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Integrating Internet-of-Things-Based Houses into Demand Response Programs in Smart Grid

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Abstract: This paper presents a novel framework that mathematically and optimally quantifies demand response (DR) provisions, considering the power availability of Internet of Things (IoT)-based house load management for the provision of flexibility in the smart grid. The proposed framework first models house loads using IoT windows and occupant behavior, and then integrates IoT-based house loads into DR programs based on a novel mathematical optimization model to provide the optimal power flexibility considering the penetration of IoT-based houses in distribution systems. Numerical results that consider a 33-bus distribution system are reported and discussed to demonstrate the effectiveness of flexibility provisions, from integrating IoT-based houses into DR programs, on peak load reduction and system capacity enhancement.

Keywords: Internet of Things; flexibility; load management; mathematical model

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1. Introduction

Residential customers, through the implementation of smart houses in a distribution system, are vital in realizing a smart grid.The presence of advanced communication technologies in the smart grid facilitates grid operators and local utility to communicate directly with customers. Smart houses can serve as flexible sources to provide capacity support for the power distribution grid when they include smart appliances and Internet of Things (IoT)-based load management that monitors and controls the energy usage of houses [1,2]. At the end-user level, IoT device sensors can help households better understand their energy-consumption patterns and make adjustments accordingly to reduce energy waste and lower electricity bills. On the other hand, demand-side management of IoT-based houses can help power grids operate efficiently, as well as improving grid reliability, by monitoring power usage more effectively and incentivizing customers to reduce their energy consumption during peak hours, and adjust the energy supply accordingly to ensure better use of energy resources.

Integrating IoT-based houses into demand response (DR) programs can have numerous benefits, such as reducing peak demand, improving energy efficiency, promoting sustainability by coordinating the loads with the availability of renewable energy, and lowering energy costs. IoT devices such as smart meters and sensors help with monitoring and optimizing energy usage, and thereby, utilities can better manage energy consumption, reduce peak demand, and enhance grid capacity and reliability. Moreover, customers can shift their energy usage to off-peak hours, leading to cost savings and more efficient energy usage. Overall, integrating IoT-based houses into DR programs in a smart grid can lead to a more sustainable energy future. DR services include "up regulation" and "down regulation". The former refers to providing additional power as needed to maintain system balance, while the latter refers to reducing the available power supply in the system [3,4]. The adoption of IoT devices in houses and integrating them into DR programs will contribute to increased system flexibility, which is the primary objective of this paper.

The current developments in the smart energy sector were reviewed in [5], highlighting some of the challenges currently faced and outlining future pathways for the sector.

The authors of [6] reviewed different aspects of the smart energy system and the IoT system. It was concluded that the use of IoT in energy business models would manage energy consumption by encouraging integration solutions, facilitating operating efficiency and processing automation in a smart grid. The challenges related to the characterization of home appliances, integration of renewable energy sources, load categorization, and consumer categorization were reviewed and discussed in [7] for IoT-enabled home-energy-management systems. Incorporating the IoT with energy systems was also reviewed in [8], with the objective of assessing the suitability of different data transfer and communication protocols of IoT for deployment in the modern grid system. The impact of the IoT paradigm toward energy-consumption prediction was extensively reviewed in [9]. It was highlighted that the integration of IoT and energy-consumption prediction can achieve the close interaction and monitoring of energy usage. The development and experimental validation of a smart power meter able to monitor the power in real time were described in [10], wherein an outline of the potentialities of the sensing systems and IoT to efficiently monitor the energy flow among nodes of an electric network was presented. An edge Internet-of-Energy application was proposed in [11] to perform a methodical set of steps to promote energy saving in buildings and enable home automation. The development of IoT-enabled applications for increasing water and energy awareness, management, and conservation, and engaging a wide range of end users, was presented and discussed in [12]. An algorithm that uses the IoT was proposed in [13] to provide real-time load control and minimize power outages in sudden grid-load changes and reduce the peak-to-average ratio. The usage behavior of consumers from their historical data was studied in [14] to assist in the understanding of how consumers use electricity and to encourage consumers to shift the peak-hour usage of appliances to nonpeak hours.The authors of [15] analyzed the main strategies for IoT-dependent medical-management systems, and provided a literature review on the available methodologies to use IoT-based medical-management systems.

An energy-management system was proposed in [16] for a distribution system with an IoT framework, with the objective of optimally controlling power and distribution system resources through continuous data monitoring, as the communication framework depends on IoT. The demand response from load is collected using the developed framework, and the data are broadcast to a centralized server. However, the control system of home appliances was not considered, nor were the features of smart houses, such as having rooftop PV generation, a BESS, and exchanging power with the main grid. Additionally, a distribution system network that consists of substations, feeders, and different load nodes or buses was not considered. Using a supervised machine learning approach, an electric-power-consumption and renewable-energy-generation short-term forecasting model was developed in [17] to enable a demand response scheme. A framework was developed in [18] for the operation of distribution systems with high penetration of renewable sources, and the IoT concept was used to monitor and measure the distribution system data for such an operation problem. The authors of [19] proposed a demand-side management model based on machine learning to maintain efficient energy utilization based on priorities and demands and to secure the IoT-enabled smart grid from malicious attacks. The development of a micro-distributed BESS in an intelligent light emitting diode (LED) streetlight system was studied in [20]. It was observed that the BESS initial installation costs could be reduced by using micro-distributed BESS and IoT-based intelligent energy management. A sustainable energy-efficient smart street road-lighting system was proposed in [21]. An IoT sensor-based smart electric pole with a controller for tuning LED lamps was included in the system. LED lamps were lighted by solar energy, which was stored in the BESS during day time and utilized at night time. Battery impedance can be measured by electrochemical impedance spectroscopy in a wide frequency range so as to reflect the internal aging state of battery energy-storage systems, such as the lithium-ion battery, which is a vital comportment in an energy-management system. Hence, the authors of [22] summarized the latest impedance spectroscopy measurement technology and electrochemical impedance spectroscopy based on battery health state estimation technology. A method was proposed in [23] to estimate the state of health of a lithium-ion battery for system safety and economic development. For providing an increase in management efficiency, the modeling of management processes in distributed organizational systems was presented in [24], wherein the structure components of the network organizational system were discussed and demonstrated. In the power system, many electrical quantity sensors, power distribution devices, and condition sensors are connected to the IoT network. This generates a huge amount of heterogeneous distribution data and presents a wide variety, multiple sources, and uncertainty. As the number of sensors within the power distribution Internet of Things has increased dramatically with the rapid advancement of the energy–internet strategy, a method was proposed in [25] to solve the problems of confusing storage and the insufficient fusion computing performance of multi-source heterogeneous distribution data. The performance of the developed method was tested by an experimental analysis of an IEEE39 node system in a regional distribution network in China.

An IoT facilitates integration and management of equipment through linking, tracking, and reacting to numerous applications. Bidirectional communication between equipment, sensors and networks is allowed using the IoT, with or without human intervention. The design, deployment, implementation, and real-time performance evaluation of an IoT-based smart energy-management system was presented and discussed in [26]. In order to maximize usage of onsite PV energy, flatten building load profiles, and reduce electricity costs of connected buildings, an iterative optimization and learning-based IoT application was proposed in [27]. For smoothing the buildings' load and reducing the total energy consumption of the connected buildings, the proposed method demonstrated better performance in cooperating and rearranging each building's electrical appliances. It was revealed that high electricity and battery costs can influence the cost to achieve the zero-energy goal. The customers can increase PV generation so as to minimize the cost of the electricity bill. Optimal management of the smart grid in the IoT-enabled structure was addressed in [28], considering different types of distributed generations, such as wind and solar energy resources and fuel-based generations. The hourly switching and reconfiguration of the smart grid according to the IoT protocol was also considered. It was found that by changing the construction topology through some remote switches, the proposed plan can enhance the system performance. With the IoT technology, an hourly monitoring and reconfiguration process was possible when making the scheduling plans, and thereby the distributed generation units could play an active role for the smart grid to reduce its costs. An incentive-based DR optimization model was proposed [29] to efficiently schedule household appliances so as to minimize the loads' peak hours. For better usage of electricity energy, and in exchange for a discount on electricity prices while minimizing the customer's welfare, all monitored and enrolled household appliances were coordinated using the proposed method. In [30], a method based on a demand-side management and control strategy was developed for an efficient energy management system in smart microgrids. For ensuring the economic and secure operation of the smart microgrids, the developed method harnesses the immense IoT aptitudes. The experiment results considering a smart microgrid lab-scale prototype demonstrated the efficacy of the proposed method and the operation effectiveness of such a microgrid. An optimal demand side management scheme was obtained while reducing the smart microgrid energy cost, emission cost, and peak-to-average ratio.

The consumer readiness for participation in IoT-based demand response business models was studied in [31]. Various customer incentives, such as green energy, environmental protection, profit and interest in new technologies, were taken into consideration in this study. The findings indicated that different types of customers require the creation of different service packages, depending on individual characteristics. Moreover, consumers showed interest in environmental conservation and reducing energy waste. Demand response provisions from residential and small- and medium-sized business sectors can help the utility to have high flexibility in controlling the electricity and supply balance for efficient and stable power grid operation. In [32], a framework was proposed to practically enable the operation and deployment of large-scale residential demand response, considering low introductory and operational costs. A DR server and a mobile app DR client were included in the prototype system that enables the centralized, automated control of IoT devices. In [33], an IoT-enabled optimal operating model was proposed for energy management among three energy hubs, while reducing operating costs and enhancing network reliability. A stochastic framework was also developed for the modeling of uncertain renewable resources in a correlated environment so as to control the severe fluctuations of renewable energy resources, and thereby made the proposed model efficient and less computationally demanding. The dependence of wind turbines was considered in the developed method. It was found that the dependence on electricity, natural resources and the overall network expenditure was reduced by the exchange of power and heat between energy hubs.A survey was presented in [34] on the application potential of 5G network-based IoT for DR in the smart grid. As 5G networks are emerging and rapidly being deployed around the world, this will lead to fundamental changes in all industries. The potential of applying 5G to DR was analyzed in [34], based on the typical application scenarios of 5G networks and the technology requirements for DR. Several factors were considered, such as high reliability for ensuring DR effectiveness, and low power consumption for widely promoting 5G devices.

From the aforementioned literature review, it is noted that most of the work concentrated on creating service models by integrating IoT technologies with information and communications technologies to increase energy efficiency by reducing power consumption. This paper examines and measures flexibility provisions from IoT-based houses integrated into DR programs, considering their penetration levels in a power distribution grid. Hence, there is a need to develop a framework to mathematically and optimally quantify DR, considering the power availability of IoT-based houses, for the provision of flexibility in the smart grid.

The innovations and contributions of the work presented in this paper can be summarized as follows:

- IoT-based houses are integreated into DR programs for the provision of flexibility in a power distribution grid.
- A new mathematical optimization framework is proposed to optimally quantify DR provisions, considering IoT-based house load management. The proposed framework consists of modeling a house load using IoT windows and occupant behavior, and a novel mathematical optimization model that determines the optimal DR considering IoT-based houses and their penetration in the distribution system.
- The IoT-based house operations are compared with those of conventional houses to demonstrate the effectiveness and need for such a transformation and management scheme in the smart grid.
- The penetration level of IoT-based houses in distribution systems is investigated, as well as its impacts on peak loads and system capacity.

The rest of the paper is organized as follows: Section 2 explains the proposed mathematical optimization model. Section 3 provides the test system and input data. The simulation results and analysis are depicted and discussed in Section 4. Conclusions are drawn in Section 5.

2. Proposed Mathematical Optimization Model

A mathematical optimization model is proposed, with the objective of minimizing the system peak load, while determining the optimal demand response provisions, considering the penetration level of IoT-based houses in the distribution system.

Objective function: Minimize the distribution system peak load, given by

$$P^{PK} \tag{1}$$

Power-flow equations: The power injected at the substation bus, the net of the load, and upward and downward DR considering IoT-based houses are governed by the power-flow equations:

$$P_{u,h}^{Sub} - Pd_{i,h}^{H}[(1-\alpha_i^{H^{IoT}})n_i^H] - Pd_{i,h}^{H^{IoT}}\alpha_i^{H^{IoT}}n_i^H + P_{i,h}^{-DR} - P_{i,h}^{+DR} = \sum_{j\varepsilon N} V_{i,h}V_{j,h}Y_{i,j}\cos(\theta_{i,j}+\delta_{j,h}-\delta_{i,h}) \qquad \forall(i,i)\in N, \forall h \tag{2}$$

$$Q_{u,h}^{Sub} - Qd_{i,h} = -\sum_{j\varepsilon N} V_{i,h}V_{j,h}Y_{i,j}\sin(\theta_{i,j}+\delta_{j,h}-\delta_{i,h}) \qquad i\forall N, \forall h \tag{3}$$

Demand response constraints: These constraints ensure that IoT-based house load management is integrated into direct DR programs as follows:

$$P_{i,h}^{-DR} \leqslant \beta \cdot [Pd_{i,h}^{H}(1-\alpha_i^{H^{IoT}})n_i^H + Pd_{i,h}^{H^{IoT}}\alpha_i^{H^{IoT}}n_i^H] \qquad i\forall N, \forall h \tag{4}$$

$$P_{i,h}^{+DR} \leqslant \beta \cdot [Pd_{i,h}^{H}(1-\alpha_i^{H^{IoT}})n_i^H + Pd_{i,h}^{H^{IoT}}\alpha_i^{H^{IoT}}n_i^H] \qquad i\forall N, \forall h \tag{5}$$

In a direct DR program, the load-shifting operation and decisions are assumed to be determined and controlled by the utility operator, not the electricity end users. In order to not shift the consumers' activities to the other day, the demand variation must be balanced within the daily hours as given below:

$$\sum_h P_{i,h}^{-DR} = \sum_h P_{i,h}^{+DR} \tag{6}$$

Coordination constraint of upward and downward demand response: The following constraint ensures that upward and downward DR does not occur simultaneously, given by

$$P_{i,h}^{-DR} \cdot P_{i,h}^{+DR} = 0 \qquad \forall h \tag{7}$$

Peak load constraint: The following constraint ensures that the peak load is minimized, in conjunction with (1):

$$P_{u,h}^{Sub} \leqslant P^{PK} \qquad \forall u,\ \forall h \tag{8}$$

Feeder capacity limits: The power flow through any distribution feeder should be within the limit of the feeder capacity:

$$-V_{i,k}^2 Y_{i,j}\cos\theta_{i,j} + V_{i,k}V_{j,k}Y_{i,j}\cos(\theta_{i,j}+\delta_{j,k}-\delta_{i,k}) \leqslant S_{(i,j)}^{Fcap} cos\theta_{(i,j),k}^{F} \qquad \forall(i,j)\in N : \exists(i,j), \forall k \tag{9}$$

$$V_{i,k}^2 Y_{i,j}\sin\theta_{i,j} - V_{i,k}V_{j,k}Y_{i,j}\sin(\theta_{i,j}+\delta_{j,k}-\delta_{i,k}) \leqslant S_{(i,j)}^{Fcap} sin\theta_{(i,j),k}^{F} \qquad \forall(i,j)\in N : \exists(i,j), \forall k \tag{10}$$

Limits of substation capacity: The capacity limit of the substation is included as follows:

$$(P_{u,h}^{Sub})^2 + (Q_{u,h}^{Sub})^2 \leqslant S_u^{Sub^{cap}2} \qquad \forall h \tag{11}$$

Voltage limits: These ensure that the bus voltage is within its limit:

$$\underline{V} \leqslant V_{i,h} \leqslant \overline{V} \qquad i\forall N, \forall h \tag{12}$$

The above proposed model is a nonlinear programming model and solved using the MINOS solver in the general algebraic modeling system (GAMS) environment [35].

3. Test System and Simulation Data

The 33-bus radial distribution system described in [36], shown in Figure 1, is employed in this study. The system peak demand is about 4 MW, with a base voltage of 12.66 kV. The

IEEE Reliability Test System [37] is used to generate the system load profiles. The house peak load is assumed to be 2.08 kW [38] to calculate the number of houses at each bus, and it is also assumed that all loads are residential loads. The percentage of flexible loads that can be deferred via direct DR programs is assumed to be 10%. To maintain diversity among households, the distribution system is divided into three different groups of households, and each group is assumed to have somehow similar activities at the house, and thereby a similar house load profile.

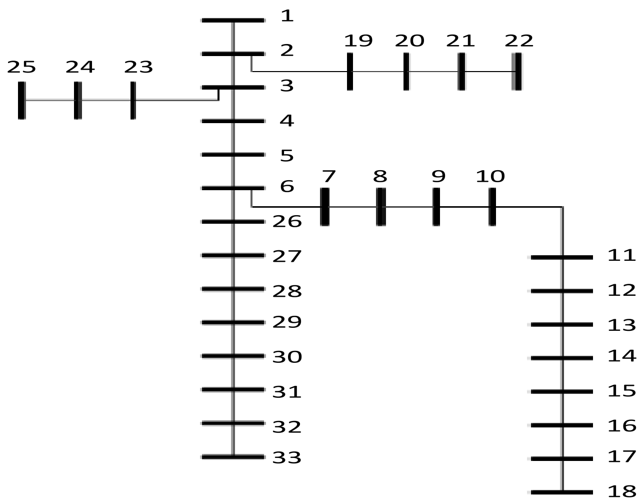

Figure 1. The 33-bus distribution system.

The modeling of a house load using IoT windows and occupant behavior is adopted from [39]. The IoT window includes a double-glazing window and has a mid-shade that can reflect more than 95% of solar light. In this study, a single family detached house is considered and modeled since it represents the biggest share of homes types in the United States (US), with more than 60% of US homes. The house devices include a fridge, washing machine, dryer, electric oven, dishwasher and LED lamp with linear control. The window-to-wall ratio (WWR) of the house is equal to 28.2%. The HVAC system of the house is a variable refrigerant flow (VRF) system which has heat recovery and a dedicated outdoor air system. The house load model includes two bedrooms, a living room, a kitchen, and a garage. The description and data of smart house devices used in this work can be found in [39]. The data of occupant behavior are adopted from [40], as the impact of occupant behavior uncertainty is below 2%. The SHGC of conventional and IoT windows in different weather conditions is presented in Figure 2. The reader may refer to [39] for further discussions of the IoT window model.

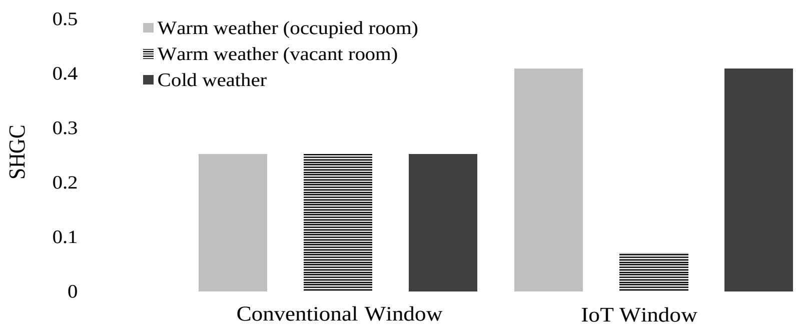

Figure 2. SHGC of conventional and IoT windows in different weather conditions.

4. Results and Discussions

Prior to determining DR provisions from conventional and IoT-based houses in a distribution system, a house load modeled using IoT windows and occupant behavior needs be determined. Hence, Figures 3–5 show conventional and IoT-based load management of houses, considering different kinds of weather conditions among households arbitrarily located in the distribution systems. The IoT window has an ability to change its SHGC widely based on weather conditions and occupant behavior. In warm weather, when the house is unoccupied, the IoT window changes its SHGC to the lowest amount so as to slow down the rate of rising temperature in the room when the HVAC system is off, and thereby the daily HVAC system energy consumption reduces, as shown in Figures 3–5. On the other hand, the mid-shade of an IoT window is always off during cold weather, and regardless of whether the room is vacant or not, the IoT window has the highest SHGC so that the sunlight transmits more solar radiation into the house, therefore keeping the room warm to reduce the daily energy consumption of the heating system.

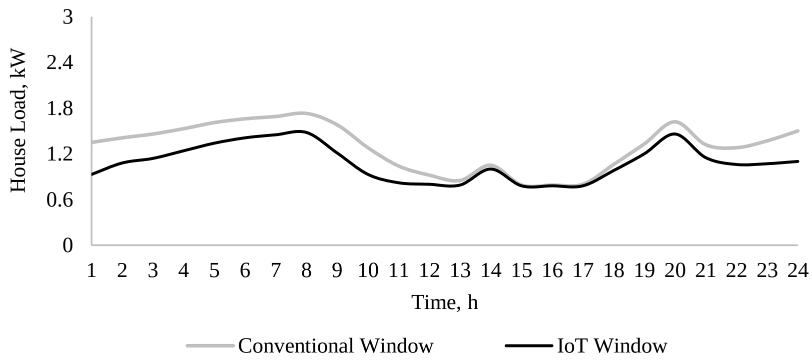

Figure 3. Load profiles of a house at locations [2–6,19–25], considering conventional and IoT windows.

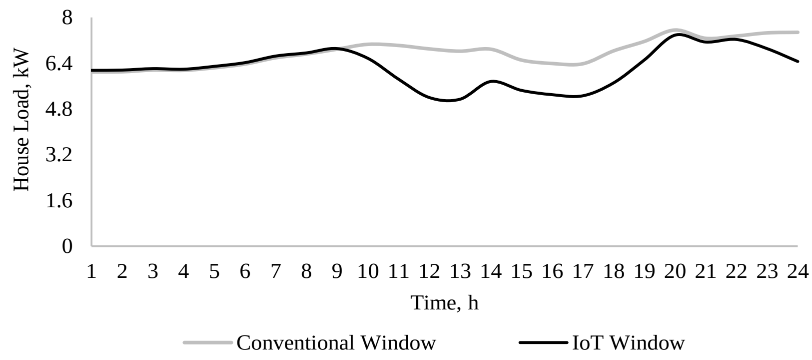

Figure 4. Load profiles of a house at locations [26–33], considering conventional and IoT windows.

Energy conservation is achieved when integrating houses with IoT windows and occupant behavior. Using the proposed model, the optimal DR provisions with and without IoT-based house load management are determined. The optimal system peak load considering different case studies is presented in Figure 6. It is observed that the system load reduces in the case of either DR- or IoT-based house management, and it reduces further with the consideration of both DR- and IoT-based house load management. It can be noticed that the impact of the direct DR program on the system peak is significant with respect to IoT-based house load management due to the fact that DR takes places based on the load-shifting operation and decisions made by the utility operator, taking into account the system needs, whereas IoT-based house load management conserves the house energy only, not shifting the house load based on the system needs. Hence, integrating IoT-based house load management into the DR program helps in achieving both energy conservation and load management, which further reduces the system peak load.

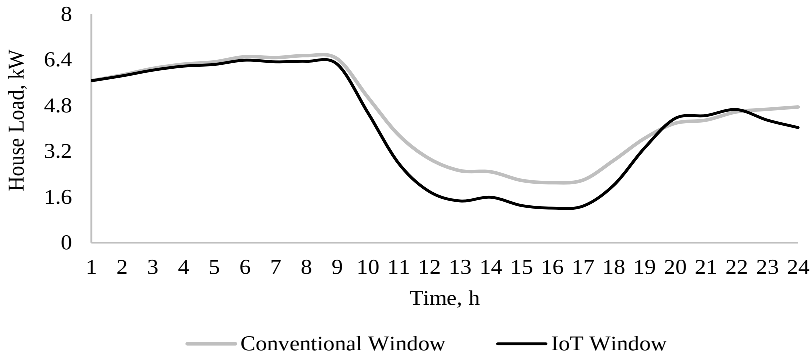

Figure 5. Load profiles of a house at locations [7–18], considering conventional and IoT windows.

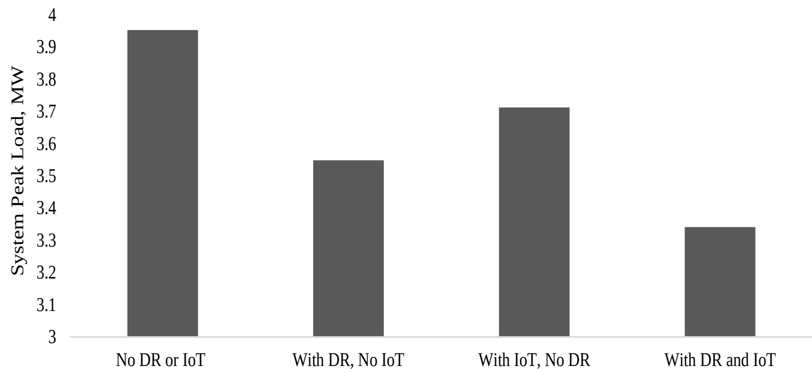

Figure 6. System peak load considering DR- and IoT-based house load management.

Figure 7 shows the impact of the varied penetration of IoT-based houses on the system peak load, with and without DR. It is observed that an inverse linear relationship exists between the system peak load and the penetration of IoT-based houses. The system peak load reduces when the penetration of IoT-based houses increases. Without the consideration of the DR program, the system peak load reduces by 0.24 MW when all houses are integrated with IoT windows and occupant behavior in the distribution system. On the other hand, when integrating IoT-based houses into the DR program, the system peak load further reduces by 0.61 MW.

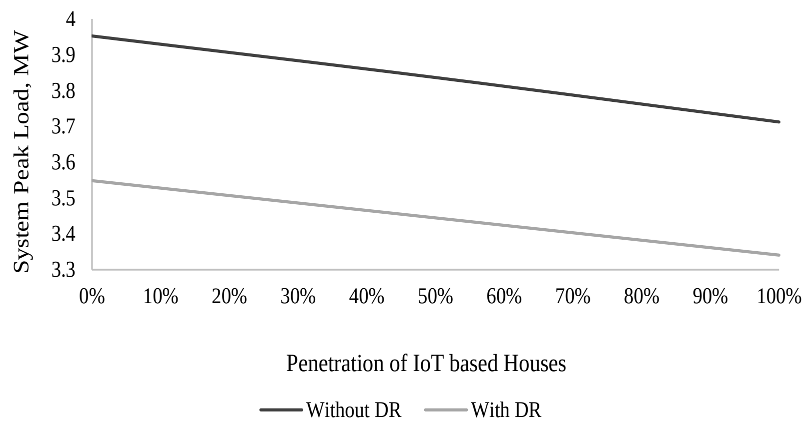

Figure 7. System peak load considering different penetration of IoT-based houses in the distribution system, with and without DR.

The power of distribution substation at location-1, with and without the consideration of IoT-based houses and DR, is presented in Figure 8. It is noted that when all houses are transformed into IoT-based houses and integrated into DR programs, the substation power reduces during all hours, and significantly reduces during the peak hours, hours 9 and 20. This enhances the distribution system capacity, and thereby the system can accommodate any future loads without the need for system upgrades.

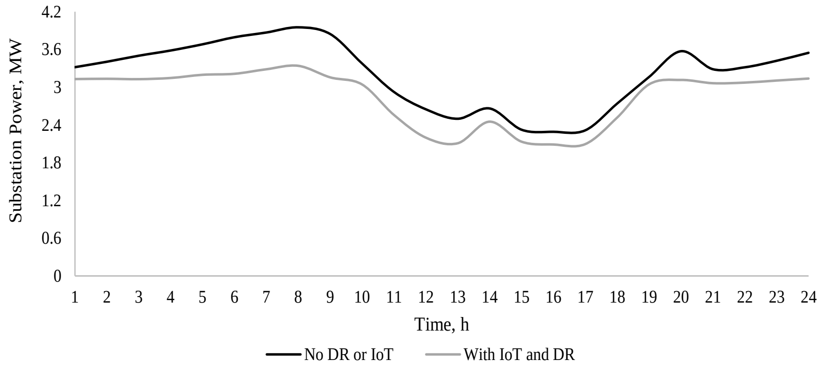

Figure 8. Power of distribution substation, with and without IoT-based houses and DR.

In order to demonstrate the effect of DR- and/or IoT-based houses on the system loads, two arbitrary locations are considered. The system loads at location-22 and -32, considering DR, are presented in Figures 9 and 10, respectively, while Figures 11 and 12 show the system loads at location-22 and -32, with the consideration of IoT-based houses. Figures 13 and 14 illustrate the effect of both DR- and IoT-based houses on the system load at location-22 and -32, respectively.

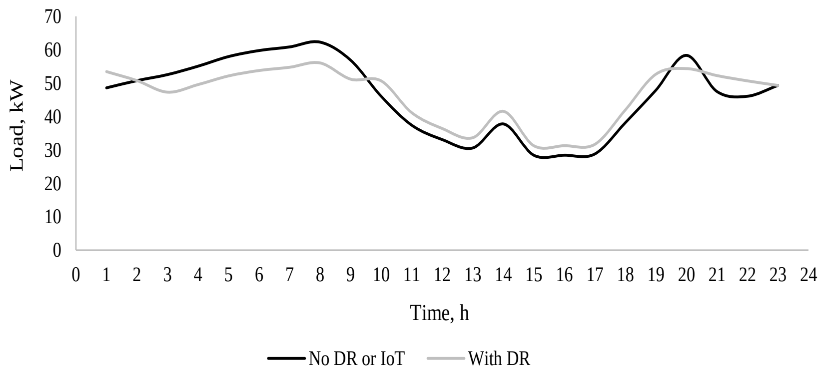

Figure 9. System load at location-22, with and without considering DR.

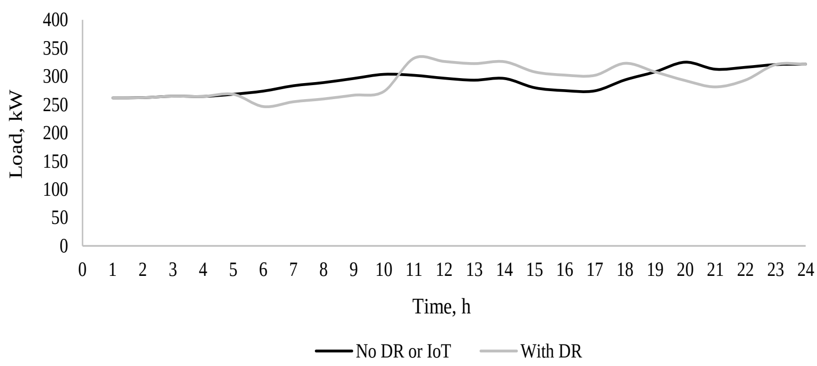

Figure 10. System load at location-32, with and without considering DR.

Load shifting and management caused by inducing DR can be observed in Figure 9 at location-22 and in Figure 10 at location-32, whereas load conservation as a result of having IoT-based houses can be realized in Figure 11 at location-22 and Figure 12 at location-32. Both load management and conservation are achieved in Figure 13 at location-22 and Figure 14 at location-32 when integrating IoT-based houses into DR programs, and this helps further reduce the system load, mainly during the peak hours, hours -9 and -20.

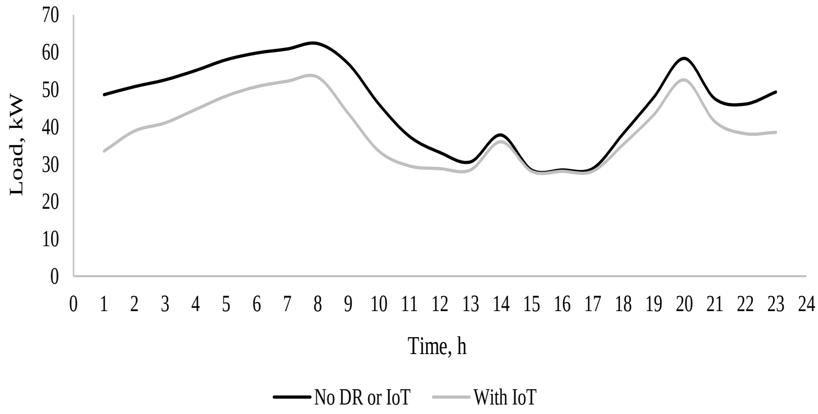

Figure 11. System load at location-22, with and without considering IoT-based houses.

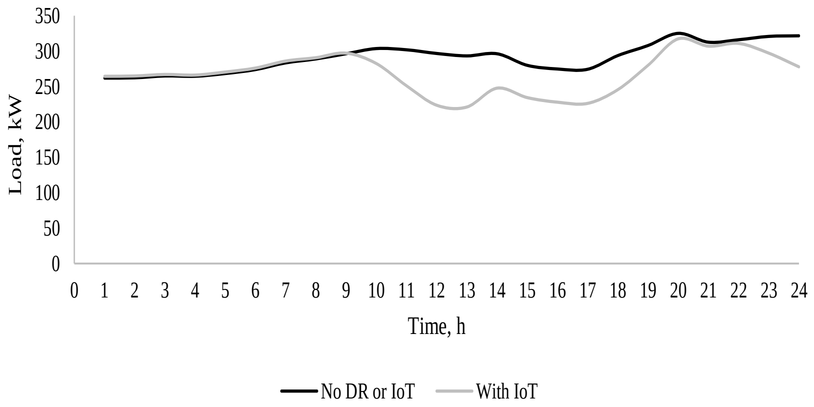

Figure 12. System load at location-32, with and without considering IoT-based houses.

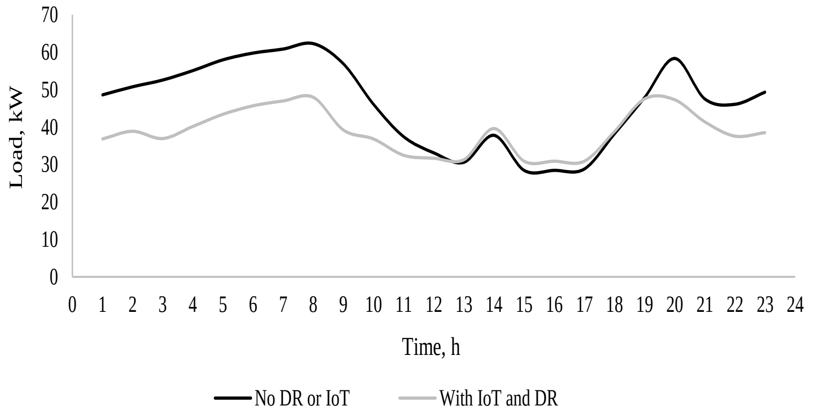

Figure 13. System load at location-22, with and without considering both DR- and IoT-based houses.

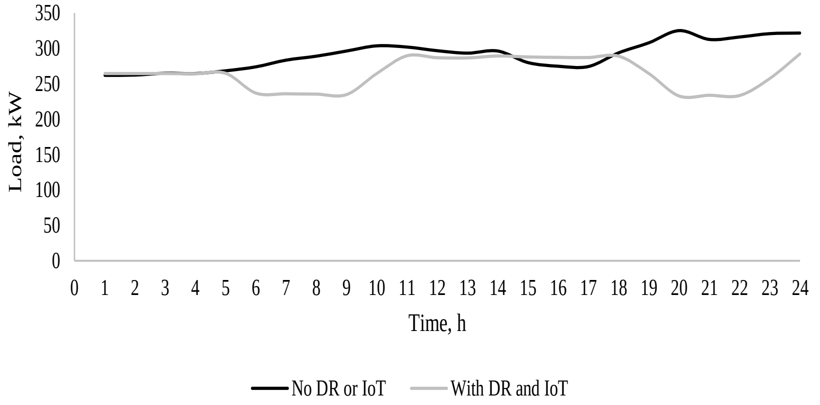

Figure 14. System load at location-32, with and without considering both DR- and IoT-based houses.

5. Conclusions

The paper presents a new framework for mathematically and optimally quantifying DR provisions from residential loads, considering the IoT concept, for the provision of flexibility in the smart grid. IoT-based loads of houses integrated with IoT windows and occupant behavior were firstly modeled. A novel mathematical optimization model was proposed to determine the optimal DR provisions, with and without the integration of IoT-based houses into DR programs, considering their penetration in the distribution system. Different case studies, along with numerical results, were presented to demonstrate the performance of the proposed framework. It was observed that the relationship between the system peak load and the penetration of IoT-based houses was found to be inverse linear. When the penetration of IoT-based houses increased, the system peak load reduced. The system peak load reduced by 0.24 MW when all houses were integrated with IoT windows and occupant behavior but without considering the DR program. On the other hand, when integrating IoT-based houses into the DR program, and all houses were transformed into IoT-based houses, the system peak load further reduced by 0.61 MW. It was also noted that, with the consideration of both DR- and IoT-based houses, the substation power reduced during all the hours and significantly reduced during the peak hours, hours -9 and -20. It can be concluded that not only peak savings but also energy conservation were achieved when integrating IoT-based houses into DR programs, which is a promising solution to promote energy efficiency, reduce energy waste, and ensure a more reliable and sustainable energy future.

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Conflicts of Interest: The author declares no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

i, j	Buses, $i, j\ \varepsilon\ N$
h	Time, $h\ \varepsilon\ H$
u	Location of distribution substation, $u\ \varepsilon\ U$
n^H	Number of houses in a distribution substation
$\alpha^{H^{IoT}}$	Penetration of IoT-based houses, $p.u$

β	Percentage of flexible loads, $p.u$
Pd^{H}	Conventional house load of a distribution system, $p.u$
$Pd^{H^{IoT}}$	IoT-based house load of a distribution system, $p.u$
Qd	Reactive load of a distribution system, $p.u$
P^{Sub}, Q^{Sub}	Active and reactive power drawn, $p.u$
P^{PK}	System peak load, $p.u$
P^{+DR}	Upward demand response, $p.u$
P^{-DR}	Downward demand response, $p.u$
P^{F}, Q^{F}	Feeder active and reactive power flow, $p.u$
V	Voltage magnitude, $p.u$
δ	Voltage phase angle, rad

References

1. Zielonka, A.; Sikora, A.; Woźniak, M.; Wei, W.; Ke, Q.; Bai, Z. Intelligent Internet of Things System for Smart Home Optimal Convection. *IEEE Trans. Ind. Inform.* **2021**, *17*, 4308–4317. [CrossRef]
2. Choi, W.; Kim, J.; Lee, S.; Park, E. Smart home and internet of things: A bibliometric study. *J. Clean. Prod.* **2021**, *301*, 126908. [CrossRef]
3. Arias, L.A.; Rivas, E.; Santamaria, F.; Hernandez, V. A review and analysis of trends related to demand response. *Energies* **2018**, *11*, 1617. [CrossRef]
4. Vahid-Ghavidel, M.; Javadi, M.S.; Gough, M.; Santos, S.F.; Shafie-Khah, M.; Catalao, J.P. Demand response programs in multi-energy systems: A review. *Energies* **2020**, *13*, 4332. [CrossRef]
5. O'Dwyer, E.; Pan, I.; Acha, S.; Shah, N. Smart energy systems for sustainable smart cities: Current developments, trends and future directions. *Appl. Energy* **2019**, *237*, 581–597. [CrossRef]
6. Ahmad, T.; Zhang, D. Using the internet of things in smart energy systems and networks. *Sustain. Cities Soc.* **2021**, *68*, 102783. [CrossRef]
7. Sharda, S.; Singh, M.; Sharma, K. Demand Side Management through Load Shifting in IoT based HEMS: Overview, Challenges and Opportunities. *Sustain. Cities Soc.* **2020**, *65*, 102517. [CrossRef]
8. Khatua, P.K.; Ramachandaramurthy, V.K.; Kasinathan, P.; Yong, J.Y.; Pasupuleti, J.; Rajagopalan, A. Application and assessment of internet of things toward the sustainability of energy systems: Challenges and issues. *Sustain. Cities Soc.* **2020**, *53*, 101957. [CrossRef]
9. Cheng, Y.L.; Lim, M.H. Impact of Internet of Things Paradigm towards Energy Consumption Prediction: A Systematic Literature Review. *Sustain. Cities Soc.* **2021**, *78*, 103624. [CrossRef]
10. Morello, R.; De Capua, C.; Fulco, G.; Mukhopadhyay, S.C. A smart power meter to monitor energy flow in smart grids: The role of advanced sensing and IoT in the electric grid of the future. *IEEE Sens. J.* **2017**, *17*, 7828–7837. [CrossRef]
11. Alsalemi, A.; Himeur, Y.; Bensaali, F.; Amira, A. An innovative edge-based Internet of Energy solution for promoting energy saving in buildings. *Sustain. Cities Soc.* **2022**, *78*, 103571. [CrossRef]
12. Curry, E.; Hasan, S.; Kouroupetroglou, C.; Fabritius, W.; ul Hassan, U.; Derguech, W. Internet of things enhanced user experience for smart water and energy management. *IEEE Internet Comput.* **2018**, *22*, 18–28. [CrossRef]
13. Mortaji, H.; Ow, S.H.; Moghavvemi, M.; Almurib, H.A.F. Load shedding and smart-direct load control using internet of things in smart grid demand response management. *IEEE Trans. Ind. Appl.* **2017**, *53*, 5155–5163. [CrossRef]
14. Tom, R.J.; Sankaranarayanan, S.; Rodrigues, J.J. Smart Energy Management and Demand Reduction by Consumers and Utilities in an IoT-Fog-Based Power Distribution System. *IEEE Internet Things J.* **2019**, *6*, 7386–7394. [CrossRef]
15. Zhang, G.; Navimipour, N.J. A comprehensive and systematic review of the IoT-based medical management systems: Applications, techniques, trends and open issues. *Sustain. Cities Soc.* **2022**, *82*, 103914. [CrossRef]
16. Krishnan, P.R.; Jacob, J. An IOT based efficient energy management in smart grid using DHOCSA technique. *Sustain. Cities Soc.* **2022**, *79*, 103727. [CrossRef]
17. Balakumar, P.; Vinopraba, T.; Chandrasekaran, K. Machine learning based demand response scheme for IoT enabled PV integrated smart building. *Sustain. Cities Soc.* **2023**, *89*, 104260.
18. Ding, S.; Zeng, J.; Hu, Z.; Yang, Y. IOT-based social-economic management of distribution system with the high penetration of renewable energy sources. *Sustain. Cities Soc.* **2022**, *76*, 103439. [CrossRef]
19. Babar, M.; Tariq, M.U.; Jan, M.A. Secure and resilient demand side management engine using machine learning for IoT-enabled smart grid. *Sustain. Cities Soc.* **2020**, *62*, 102370. [CrossRef]
20. Park, S.; Kang, B.; Choi, M.i.; Jeon, S.; Park, S. A micro-distributed ESS-based smart LED streetlight system for intelligent demand management of the micro grid. *Sustain. Cities Soc.* **2018**, *39*, 801–813. [CrossRef]
21. Chen, Z.; Sivaparthipan, C.; Muthu, B. IoT based smart and intelligent smart city energy optimization. *Sustain. Energy Technol. Assess.* **2022**, *49*, 101724. [CrossRef]
22. Zhang, M.; Liu, Y.; Li, D.; Cui, X.; Wang, L.; Li, L.; Wang, K. Electrochemical impedance spectroscopy: A new chapter in the fast and accurate estimation of the state of health for lithium-ion batteries. *Energies* **2023**, *16*, 1599. [CrossRef]

23. Guo, Y.; Yang, D.; Zhang, Y.; Wang, L.; Wang, K. Online estimation of SOH for lithium-ion battery based on SSA-Elman neural network. *Prot. Control Mod. Power Syst.* **2022**, *7*, 40. [CrossRef]
24. Zelenina, A.; Petrosov, D.; Pleshakova, E.; Osipov, A.; Ivanov, M.; Choporov, O.; Preobrazhenskiy, Y.; Petrsova, N.; Roga, S.; Lopatnuk, L.; et al. Modeling of management processes in distributed organizational systems. *Procedia Comput. Sci.* **2022**, *213*, 377–384. [CrossRef]
25. Yuan, Q.; Pi, Y.; Kou, L.; Zhang, F.; Li, Y.; Zhang, Z. Multi-source data processing and fusion method for power distribution internet of things based on edge intelligence. *Front. Energy Res.* **2022**, *10*, 470. [CrossRef]
26. Saleem, M.U.; Usman, M.R.; Usman, M.A.; Politis, C. Design, deployment and performance evaluation of an IoT based smart energy management system for demand side management in smart grid. *IEEE Access* **2022**, *10*, 15261–15278. [CrossRef]
27. Gao, Y.; Li, S.; Xiao, Y.; Dong, W.; Fairbank, M.; Lu, B. An Iterative Optimization and Learning-based IoT System for Energy Management of Connected Buildings. *IEEE Internet Things J.* **2022**, *9*, 21246–21259. [CrossRef]
28. Wang, B.; Ma, H.; Wang, F.; Dampage, U.; Al-Dhaifallah, M.; Ali, Z.M.; Mohamed, M.A. An IoT-Enabled Stochastic Operation Management Framework for Smart Grids. *IEEE Trans. Intell. Transp. Syst.* **2022**, *24*, 1025–1034. [CrossRef]
29. Ruzbahani, H.M.; Karimipour, H. Optimal incentive-based demand response management of smart households. In Proceedings of the 2018 IEEE/IAS 54th Industrial and Commercial Power Systems Technical Conference (I&CPS), Niagara Falls, ON, Canada, 7–10 May 2018; pp. 1–7.
30. Sedhom, B.E.; El-Saadawi, M.M.; El Moursi, M.; Hassan, M.A.; Eladl, A.A. IoT-based optimal demand side management and control scheme for smart microgrid. *Int. J. Electr. Power Energy Syst.* **2021**, *127*, 106674. [CrossRef]
31. Radenković, M.; Bogdanović, Z.; Despotović-Zrakić, M.; Labus, A.; Lazarević, S. Assessing consumer readiness for participation in IoT-based demand response business models. *Technol. Forecast. Soc. Chang.* **2020**, *150*, 119715. [CrossRef]
32. Mashima, D.; Chen, W.P. Residential demand response system framework leveraging IoT devices. In Proceedings of the 2016 IEEE International Conference on Smart Grid Communications (SmartGridComm), Sydney, NSW, Australia, 6–9 November 2016; pp. 514–520.
33. Kazemi, B.; Kavousi-Fard, A.; Dabbaghjamanesh, M.; Karimi, M. IoT-enabled operation of multi energy hubs considering electric vehicles and demand response. *IEEE Trans. Intell. Transp. Syst.* **2022**, *24*, 2668–2676. [CrossRef]
34. Hui, H.; Ding, Y.; Shi, Q.; Li, F.; Song, Y.; Yan, J. 5G network-based Internet of Things for demand response in smart grid: A survey on application potential. *Appl. Energy* **2020**, *257*, 113972. [CrossRef]
35. Corporation, G.D. General Algebraic Modeling System (GAMS), Software. Available online: https://www.gams.com/ (accessed on 12 December 2022).
36. Baran, M.E.; Wu, F.F. Network reconfiguration in distribution systems for loss reduction and load balancing. *IEEE Trans. Power Deliv.* **1989**, *4*, 1401–1407. [CrossRef]
37. Pinheiro, J.; Dornellas, C.; Schilling, M.T.; Melo, A.; Mello, J. Probing the new IEEE reliability test system (RTS-96): HL-II assessment. *IEEE Trans. Power Syst.* **1998**, *13*, 171–176. [CrossRef]
38. Alharbi, W.; Almutairi, A. Planning Flexibility With Non-Deferrable Loads Considering Distribution Grid Limitations. *IEEE Access* **2021**, *9*, 25140–25147. [CrossRef]
39. Fekri, H.; Soltani, M.; Hosseinpour, M.; Alharbi, W.; Raahemifar, K. Energy simulation of residential house integrated with novel IoT windows and occupant behavior. *Sustain. Cities Soc.* **2022**, *78*, 103594. [CrossRef]
40. Habara, H.; Yasue, R.; Shimoda, Y. Survey on the occupant behavior relating to window and air conditioner operation in the residential buildings. In Proceedings of the 13th Conference of International Building Performance Simulation Association, Chambery, France, 25–28 August 2013; pp. 2007–2013.