shifts from hours 1-7, 13, 15-18, and 24 to hours 8-12, 14, and 19-23 regarding the energy market prices. Since for the same amount of load consumption in hours 13 and 14, the energy price in hour 13 is lower than 14, the load shifts up in hour 13 and it shifts down in 14.

This behaviour has changed the hours of the peak load of the second and the third edge clouds. The peak load of the second and the third edge clouds, without shifting the loads, occur in hour 20 and hours 10-14 except 12, respectively. With load shifting, these peak load hours shift to the hours 18 and 13 for the second and the third edge clouds, respectively. Without considering the ability of shiftable loads in MGs, the total cost of all edge clouds is 1,625.23 €, while optimising the load consumption regarding the shiftable load decreases the total cost of the system to 1,393.03 €, i.e., 14.28% reduction. Therefore, increasing the ability of the network's load to shift their consumption with the market prices decreases the total operation cost of the system.

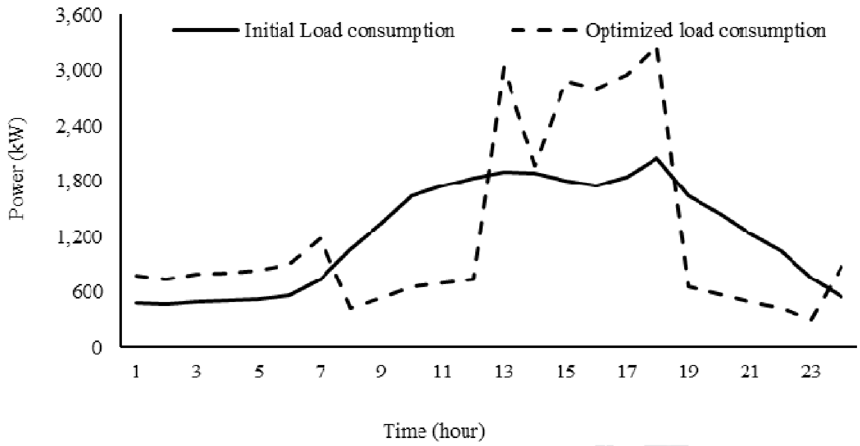

Fig. 9. The effect of optimal behaviour of shiftable loads on the load consumption of the first edge cloud

Table 2: The results of the shiftable load optimisation for the first edge cloud

Time (hour)	Energy price (€/kWh)	Initial load (kW)	The amount of shift up demand (kW)	The amount of shift down demand (kW)	Optimised load (kW)
1	0.00192	484.23	145.27	0	629.5
2	0.00103	463.44	139.03	0	602.47
3	0.00055	493.14	147.94	0	641.08
4	0.00047	502.06	150.62	0	652.68
5	0.00012	522.85	156.86	0	679.71
6	0.0021	558.5	167.55	0	726.05
7	0.02896	736.75	221.02	0	957.77
8	0.03916	1,054.6	0	316.39	738.21
9	0.03999	1,348.7	0	404.62	944.08
10	0.03948	1,645.8	0	493.74	1,152.06
11	0.03936	1,746.8	0	524.04	1,222.76
12	0.03732	1,835.9	0	550.78	1,285.12
13	0.03142	1,895.3	566.91	0	2,462.21
14	0.0319	1,883.5	43.579	0	1,927.08
15	0.0293	1,797.3	539.19	0	2,336.49
16	0.0268	1,746.8	524.04	0	2,270.84
17	0.02655	1,841.9	552.56	0	2,394.46
18	0.02766	2,040.9	612.27	0	2,653.17
19	0.03701	1,639.9	0	491.96	1,147.94
20	0.03826	1,449.7	0	434.92	1,014.78
21	0.03971	1,241.8	0	372.53	869.27
22	0.03991	1,051.6	0	315.49	736.11
23	0.03676	754.57	0	226.37	528.2
24	0.01441	546.62	163.99	0	710.61

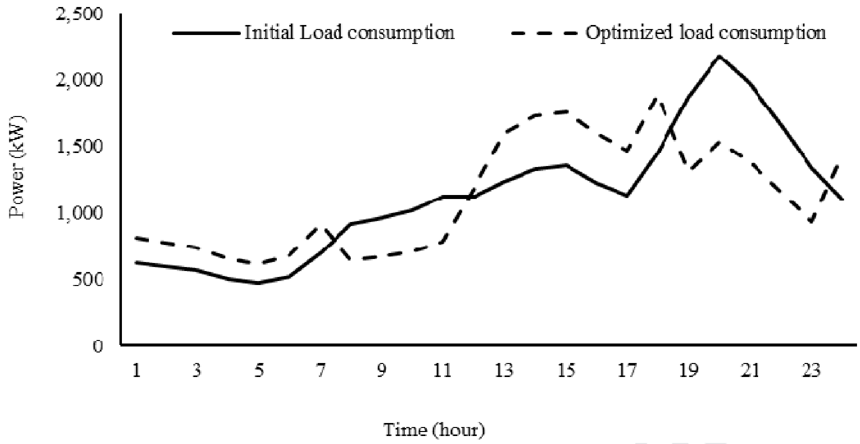

Fig. 10. The effect of optimal behaviour of shiftable loads on the load consumption of the second edge cloud

Table 3: The results of the shiftable load optimisation for the second edge cloud

Time (hour)	Energy price (€/kWh)	Initial load (kW)	The amount of shift up demand (kW)	The amount of shift down demand (kW)	Optimised load (kW)
1	0.00192	620.885	186.265	0	807.15
2	0.00103	597.119	179.136	0	776.255
3	0.00055	564.441	169.332	0	733.773
4	0.00047	505.026	151.508	0	656.534
5	0.00012	472.348	141.704	0	614.052
6	0.0021	525.821	157.746	0	683.567
7	0.02896	704.066	211.22	0	915.286
8	0.03916	917.959	0	275.388	642.571
9	0.03999	962.52	0	288.756	673.764
10	0.03948	1,015.99	0	304.798	711.192
11	0.03936	1,122.94	0	336.882	786.058
12	0.03732	1,122.94	66.8417	0	1,189.7817
13	0.03142	1,232.86	369.857	0	1,602.717
14	0.0319	1,330.89	399.268	0	1,730.158
15	0.0293	1,354.66	406.397	0	1,761.057
16	0.0268	1,226.92	368.075	0	1,594.995
17	0.02655	1,128.88	338.664	0	1,467.544
18	0.02766	1,452.69	435.808	0	1,888.498
19	0.03701	1,865.62	0	559.687	1,305.933
20	0.03826	2,183.49	0	655.048	1,528.442
21	0.03971	1,972.57	0	591.771	1,380.799
22	0.03991	1,660.64	0	498.193	1,162.447
23	0.03676	1,336.83	0	401.05	935.78
24	0.01441	1,099.17	329.752	0	1,428.922

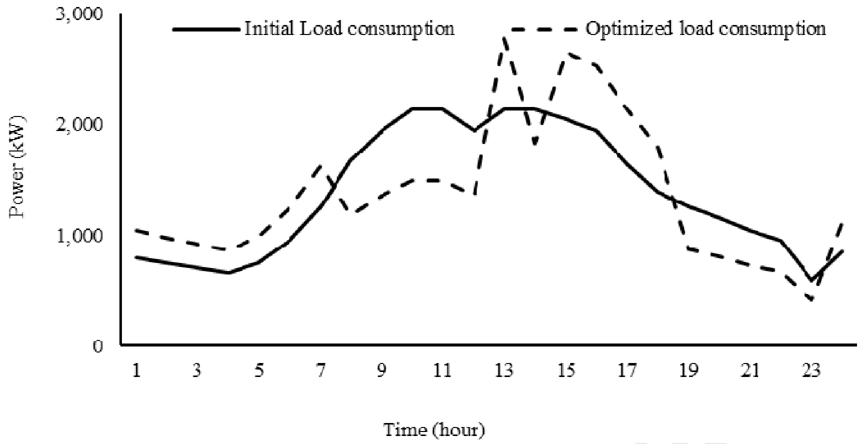

Fig. 11. The effect of optimal behaviour of shiftable loads on the load consumption of the third edge cloud

Table 4: The results of the shiftable load optimisation for the third edge cloud

Time (hour)	Energy price (€/kWh)	Initial load (kW)	The amount of shift up demand (kW)	The amount of shift down demand (kW)	Optimised load (kW)
1	0.00192	799.133	239.74	0	1,038.873
2	0.00103	748.63	224.589	0	973.219
3	0.00055	710.01	213.003	0	923.013
4	0.00047	659.507	197.852	0	857.359
5	0.00012	754.572	226.372	0	980.944
6	0.0021	953.612	286.084	0	1,239.696
7	0.02896	1,250.69	375.206	0	1,625.896
8	0.03916	1,675.51	0	502.652	1,172.858
9	0.03999	1,936.93	0	581.08	1,355.85
10	0.03948	2,135.97	0	640.792	1,495.178
11	0.03936	2,135.97	0	640.792	1,495.178
12	0.03732	1,936.93	0	581.08	1,355.85
13	0.03142	2,135.97	632.22	0	2,768.19
14	0.0319	2,135.97	0	308.705	1,827.265
15	0.0293	2,040.91	612.272	0	2,653.182
16	0.0268	1,942.87	582.862	0	2,525.732
17	0.02655	1,639.86	491.957	0	2,131.817
18	0.02766	1,384.37	415.311	0	1,799.681
19	0.03701	1,250.69	0	375.206	875.844
20	0.03826	1,149.68	0	344.905	804.775
21	0.03971	1,045.71	0	313.712	731.998
22	0.03991	950.642	0	285.193	665.449
23	0.03676	594.151	0	178.245	415.906
24	0.01441	849.636	254.891	0	1,104.527

The energy balance of the core cloud is shown in Fig. 12 and the energy balance in the feeders is illustrated in Figs. 13-15. The operator of the distribution network can use the energy storages in each feeder to decrease the operation costs to meet the demand of the network. The power trading of the MGs with the main grid was optimised in the previous step (see Figs. 6-8). The MGs sold power to the grid in hours 10-14 and purchased power in other hours. The energy storages are charged in hours 4, 5, 16, and 17 regarding the market's low energy prices and they are discharged in hours 9, 10, 21, and 22 regarding the high market energy prices. As shown in Figs. 13 and 14, the large amount of the demand of feeder 1 and feeder 2 is supplied by the wind turbines so that their extra power is transferred to the output of the feeder in hours 6, 7, and 9 for feeder 1 and in hours 5-7, 9, and 13 for feeder 2. This is while in feeder 3, which does not have the wind turbine, the feeder's demand is mostly supplied through purchasing power from the market as shown in Fig. 15.

The dynamic behaviour of energy storages is shown in Fig. 16. The total cost of the core cloud without energy storages is 4,124.71 €, while in their presence and with the optimisation of their dynamic behaviours in the operation period, the total cost of the core cloud reaches 3,932.12 €, i.e. 4.67% reduction.

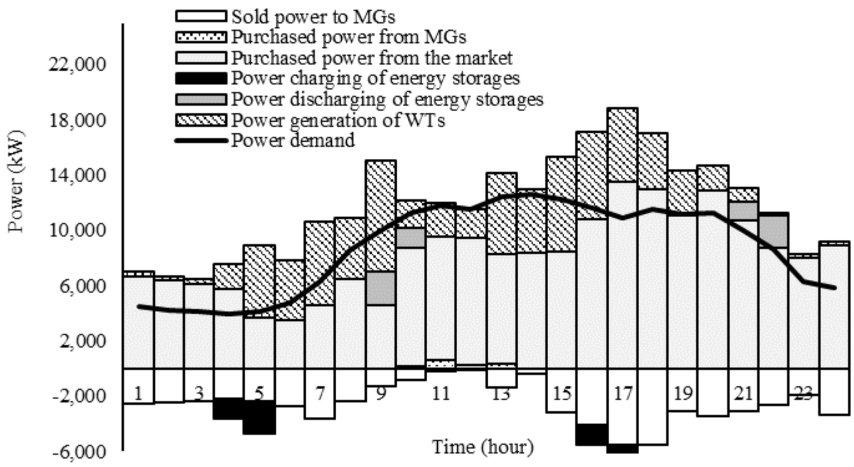

Fig. 12. The energy balance of the core cloud

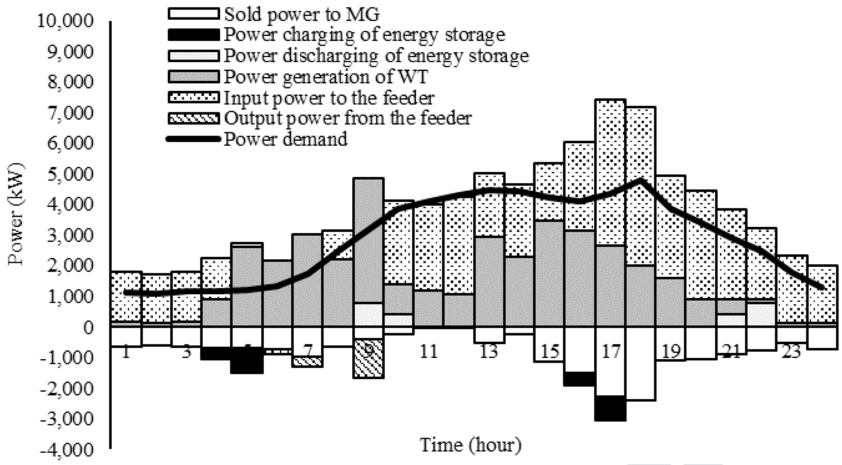

Fig. 13. The energy balance in feeder 1

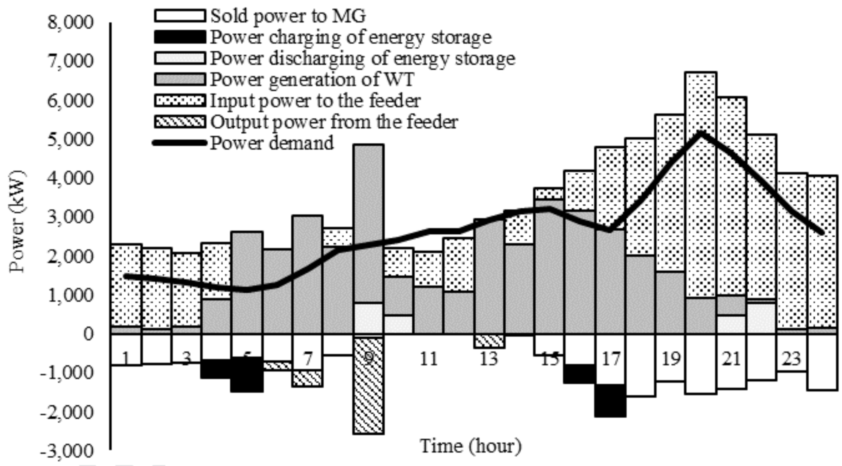

Fig. 14. The energy balance in feeder 2

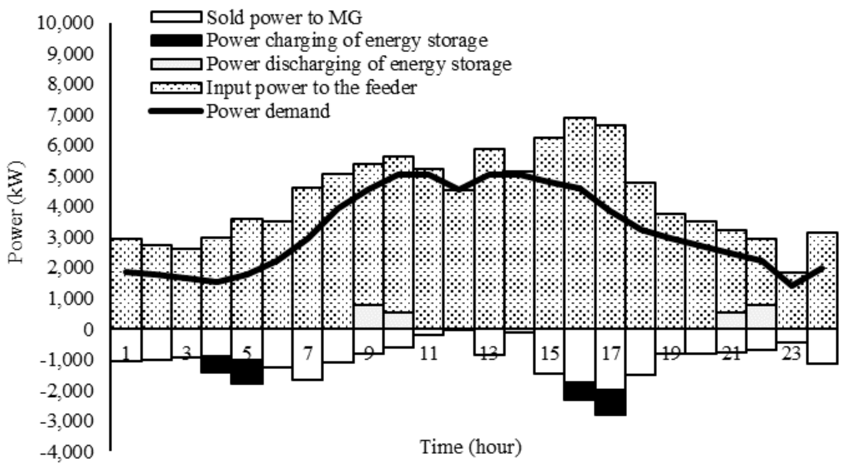

Fig. 15. The energy balance in feeder 3

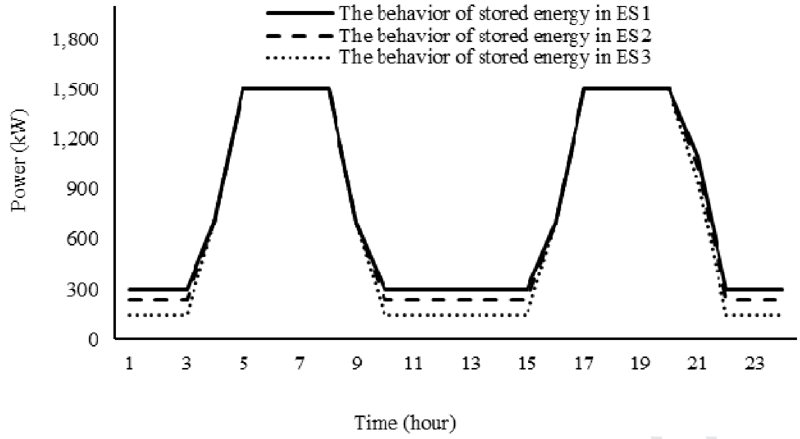

Fig. 16. The optimal behaviour of the energy storages in the core cloud

5.2 Sensitivity analysis

In this sub-section a sensitivity analysis is done to investigate the effect of load shifting capability percentage and the capacity of energy storages on the results. The sensitivity of the power trading of the edge clouds to the percentage of the load shifting capability is shown in Fig. 17. It is assumed that the maximum amount of the load shifting capacity of the MGs is equal to 70 percent of their load, since there are several loads that cannot be shifted to the other hours. In fact, it is impossible to assume that all the capacity of the demand can be shifted in the time period of the operation (i.e., 24 hours in this paper). The sensitivity of the total shifted load and the total cost of the edge clouds to this parameter is shown in Fig. 18. As shown in Figs. 17 and 18, the MGA has two main strategies to decrease the total cost of the edge clouds; 1) When the percentage of load shifting capacity is between 0 and 20, regarding the low amount of shiftable loads, the MGA decides to decrease the purchased power from the main grid in the hours with high energy prices through shifting the load to the other hours with low energy prices. In this strategy the sold power to the grid by the MGA decreases in the other hours. 2) When the percentage of load shifting capacity increases from 20 to 70, regarding the high amount of shiftable loads, the MGA shifts down the loads in the hours with high price and it consequently sells more power to the grid in these hours. The shifted down loads are supplied in the hours with low energy prices regarding which the purchased power by the MGA increases. Therefore, as the percentage of the load shifting capacity increases, the total cost of the edge clouds decreases with the optimal power trading of the MGA with the main grid.

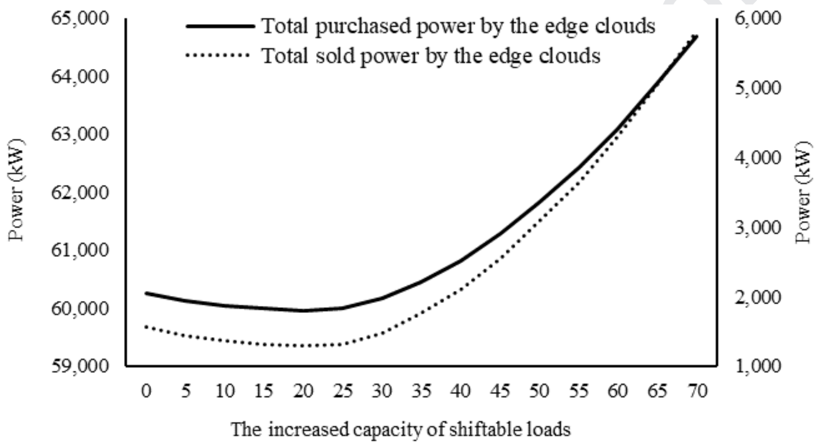

Fig. 17. The sensitivity of power trading with the grid to the capacity of shiftable load

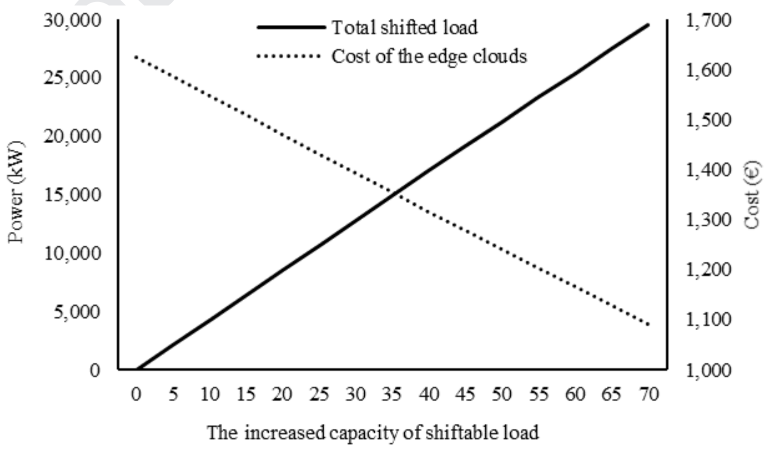

Fig. 18. The sensitivity of total shifted load and cost of the edge clouds to the capacity of shiftable load

The sensitivity of the core cloud optimisation's results to the capacity of the energy storage is shown in Figs. 19 and 20. Increasing the capacity of energy storages in comparison with the base case, the DSO purchases more energy from the market to charge the energy storages in hours with low market prices. This, consequently, increases the purchased power from the market. On the other hand, the stored energy in energy storages is used by the DSO in the hours with high energy prices which leads to decreasing the total operation cost of the core cloud.

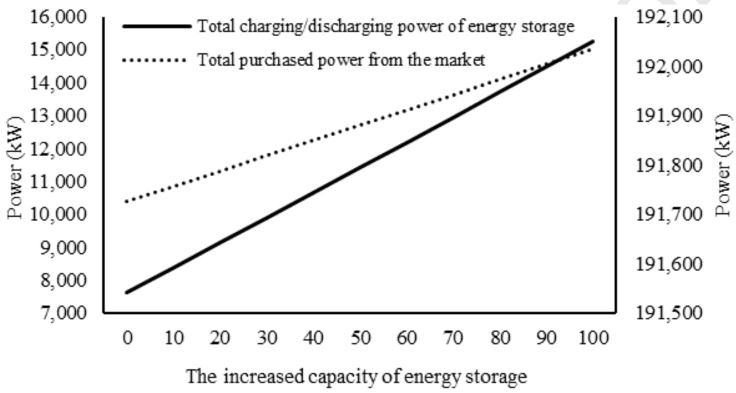

Fig. 19. The relation between the capacity of energy storages and the decisions of the DSO in core cloud

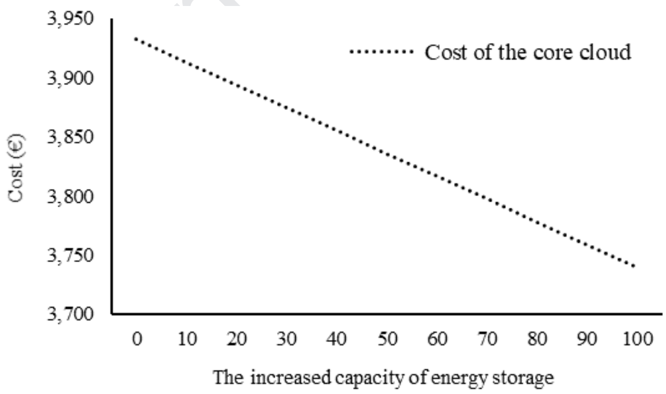

Fig. 20. The relation between the energy storages capacity and the total cost of the core cloud

6 Conclusion

In this paper, an optimal cloud-based EM framework is proposed for the distribution networks in the SCs based on the IoT technology. For this purpose, the decision-making framework of the distribution network is divided into two main layers as a "core cloud" and the "edge clouds". In each edge cloud, managing the energy of several MGs is done by the MGA operator and the DSO is responsible to manage the energy of the core cloud. The results show that the load shifting capability of the MGs decreases the total operation cost of the edge clouds, approximately by 14.28%. Moreover, the shiftable loads change the load consumption pattern of the edge clouds and consequently change their peak load hours. In this regard, two strategies of the MGA to decrease the total cost of the edge clouds are analysed considering the low load shifting capacity (0%-20%) and the high load shifting capacity (20%-70%). The first strategy results in decreasing the amount of the purchased power from the grid in high energy price hours as well as shifting the loads and, therefore, decreasing the amount of the sold power to the grid in the other hours. The second strategy results in shifting down the loads in high energy price hours to increase the amount of the sold power to the grid in these hours, and increasing the purchased power in low energy price hours to compensate the shifted loads. All the aforementioned behaviours of the MGs occur directly and logically regarding the market energy prices.

The proposed cloud-based structure introduced in this paper is formulated as a mixed integer linear optimisation problem to obtain an optimal solution using exact solution approaches. The optimal power trading of the MGA with the main grid is considered as the output decision variable of the edge clouds, which is considered as a parameter in the optimisation problem of the core cloud. The DSO optimises the total operation cost of the distribution network with optimal scheduling of energy storages in the network. Regarding the pattern of the energy market prices, the energy storages are charged in low energy prices through the purchasing power from the market and discharged in high energy prices to meet the demand of the distribution network and to satisfy the energy required by the edge clouds. Therefore, the shiftable loads and energy storages as the flexible energy resources can be used by the DSO and MGs to meet their energy balance with the minimum costs.

In this study, the failure rate of the smart sensors, PVs systems, energy storages, wind turbines, and the distribution network as well as the uncertainties related to noisiness of data from the sensors are not modelled in the decision-making problem, which can be considered in future studies. Moreover, some other studies can be done as the future works are as follows:

- The uncertainties of demand, energy prices, PVs, and WTs can be considered in the model.
- The MGs can participate in the ancillary service energy markets including reserve and flexibility besides their participations in the energy market.
- The heat demand can be modeled in the proposed model through replacing the MGs considered in this study with multi carrier energy systems including heat energy storages, the electrical and the heat demands, combined heat and power (CHP), and combined cooling, heat, and power (CCHP) system.

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- IoT-based optimization of smart city energy management under a multi-stage problem.
- Formulating a novel IoT-oriented MILP problem to smart city energy management.
- Decision making is shared between layers as edge clouds (MGs) and a core cloud (DSO).
- Obtaining mathematically optimal energy balance of the core and edge clouds.
- Analyzing the effect of the shiftable load consideration in a near real-world application.

Conflict of Interest

Potential conflict of interest exists:

We wish to draw the attention of the Editor to the following facts, which may be considered as potential conflicts of interest, and to significant financial contributions to this work:

The nature of potential conflict of interest is described below:

☒No conflict of interest exists.

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We the undersigned agree with all of the above.

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