Hafiz Majid Hussain

HEURISTIC-BASED PACKETIZED ENERGY MANAGEMENT FOR RESIDENTIAL ELECTRICITY DEMAND

ACTA UNIVERSITATIS LAPPEENRANTAENSIS 1079

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Abstract

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The unprecedented growth of distributed energy resources (DERs) has brought limitless opportunities to reshape the energy infrastructure and instigate urgent reforms for techno-economic advancements, business models, sustainability, environmental impacts, and resource management. The incorporation of DERs is a remarkable choice to replace fossil fuels-based generation and transform the electric power grid from a centralized into a decentralized network, unlocking the opportunities for a green, sustainable, and cost-effective energy ecosystem. To realize this transformation, the concept of the Energy Internet (EI) has emerged aiming to combine DERs, such as renewable energy resources, energy storage systems, flexible loads, and other energy networks, such as heat and gas networks, through advanced information and communication technologies (ICTs). In this context, this doctoral dissertation first puts forward the basic foundation of the EI and proposes a universal definition through an extensive review of the state of the art. The EI powers a revolutionary technological transformation in the power system by integrating multiple energy networks, intelligent devices, smart metering infrastructure), and flexible management of energy resources by packetized energy management (PEM). What is more, the potential challenges and key requirements, such as system complexity, system security, and social acceptance, are identified for establishing the EI framework.

Second, this dissertation investigates the two essential features of the EI in the context of managing energy resources in smart homes: the home energy management system (HEMS) and the energy router (ER). Primarily, the hierarchical structure of the HEMS is described comprehensively considering the key components, demand response (DR) benefits, and energy management solutions based on heuristic optimization methods (HOMs). The main objectives accomplished by the HEMS are efficient energy management plans for smart homes, minimizing the electricity bill for smart home users, and reducing the peak-to-average ratio. This accomplishment of the HEMS benefits smart home users and maintains stable power grid operation in peak demand. Moreover, energy management solutions provided by the HEMS are tested in the case of a cyberattack to validate the performance of the HEMS in terms of the resilience index.

Last but not least, a comprehensive ER system is designed to provide efficient PEM plans for smart homes based on the energy packet scheduling parameters, energy packet transaction parameters, grid-connected photovoltaic systems, and energy storage systems.

First, the key features of the ER-based PEM are comprehensively described and a system model is developed for single and multiple smart homes including their formulation and respective constraints to jointly minimize the average aggregate system cost. The joint optimization problem is mathematically solved through the implemented HOMs. The simulation-based results are analyzed, and it is demonstrated that the designed ER-based PEM system is capable of minimizing the average aggregated cost and providing efficient PEM plans for a single home or multiple homes in varying weather conditions.

Keywords: energy internet, energy router, heuristic optimization, packetized energy management, demand response

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Hafiz Majid Hussain
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To my mother Shahida Nasreen and my sister Wajiha Samer

Contents

List of publications

This doctoral dissertation is based on the following papers. The rights have been granted by the publishers to include the papers in the dissertation.

I. Hussain, H. M., Narayanan, A., Nardelli, P. H., and Yang, Y. (2020). What is Energy Internet? Concepts, technologies, and future directions. *IEEE Access*, Vol. 8, pp. 183127–183145.

II. Hussain, H. M. and Nardelli, P. H. (2020). A Heuristic-based Home Energy Management System for Demand Response, Conference article. In *2020 IEEE Conference on Industrial Cyberphysical Systems (ICPS)*, Vol. 1, pp. 285–290.

III. Hussain, H. M., Narayanan, A., Sahoo, S., Yang, Y., Nardelli, P. H., and Blaabjerg, F. (2022). Home Energy Management Systems: Operation and Resilience of Heuristics Against Cyberattacks. *IEEE Systems, Man, and Cybernetics Magazine*, 8(2), pp. 21–30.

IV. Hussain, H. M., Ahmad, A., Narayanan, A., Nardelli, P. H., and Yang, Y. (2021). Packetized Energy Management Controller for Residential Consumers. In *2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*, pp. 1–6.

V. Hussain, H. M., Ahmad, A., Narayanan, A., Nardelli, P. H., and Yang, Y. (2022). Benchmarking of Heuristic Algorithms for Energy Router-Based Packetized Energy Management in Smart Homes. *IEEE Systems Journal*.

Author's contribution

Hafiz Majid Hussain is the principal author and conducted an extensive literature review, designed the system models, developed the mathematical formulation and the optimization solution, implemented the heuristic optimization algorithms, and presented simulation-based results in Publications I–V. The coauthors provided insightful suggestions, supportive ideas, and guidance to improve the scientific ideas and write-up of the above-mentioned publications.

Other relevant publications

- de Castro Tomé, M., Nardelli, P. H. J., Hussain, H. M., Wahid, S., and Narayanan, A. (2020). A cyber-physical residential energy management system via virtualized packets. *Energies*, 13(3), p. 699.
- Nardelli, P., Hussain, H. M., Narayanan, A., and Yang, Y. (2021). Virtual microgrid management via software-defined energy network for electricity sharing: Benefits and challenges. *IEEE Systems, Man, and Cybernetics Magazine*, 7(3), pp. 10–19.
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Book chapter

- Hussain, H. M., Narayanan, A., and Nardelli, P. H. J. (2021). Key Technologies for the Energy Internet. In: Fathi, M., Zio, E., Pardalos, P. M. (eds.). *Handbook of Smart Energy Systems*. Springer, Cham. https://doi.org/10.1007/978-3-030-72322-4_1081

Nomenclature

Latin alphabet

$\mathcal{C}_{\mathcal{A}}$	Electricity cost per hour without a cyberattack
$\mathcal{C}_{O}$	Electricity cost per hour during a cyberattack
$\overline{K}_{T_0}^{M,s}$	Cost function based on the energy storage system tasks for M smart homes over T_0
$\overline{K}_{T_0}^{M,tx}$	Cost function associated with energy packet transactions of M smart homes over T_0
$\overrightarrow{v_r}_{\max}$	Maximum velocity of a particle r at a random point in a swarm
$\overrightarrow{v_r}_{\min}$	Minimum velocity of a particle r at a random point in a swarm
B_{max}	Maximum value of J_t^{buy} during energy packet transactions
b_{max}	Maximum bandwidth of musical note
b_{min}	Minimum bandwidth of musical note
$c_t^{j,(+)}$	Admission cost for the charging event of a storage system in a smart home j at t
$c_t^{j,(-)}$	Admission cost for the discharging event of a storage system in a smart home j at t
$C_{T_0}^{N}$	Total energy cost by all loads N over T_0
D_{PAR}	Peak-to-average ratio
$d_t^{j,i}$	Delay experienced by a load i in smart home j at time t
$E_{min}^{j,s}$	Per slot minimum required $E_t^{j,s}$ for a energy storage system
$E_{t,pv}^{j}$	Harvested energy from a PV system by smart home j at t
$E_{t,pv}^{j,c}$	Residue PV energy stored by a smart home j at t
$E_{T_0}^{N}$	Total energy consumed by all loads over T_0
E_t	Energy consumed by appliance in t
E_t^{g}	Energy packets supplied by the utility grid
$E_t^{j,s}$	Charged energy in a storage system of a smart home at t
$H_{T_0}^{M,L}$	Operational time slots T_0 of all loads L of smart homes M
$H_t^{j,buy}$	Energy packets procured by smart home j from E_t^{g}
$H_t^{j,sell}$	Energy packets sold by smart home j to E_t^{g}
J_t^{buy}	$P_t^{j,i}$ procured by P-ESP from E_t^{g} at t
J_t^{sell}	$P_t^{j,i}$ sold by P-ESP to the utility grid at t
$K_d(\overline{d}_{T_0}^{M,N})$	Cost function based on average delay experienced by M smart homes of N loads over T_0
$K_t^{j,buy}$	Cost of $P_t^{j,i}$ buying by smart home j from utility grid at t
$K_t^{j,sell}$	Cost of $P_t^{j,i}$ selling by smart home j from utility grid at t
k_t^{j}	Discharged energy from a storage system of a smart home at t
p_g	Global position of the particle in a swarm
p_r	Local position of the particle in a swarm
$P_{t,max}^{j,i}$	Upper bound of the $P_t^{j,i}$
$P_{t,min}^{j,i}$	Lower bound of the $P_t^{j,i}$

$P_{T_0}^{M,N}$	Total energy packets demanded by M smart homes of N loads over T_0
$P_t^{j,i}$	Energy packet demand by smart home j at t
$x_t^{j,i}$	Available time slots for scheduling of $P_t^{j,i}$
p_e^U, p_e^L	Upper and lower bounds of population generated by DE

Greek alphabet

α_t	Decay rate of the energy storage system at time t
η_{pv}	Conversion efficiency of PV panels
$\eta_t^{(+)}, \eta_t^{(-)}$	Charging and discharging efficiencies of energy storage system
γ_t	Electricity pricing signal at time t
π_t^i	Operational status of the appliance t at time t
$\tau_t^{j,i}$	Departure time of load i in a smart home j at time t
$\varrho_t^{j,i}$	Arrival time of load i in a smart home j at time t
$\varsigma_t^{j,i}$	Length of operation time of load i in a smart home j at time t
$\zeta_t^{j,i}$	Scheduling start time of load i in a smart home j at time t

Superscripts

$'$	Derivative
c	Consumed energy
DS	Demand supply
g	Utility grid
i	Superscripts for loads from 1 to N
j	Superscripts for smart homes from 1 to M
L	Lower bound
s	State of the battery
U	Upper bound
—	Average

Subscripts

bt	Bit wise operation
c	Crossover
m	Mutation
max	Maximum
min	Minimum
r	Particle in the swarm
t	Time step
T_0	Total length of time

Abbreviations

AC	Alternating current

AM	Algorithm management
AMI	Advanced metering infrastructure
BPSO	Binary particle swarm optimization
CCP	Critical peak pricing
CPS	Cyber-physical system
DC	Direct current
DE	Differential evolution
DERs	Distributed energy resources
DGI	Distributed grid intelligence
DoS	Denial-of-service
DR	Demand Response
DSDs	Distributed storage devices
DSM	Demand-side management
EI	Energy Internet
EMS	Energy management system
ER	Energy router
FDI	False data injection
FREEDM	Future renewable electric energy delivery and management
GA	Genetic algorithm
HEMS	Home energy management system
HMCR	Harmony memory consideration rate
HSA	Harmony search algorithm
ICTs	Information and communication technologies
IEM	Internet equipment management
IFM	Intelligent fault management
IoT	Interent of things
MAs	Multiagents
P-ESP	Packetized energy service provider
PAR	Peak-to-average-ratio
PEC	Packetized energy cost
PEM	Packetized energy management
PEMC	Packetized energy management controller
PLC	Power line communication
PV	Photovoltaic
QoS	Quality-of-service
QR	Software-defined network
RRs	Renewable resources
RTP	Real-time pricing
SDN	Software-defined network
SNM	Software network management
SST	Solid-state transformer
ToU	Time of use

1 Introduction

This chapter provides the general background, motivation, and aims of the doctoral dissertation. It also covers the research questions and scientific contributions of the dissertation.

1.1 Background

Electricity is a vital source for the human well-being and the global economic development [1]. Today, the electricity demand is growing exponentially because of the unprecedented rise in the global population and different types of electricity-consuming devices [2]. This increasing trend demands electric power grids to produce a sufficient amount of electricity to maintain a balance between demand and supply. Generally, electric power grids are large and complex networks of separated power grids that are connected in a centralized fashion through long-haul transmission lines and distribute electricity to the consumers. However, since the inception of the electric power grid, it has faced twofold serious problems. First, it is highly reliant on the combustion of nonrenewable energy resources, such as coal, oil, and natural gas, which leads to the depletion of resources and severe climate changes including flooding and glacial melting. Second, the aging and centralized structure of the electric power grid is limited to a one-way flow of power, i.e., from generation to end consumers without leveraging renewable-based energy resources and advanced communication technologies [3]. To address these problems, the concept of a smart grid has emerged, which has transformed the electric power grid and integrated renewable energy resources (RESs) and advanced technologies [4]. The smart grid enables a high penetration of RESs, such as photovoltaic (PV), wind, and biomass energies, and supports the bidirectional flow of power and information through smart devices: e.g., the Internet of Things, smart meters, and smart management systems [5]. The smart grid can be defined as: "an electric system that uses information, two-way, cyber-secure communication technologies, and computational intelligence in an integrated fashion across the entire spectrum of the energy system from the generation to the endpoints of consumption of the electricity" [6].

The emergence of the smart grid has provided a breakthrough to deal with the major concerns of the electric power grid. Yet, it still lacks in providing flexibility in the following aspects: distributed access of multienergy carrier systems and massive integration and scheduling of renewable generation and electrical devices [7]. In addition, the smart grid accommodates communication technologies to connect only one form of energy network (i.e., electricity) in a centralized way without considering other energy networks including thermal and heat energy [8]. This makes smart grid features inadequate and limited, and hence, has paved the way for the evolution of smart grid known as the *Energy Internet* [9], [10]. The term Energy Internet (EI) was coined by Jeremy Rifkin and refers to "an intelligent grid that transforms power grid into an info-energy net, allowing millions of people who produce their own energy to share surpluses peer-to-peer" [11]. The EI is regarded as the next version of the smart grid dominated by internet and communication technologies. The EI enables the following features that make it superior to the smart

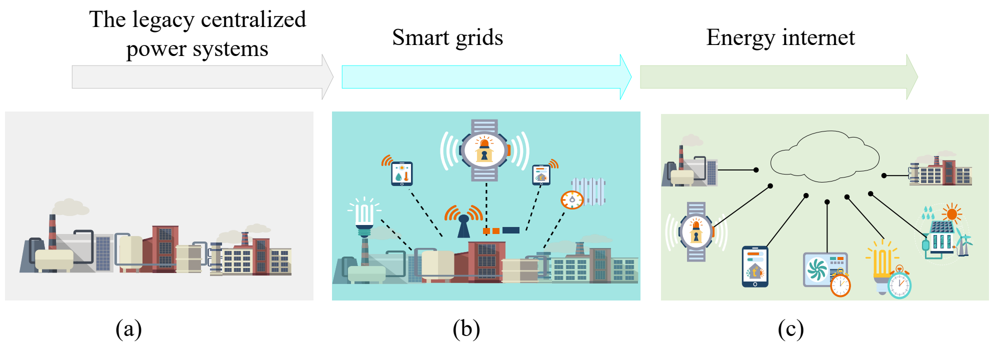

Figure 1.1: (a) Separate power grids connected together through long-distance transmission lines in a centralized fashion. (b) An intelligent or a smart grid integrates advanced sensing technologies, control methods, and integrated communications into the current electricity grid. (c) The power grid will be transformed into an info-energy net, allowing energy sharing and trading [12].

grid: (i) it merges the multiple energy networks, i.e., electricity networks, gas networks, and heat networks; (ii) it incorporates smart sensing and management equipment, i.e., energy routers, smart meters, and EI access equipment; and (iii) it provides scheduling, sharing, and trading of energy resources [12], [13]. Figure 1.1 presents an overview of the traditional power grids, smart grids, and the EI.

Essentially, the EI is a radical transformation of the power industry and orchestrates energy generation sources through internet and communication technologies, smart control devices, and intelligent management methods [14], [15]. To enable these features of the EI, particularly ER is envisioned as a pivotal component and resembles the role of an internet router in the data network in terms of connecting and sharing various resources. Broadly speaking, an ER is entitled to enable multiway communication, power conversion technologies, and a unified way to utilize energy resources through plug-and-play services [10]. At the residential level, the ER plays a crucial role in managing the demand–supply equilibrium and provides demand response (DR) applications. DR assists smart home users to reshape their energy usage profile in response to DR programs. DR can be defined as “a tariff or program established to motivate changes in electric use by end-use customers, in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized” [16].

Recently, packetized energy management (PEM) has been introduced as a method of DR that aims to motivate consumers by scheduling their energy packet demand while ensuring the quality of service (QoS) [17]. PEM is an interesting approach derived from the data transmission in a communication network, which means that in the same way as data can be broken into packets, energy can also be broken into energy packets. The energy packet refers to “fixed power consumed by the load during a predefined time interval, e.g., 1 kW in an hour” [18]. PEM in conjunction with the ER is expected as one of the key attributes of the EI network for controlling energy usage and meeting the demand for smart homes. In this context, this doctoral dissertation presents the background of the EI along with supporting technologies and potential challenges and provides energy management solutions for smart homes in terms of home energy management systems (HEMs) and ER-based PEM systems. In addition, the dissertation extends the research contributions by describing the architecture of HEMSs and ER-based PEM systems and designing system models based on the core objectives, distinctive characteristics, associated constraints, and heuristic-based optimization methodology. The following subsections highlight the general objectives and research questions, scientific contributions, and organization of the dissertation.

1.2 General objectives and research questions

This doctoral dissertation aims to provide the modeling of an energy management system for the optimal use of energy resources on customer premises under the EI paradigm. Firstly, a comprehensive description of the EI is provided and a universal definition of the EI is inspected by reviewing the state of the art, technological features, and implementation challenges. Secondly, the energy management system for smart homes known as the HEMS is proposed to optimize the scheduling of the energy consumption demand of smart homes based on DR-based flexibility. The operation of the HEMS is also investigated under a specific type of cyberattack to evaluate the degree of resilience in the scheduling processes. Finally, the modeling of the ER-based PEM system is proposed to minimize the average system cost considering the energy packet scheduling parameters, transactions of energy packets, rooftop panels, and management of the energy storage system. The main foci of the study are summarized as:

- A general definition of the EI is proposed by investigating numerous concepts, assumptions, scopes, and application areas of the EI.
- Extensive details of the HEMS are provided in terms of the framework, key features, and scheduling operation. The operation of the HEMS is also assessed against the specific type of cyberattacks on the energy pricing model.
- An ER-based PEM system is developed to provide flexible PEM plans for grid-connected smart homes and to minimize the average system cost based on the joint optimization of: scheduling parameters, transactions of energy packets, rooftop panels, and management of the energy storage system.

To support our research, we focus on three research questions: ***Q1, Q2, Q3***.

Q1 *What is the Energy Internet? Further, how does it impact the development of the electric power grids? What are the design and technological measures that must be taken to implement the Energy Internet?*

Based on ***Q1***, this dissertation extensively describes the evolution of the electric power grid to the EI based on three general perspectives: physical development of the EI network, its technological development, and requirements. The technological development covers the EI-based devices and management methods/algorithms to control and optimize the operation and integration of large-scale distributed energy generation. The answer of ***Q1*** also leads us to focus further on the management aspect of the EI for residential customers by means of a demand–supply equilibrium and economic flexibility while leveraging HEMSs and ERs and management methods.

Q2 *What are the hierarchical steps and advantages of designing an HEMS for a smart home? Further, what are the critical impacts of a cyberattack against the HEMS during the scheduling process of energy usage and on the electricity bills of the smart home customer?*

Based on ***Q2***, the impact of the HEMS on managing the energy resources for smart home customers is analyzed. ***Q2*** also drives to shed light on the architecture and operation of the HEMS by investigating the impact of cyberattacks on the HEMS operation during the scheduling process of energy consumption. Therefore, based on ***Q2***, the performance of the HEMS is evaluated considering the allocation of energy usage and the resilience index against cyberattacks. In addition, ***Q2*** guides us to expand our research and examine smart EI-based devices, such as ERs, in the context of energy management for smart homes.

Q3 *What is the role of ERs in developing the EI network and enabling optimal PEM plans for smart homes considering multiple agents, such as household loads, energy packet transactions, rooftop panels, and energy storage systems?*

We continue to research various EI-based devices, such as HEMSs, ERs, and others. In ***Q3***, we aim to analyze the role of ERs in the EI network and design an ER-based system to jointly optimize household loads and energy sources. Different from the existing work, ***Q3*** sheds light on the role of ER-based systems in enabling PEM plans for smart homes where multiple agents are operating at various instants.

1.3 Scientific contributions

This doctoral dissertation provides energy management solutions for a smart home user to manage energy usage based on economic and demand-side flexibility. The main set contributions of the dissertation are as follows:

1. A comprehensive description of the EI concept is put forward considering various understandings and interpretations of the EI. The core technologies of the EI include ERs, smart metering infrastructure, software-defined networks, and energy management and control models. Lastly, the potential challenges and requirements are identified for the formation of an EI network, such as system complexity, system security, and standardization (**Publication I**).

This contribution provides a thorough analysis of the EI concepts described in the state of the art and proposes a conceptual definition of the EI underpinning its scope of applications. The development of the EI allows to integrate cutting-edge technologies, combine multiple energy networks to balance demand and supply, and enhance the energy efficiency, coordination and control, and real-time management of energy resources in the power industry. At the same time, the implementation of the EI raises several challenges, including system complexity, system security, and standardization, to name but a few.

2. An HEMS architecture is designed for a smart home based on DR-based flexibility with the aim to promote economic benefits and efficiently control the power peaks (**Publication II**). The designed HEMS is investigated under a cyberattack to analyze the operation and degree of resilience of the scheduling process of the HEMS (**Publication III**).

This contribution provides extensive details of the HEMS architecture, its key characteristics, and scheduling operations. The HEMS enables energy management solutions for smart home users based on heuristic optimization methods to improve energy efficiency, reduce the electricity bill, and flatten the load profile. In addition, the scheduling operation of the HEMS is assessed against a specific type of cyberattacks in terms of the resilience index. The results demonstrate the scheduling process of energy consumption under cyberattacks on the HEMS and performance metrics, such as electricity bill, shaving the power peaks, and resilience index.

3. The modeling of an ER-based PEM system is developed for a smart home that aims to provide PEM plans for a smart home while jointly optimizing energy usage considering household loads, PV systems, storage systems, and the utility grid. A case study for smart homes is conducted to evaluate average aggregated system cost parameters (**Publication IV**). The modeling ER-based PEM system is extended to a joint optimization problem for multiple smart homes with their respective attributes and constraints, a set of heuristic methods, and varying weather conditions (**Publication V**).

The contribution of this work lies in the modeling of an ER-based PEM system for single and multiple smart homes. The ER-based PEM system provides efficient management plans for smart homes based on the joint optimization of energy scheduling parameters, transactions of energy packets, rooftop panels, and management of the energy storage system. A comprehensive analysis of the ER-PEM system is carried out based on well-known heuristic optimization methods and their hyperparameter selection. The results demonstrate that the ER-PEM system is capable of solving the joint optimization problem as well as providing flexible PEM plans for smart homes in terms of minimization of the average system cost. Figure 1.2 provides a summary of the above discussions and presents an overview of the dissertation.

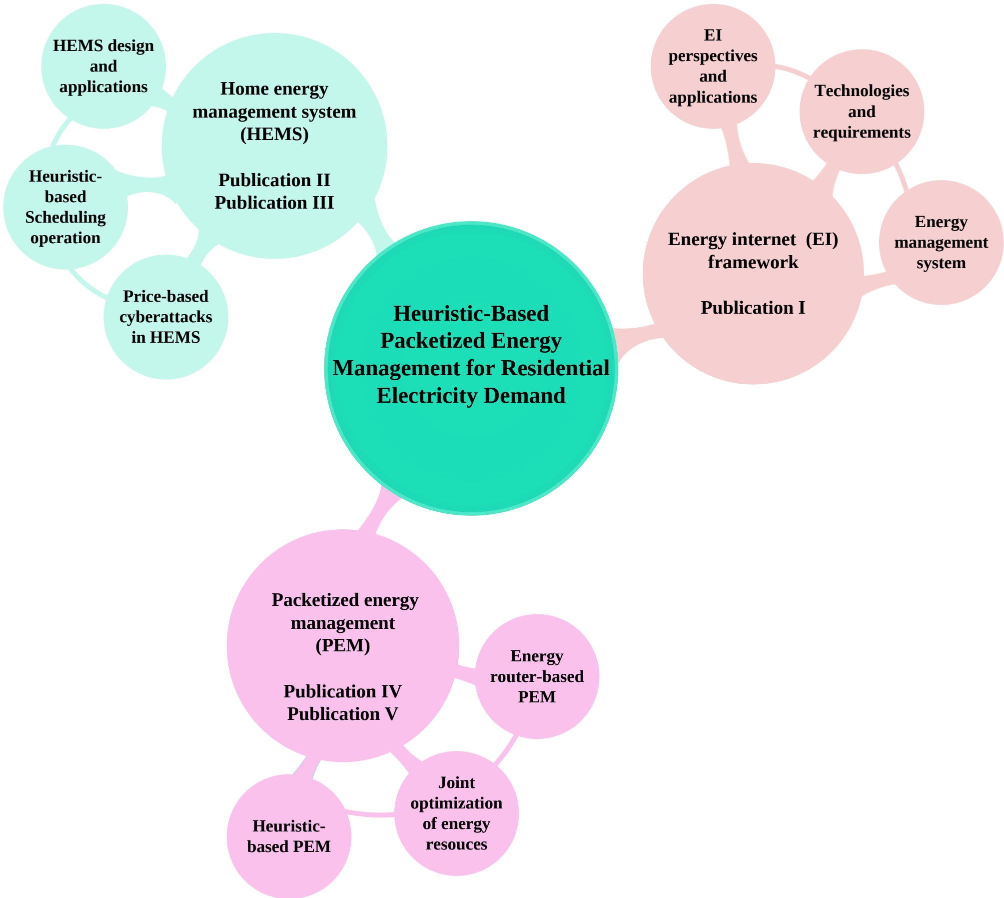

Figure 1.2: Structure of the dissertation.

1.4 Organization of the doctoral dissertation

Chapter 1 This chapter provides the general background, motivation, research questions, and scientific contributions of the dissertation.

Chapter 2 This chapter offers a comprehensive description of the EI concept underpinning its scope of application, core technologies, and requirements.

Chapter 3 This chapter introduces the research methodology implemented in the doctoral dissertation. The optimization problem and heuristic optimization are delineated based on their key steps.

Chapter 4 This chapter presents a summary of the research publications. The research publications based on the research questions are highlighted. The research aims and context of publications are explained in brief. Finally, a summary and key contributions of the chapter are presented.

Chapter 5 This chapter provides the conclusion of the dissertation and highlights topics of future research.

2 Energy Internet

This chapter provides the background of the key concepts explained and employed in this doctoral dissertation and Publications II–V. The contents of this chapter are mostly based on the extensive literature review presented in Publication I.

2.1 Background

The integration of internet-oriented technologies has transformed the smart grid into a next generation of power grids known as the energy internet (EI). The EI incorporates various energy systems (solar, wind, gas, and heat) to relieve the dependence on fossil fuels, promote sustainability and economy, and address environmental concerns. The concept of EI was first proposed by Jeremy Rifkin in [19], where the EI is anticipated to be an internet-enabled grid that combines multienergy systems through real-time information and communication technologies (ICTs). The idea of the EI has received widespread attention in the research community across the world, in particular, in Europe, China, and the United States, and scientists have come up with different understandings of the EI. For example, in Germany, the EI is known as the Internet of Energy (E-Energy), and the aim of E-Energy is to digitally connect the power generation side to the transmission, distribution, and consumption sides employing ICTs [20]. In China, the broad perspective of the EI is defined by the organization called Global Energy Interconnection Development and Cooperation Organization (GEIDCO), which aims to connect renewable-based generation globally [21]. Further, systematic research was established by the United States Future Renewable Electric Energy Delivery and Management (FREEDM) Systems Engineering Research Center, which presented the basic assumptions, architectural requirements, and initial implementation plan of the EI [13]. Since then, the EI has been defined from different understandings and perspectives. The summary of the EI concepts is given as follows:

2.1.1 EI as a smart grid

The EI is typically known as a smart grid or an advanced version of a smart grid, which means that the EI has essential features of smart grid technologies and internet-enabled communication. For example, Tsoukalas et al. described the EI in [22] as follows: "An implementation of smart grids is EI, where energy flows from suppliers customers like data packets do in the Internet"; a similar description of the EI is also given in [23], where the authors presented an analogy between the EI and an internet network, e.g., they considered functions of an internet router and packet-based transmission in an EI network. Although the description of the EI in the context of a smart grid and an internet network is promising, the authors did not identify the framework and potential features of the EI. Subsequently, the authors in [8] and [10] elucidated the concept of EI in the context of the FREEDM structure and also pointed out the differences between the EI and smart grids in terms of the physical structure, key characteristics, and communication design. Chinese researchers [24], [25], in turn, viewed the EI as a *strong smart grid* and entitled it *Global Energy Internet* that would connect the RESs on a global scale and enable sustainable, green, and secure energy network across the globe.

2.1.2 EI as a quantum grid

Interestingly, a group of researchers in [26] explored a unique perspective of the EI in terms of the quantum grid. The quantum grid identified the basic structure of the EI and provided an analogy between the electrical grid and the data network in certain aspects. For instance, the authors explained the energy packet-based transmission in the EI network, where addresses can be assigned to system nodes such as generation plants, consumers, and transmission lines similar to the data network. The system nodes are referred to as quantum grid routers that function to optimize, control, and efficiently route the energy packets. The perspective of the quantum grid-based EI complemented the preliminary idea of the EI as well as described the packet-based power transmission, opening the door for future research directions, such as the physical transmission of energy packets [27], the power packet distribution network [28], and packetized energy management [14]. Moreover, recently, Wang et al. [8] have studied the physical design aspects of the EI including technological development and communication requirements considering the FREEDM architecture.

2.1.3 EI as a cyber-physical system

Based on the existing interpretations and perspectives, it is clear that the electrical power grid is the core of the EI concept. The EI, from a physical development point of view, merges various energy system networks (e.g., PV, wind, heat, and gas) to address energy demand challenges and implement real-time energy sharing. Similarly, the EI, from a system design point of view, incorporates internet technology to provide coordination among energy system networks and real-time communication between energy generation sources and energy users. In this regard, we provide a comprehensive definition of the EI as “a cyber-physical system in which physical energy infrastructures and physically distributed RRs are interconnected and managed via a software-defined cyber energy network using packetized energy management techniques.” The transmission of energy is carried out by an energy router (ER), and it is ascribed to packet-based energy transmission. Subsequently, the ER performs tasks such as packetized energy management (PEM), control and coordination of the sub-energy routers, optimal decision-making, and energy conversions for the energy system networks. Hence, the EI can also be seen as a large *cyber-physical system* (CPS), where physical and cyber systems are combined through cutting-edge technologies, e.g., software-defined networks, information processing, smart metering infrastructure, real-time communication technologies, and control systems [29]. Figure 2.1 presents the basic structure of an EI. A detailed description of the crucial EI technologies is provided in the coming subsection.

2.2 Technological development of the EI

The EI is a large complex architecture, and the development of the EI requires support from multiple disciplines and advanced technologies. Here, we will discuss fundamental

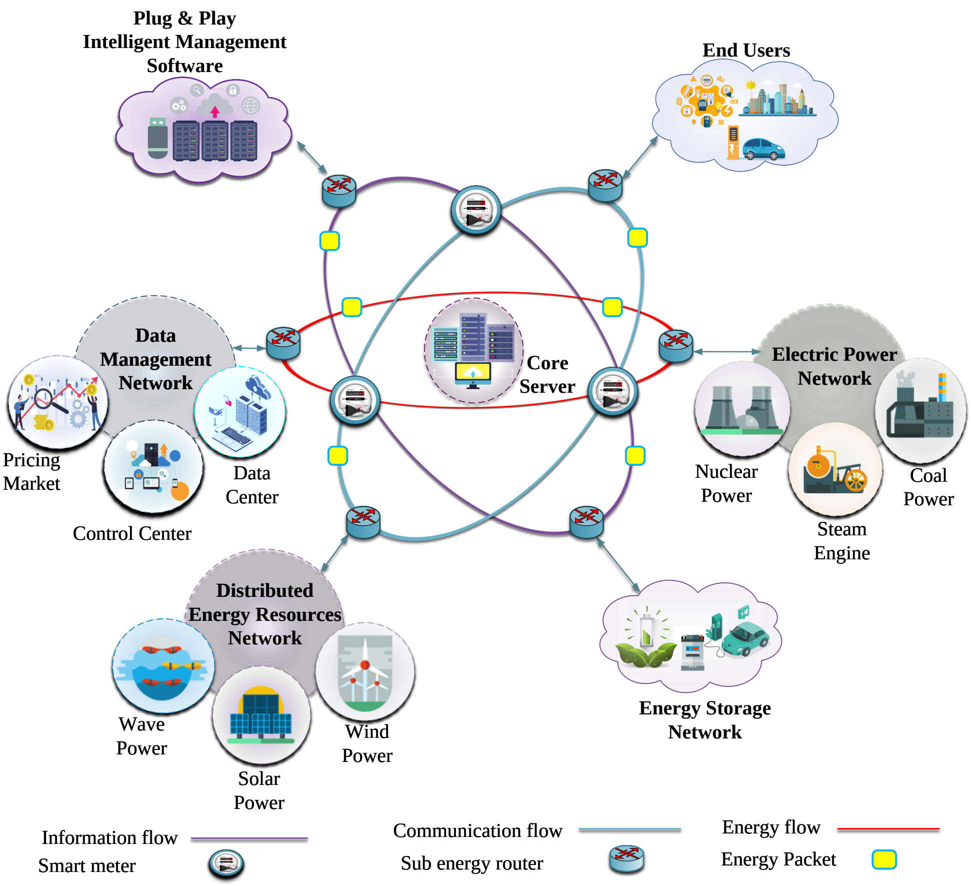

Figure 2.1: Basic structure of an EI comprising multiple networks, such as a distributed energy resources network, energy storage network, data management network, and internet and communication networks with features, like plug-and-play, intelligent software, sub-energy routers, and smart meters.

technologies required to build an EI infrastructure, e.g., ERs, integration of DERs, smart metering infrastructure, and a software-defined network.

2.2.1 Energy router

Interconnecting various energy commodities, controlling the power flow, and enabling ubiquitous sharing of energy are important features of the future EI structure. To enable these features, an ER is envisioned that is inspired by the internet router and acts as the core component of the EI. Initially, the idea of the ER was developed by the FREEDM as a solid-state transformer (SST) that supports the following tasks.

- To carry out power conversion and distribution at different voltage levels to provide flexible delivery of energy resources;
- To unify various energy networks and allow the use of energy flexibly through plug-and-play interfaces;
- To support the communication infrastructure and enable management of energy generation sources and ubiquitous loads in an energy commodity through distributed grid software.

Based on the above tasks, three types of ERs have been described [10]: (a) an SST-based ER; (b) a multiport converter-based ER; and (c) a power line communication-based ER. Particularly, types (a) and (b) are responsible for the integration, electronic conversion, and management of energy resources, while type (c) provides the transmission of energy and processes the information and communication flow.

2.2.2 Distributed energy resources

Distributed energy resources (DERs) are the basic foundation of the EI network and enable clean, sustainable, and affordable RRs and distributed storage devices (DSDs). Since the early 2000s, the penetration of massive DERs, specifically PV and wind energy, has been rapidly increasing and making an imminent impact on the electrical power grid infrastructure [30]. The integration of DERs is promised to provide solutions to energy crises, low investments, and environmental concerns. On the other hand, it also gives rise to potential problems, e.g., related to the control and management of DERs, voltage/frequency control, and fault management. Thus, to tackle these problems, the FREEDM system has described three significant features of the EI: distributed grid intelligence (DGI), internet equipment management (IEM), and intelligent fault management (IFM). The key roles of these features are summarized in [13]:

- DGI acts as a central component in the FREEDM and provides real-time management of loads, DERs, and DSDs through DGI software.
- DGI provides the stability of the grid by improving the power quality, system efficiency, and power factor unity.

- IEM acts as an electronic component and provides power conversion at low voltage levels to residential users.
- IEM provides bidirectional power flow and enables plug-and-play features for the users.
- IFM acts as a fault isolation component and provides isolation and reconfiguration during and after a fault and ensures to maintain the stability of the grid during the operation of DERs-based generation.

2.2.3 Advanced metering infrastructure

In the EI network, advanced metering infrastructure (AMI) plays a significant role to collect, monitor, and precisely identify data using two-way communication by applying internet technologies. In the AMI, various systems, ubiquitous smart metering, and sensing devices are interconnected to collect, measure, and analyze real-time information from energy generation, transmission, and consumption. For example, on consumer premises, smart meters are installed to obtain energy consumption information and exchange it with the distribution system operator or the utility grid to monitor, observe, and enable features like demand-side management (DSM) and DR. DSM, together with DR, offers various programs/plans to encourage consumers to adjust their electricity usage with respect to prices of electricity in a certain time interval. The key advantages of the AMI are as follows [31].

- It facilitates bidirectional communication between smart meters and the utility grid.
- It collects and monitors energy usage information to address the peak demand and awareness among energy users through DSM and DR to improve the reliability and stability of the grid.
- Analysis of the power flow allows the system operator to react to faults and inexplicable variations in the energy consumption profile.

2.2.4 Software-defined network

The software-defined network (SDN) is an emerging approach for enabling ubiquitous communication, efficient routing, and control functionality of highly interconnected multiple energy systems of the EI network through software. The SDN monitors and communicates the status of energy in various energy networks (heat, electricity, chemical, and others) via the ER and maintains an energy equilibrium in the EI network. Further, the efficient routing and control functionality of the SDN makes energy accessible and available to everyone and enables ubiquitous sharing between energy networks and users to balance the demand. The SDN splits the EI network into three separate planes: the energy plane, the data plane, and the control plane [32]. The energy plane is related to the physical flow of energy, the data plane provides the energy-based data, and the control plane enables the flexible coordination between the energy plane and the data plane through dynamic reconfiguration. As a result, the EI structure becomes more flexible, highly reliable, and self-organized. The key features of the SDN described by [33] are summarized below:

- It facilitates the coherent coupling of interconnected networks through internet-style ubiquitous communication.
- It allows a separation between the energy plane, control plane, and data plane, which helps to develop various technologies independently.
- It enhances the coordination and cooperation among energy networks and enables the self-organization of resources through ubiquitous sharing.

2.3 Energy management systems in the EI

In this subsection, we provide a brief overview of the energy management systems for the smart homes in the EI network described in Publications II–V.

2.3.1 Home energy management system

The unprecedented growth in the prevalence of IoT devices and smart home appliances has led to significant fluctuations in the load curve and increased power demand, which causes immense stress on the efficient operation of the electrical power grid. Recently, HEMSs (home energy management systems) have gained significant attention in addressing fluctuating load curves and power peaks [34]. The HEMSs aim to encourage renewable-based energy generation, reduce carbon emissions, and manage the energy demand of household appliances to enhance the stable and reliable operation of the power grid [35].

Typically, an HEMS is installed in smart homes and communicates with the utility grid through a smart meter to employ demand response-based (DR) programs. DR programs allow smart home users to alter the energy profile of household appliances with respect to the price of electricity and offer a monetary incentive while doing so [36]. An HEMS based on DR programs performs two main tasks: it controls and optimizes the energy consumption of household loads and reduces electricity bills for smart homes. To do so, the HEMS utilizes two broad categories of DR: (i) incentive-based and (ii) price-based DR. The incentive-based DR offers monetary incentives or discounts on the electricity bill to users based on curtailing or shifting energy usage during power peaks. The main types of the intrinsic DR are direct load, demand bidding, and interruptible/curtailable programs. On the other hand, price-based DR provides the electricity price for a specific duration of time, and based on the price, consumers can adjust their energy usage and reduce their electricity bill [37]. The HEMS, together with DR programs, enables twofold advantages: from the utility grid's point of view, it assists in reducing power peaks and improving power quality, whereas from the consumer's point of view, electricity bills can be reduced to modify energy usage patterns. The price-based DR includes time of use (ToU), real-time pricing (RTP), and critical peak pricing (CPP) [37]. The classification

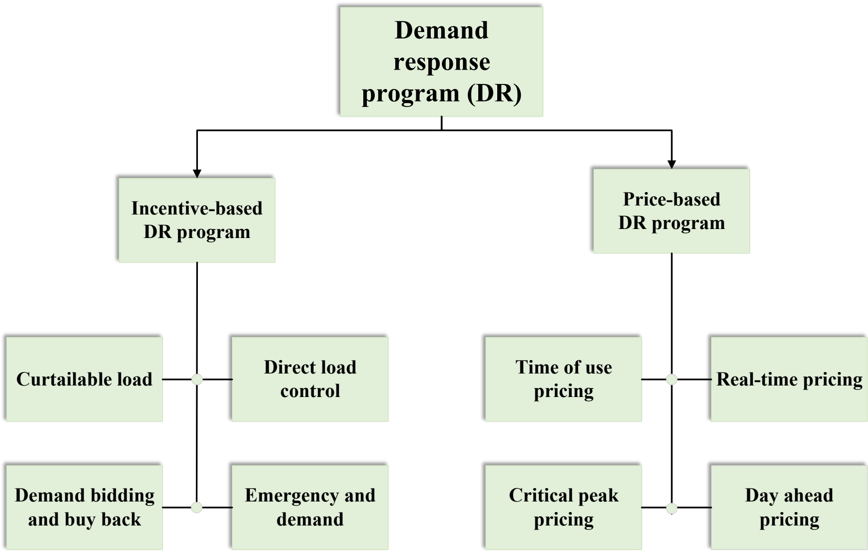

Figure 2.2: Classification of DR programs [37].

of DR programs is presented in Figure 2.2. In this context, this dissertation presents the architecture of the HEMS and describes the scheduling process under a price-based DR program. Figure 2.3 shows the internal architecture of the HEMS based on four key blocks: (i) a data aggregator; (ii) software and network management; (iii) an appliance management system; and (iv) algorithm management. These four blocks are connected through a communication channel and perform different functions to achieve the objective of optimal resource allocation of energy usage considering the cost and demand of electricity. For example, the function of the data aggregator is to receive data from smart meters about the price signal and energy production, i.e., the utility grid, PV systems, and storage systems and shared with the algorithm management (AM) and software and network management (SNM) blocks. The function of SNM is to collect data from the data aggregator and the appliance management system and process the flow of instructions in the HEMS after output from the AM block. The AM block is an essential part of the HEMS and provides the scheduling process under DR programs with the objective to reduce the electricity bill and facilitate optimal resource allocation of energy usage. The scheduling operation of the HEMS is explained in Publications II–III and discussed in brief in Chapter 4. Next, we focus on cyberattacks in the HEMS.

2.3.2 Cyberattacks in the HEMS

Despite its features, the HEMS is vulnerable to cyberattacks during the transmission of pricing signals and communication between the utility grid and smart meters. Typically,

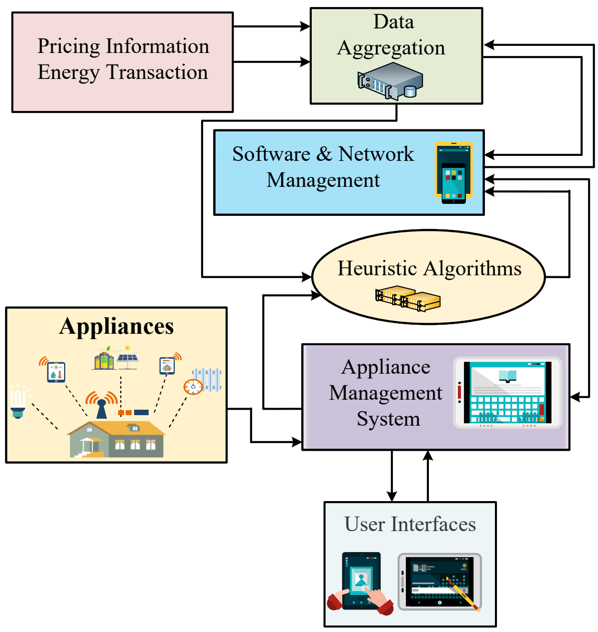

Figure 2.3: Internal architecture of the HEMS.

cyberattackers target smart meters (as they are key components between the HEMS and the utility grid and lack basic security protocols) and induce a false data injection (FDI) to manipulate energy supply–demand information, grid network states, and energy pricing signals [38]. The impact of the FDI attack on the electricity pricing signal was studied in [39] by Tan et al., who described two major types of cyberattacks on smart meters: (i) scaling and (ii) delay. In scaling cyberattacks, *the prices advertised to smart meters are compromised by a scaling factor (so that the meters will use the wrong prices)*, while delay attacks mean *corruption of timing information (so that the meters will use old prices)*. Accordingly, Giraldo et al. proposed [40] countermeasures against these types of cyberattacks and evaluated the proposed countermeasures to enhance the stability of the entire system. Figure 2.4 presents possible cyberattacks on the communication infrastructure between the utility grid and the end users. It is shown that the communication channel is exposed to three types of cyberattacks: (i) a direct attack on the utility grid, where the adversary manipulates the pricing signal and injects fake pricing information into the system; (ii) a direct attack on smart meters and tampering of data; and (iii) an attack on the communication node between the utility grid and the end users.

In the above context, this dissertation investigated the impact of a direct attack on smart meter where a cyberattacker has the resources to tamper with smart meter and inject corrupted ToU pricing data. The cyberattacker aims to mislead the scheduling operation of HEMS by injecting (fake) arbitrarily peak prices. The fake pricing signal is fed to the

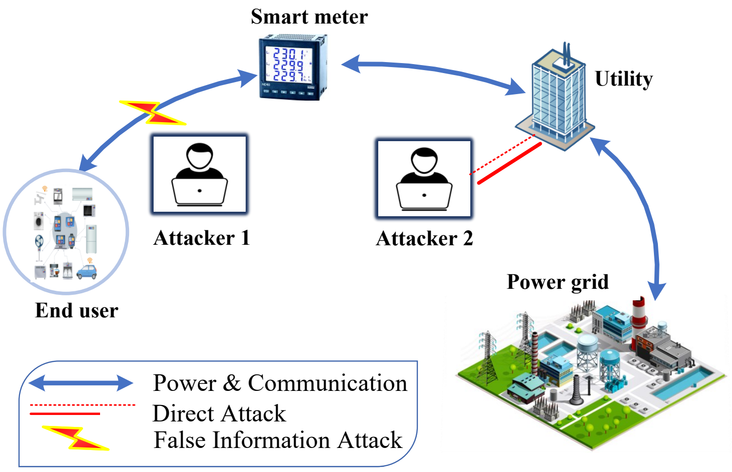

Figure 2.4: Cyberattack scenarios: Attacker 1 aims to induce fake pricing data or energy demand, and Attacker 2 directly attacks to hack the utility main system.

HEMS to perform scheduling operations, which certainly fabricates a mismatch between the energy generation and consumption and hence impacts the demand–supply balance and electricity cost. On this point, Chapter 4 discusses the critical impacts of a cyberattack and Publication III presents the simulation results to demonstrate the performance of HEMS against cyberattack.

2.3.3 Packetized energy management systems

As mentioned previously, packetized energy management (PEM) is one of the essential aspects of the EI network. PEM provides energy packet-based scheduling for smart home users while ensuring the quality of service (QoS) [17]. Originally, the concept of PEM was derived from the data network; like data can be broken down into packets, energy can also be split into energy packets [18]. In addition to PEM, the ER is another attribute of the EI that resembles a data network. The features of the ER include the interconnection of various energy networks via ICTs, power conversions, IEM and IFM operations, and real-time PEM. Therefore, in this dissertation, we explored the functionalities of the ER in Subsection 2.2.1, and now, the concept of PEM is combined with the ER (an ER-based PEM system) to enable features such as flexible scheduling and economic transactions of energy usage. Moreover, the ER-based PEM system is designed for smart homes based on multiple agents, i.e., household loads, PV generation, energy storage systems, and the utility grid, and their associated constraints. The objective of the ER-based PEM system

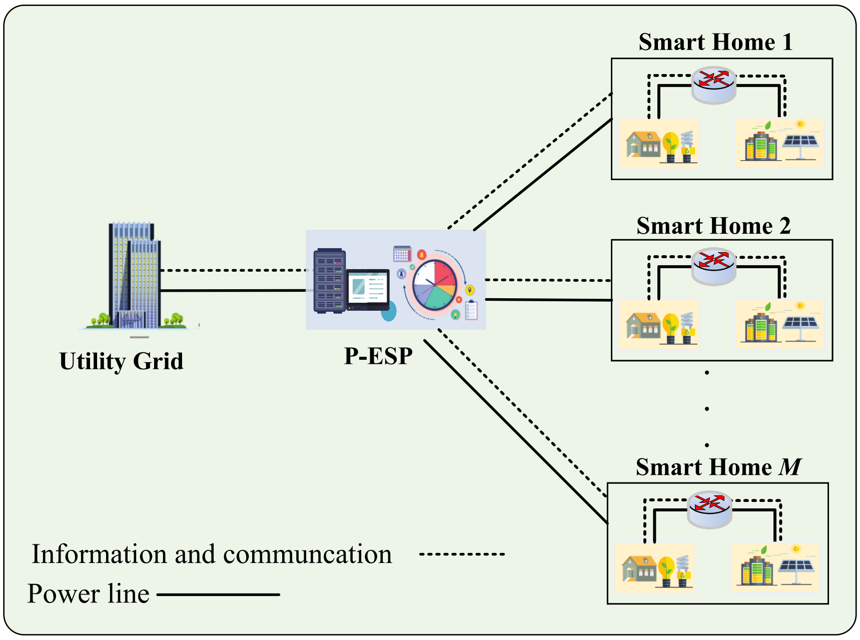

Figure 2.5: Overview of ER-based PEM system smart homes; household loads, the PV and battery storage system. P-ESP: Packetized energy service provider.

is to provide PEM plans for smart home users and minimize the average aggregated cost of the system. An overview of the ER-based PEM system is shown in Figure 2.5, and the modeling of multiagents (MAs) is investigated in Publications III and IV and discussed in brief in Chapter 4.

2.4 Requirements and challenges

As mentioned above, the EI is a broad concept that accommodates the major energy systems including electricity, heat, gas, and others. Therefore, the establishment of the EI framework not only requires technological advancement but also a common agreement from social, business, and policy-making perspectives. Hence, this section identifies the fundamental requirements and challenges of the EI framework.

2.4.1 System complexity

The EI is a large and complex network of interconnected systems that must simultaneously satisfy, e.g., the requirements of communication, power flow, and control [41], [42]. Considering the communication requirements, latency is the main challenge. For example, electric grid protection requires a communication latency of 8–12 ms, whereas the requirement is even stricter in the case of machine-to-machine communication. Similarly, in the case of power flow and control, the demand for advanced power electronics is high to provide efficient conversion as well as the desired level of frequencies and voltage. The application of power electronics is of great significance in the EI network, e.g., plug-and-play interfaces; however, efficiency and reliability are challenges that call for special attention.

2.4.2 System security

The bidirectional flow of energy, communication, and information is simultaneously processed, monitored, and controlled in the EI through, e.g., ubiquitous intelligent sensing, metering, ERs, HEMSs, and IoT devices. These millions of ubiquitous devices transmit, share, and communicate in real time, which makes them prone to many security challenges and causes serious threats to the stability, operation, and efficiency of the electrical grid. In addition, the development of advanced technologies, such as machine-type communication, forecasting, cloud/edge computing, and big data analytics generate a large amount of data that can be manipulated by adversaries and may lead to serious damage as described in [43]. The major security challenges can be malware injection, fake energy pricing, and denial-of-service (DoS) attacks. To overcome these attacks, researchers from different disciplines must design robust control methods/algorithms for reliable, feasible, and secure EI networks.

2.4.3 Social acceptance and policy-making

To support the progress of EI technologies, social acceptance is an essential factor to be involved in the implementation and employment of advanced technologies. The steps for social acceptance may include awareness of environmental repercussions and adequate knowledge of technologies, benefits of the technologies in terms of cost evaluation and comfort support, and openness and trust-based decision-making. A high acceptance level means a low social resistance, which leads to smooth policy-making. The policy-making process also requires addressing challenges such as standardization, incentivization, and private or public sector participation [44].

2.5 Summary

This chapter presented a background of the dissertation based on the concepts explained in Publications I–V. First, the chapter provided the background of the EI in terms of different interpretations and perspectives considering state-of-the-art works and proposed a definition of the EI in accordance with the physical architecture and system design aspects. Second, the potential supporting technologies of the EI were described for the implementation of the EI network. Then, the impacts and functions of energy management systems were discussed to cope with energy demand issues in energy communities. Lastly, the essential requirements and technological challenges of the future EI were identified including system complexity, system security, social acceptance, and policy-making. In the following chapters, we provide: a methodology implemented in Publications II–V, a summary of each publication presented in the dissertation, and implications of the results based on the research questions and publications.

3 Methodology

This chapter presents the methods used in Publications II–V to solve the scheduling optimization problem.

3.1 Optimization methods

Generally, optimization includes an extensive list of problems with the aim to find suitable solutions under certain circumstances [45]. The classification of optimization problems depends on or varies from problem to problem, i.e., there is no unified approach. However, the optimization problem can be designed based on the following: problem formulation, problem modeling, problem optimization, and implementation [46]. In addition, there are several ways of modeling optimization problems; for example, classical optimization models include: mathematical programming models, combinatorial optimization, constraint satisfaction models, and nonanalytic models. Similarly, the optimization problem can be solved by using a wide range of methods or algorithms depending on the complexity of the problem. Typically, the two broad categories of optimization methods are exact and approximate or heuristic methods [46]. According to [46], *exact methods obtain optimal solutions and guarantee their optimality* while *heuristic (approximate) methods generate high-quality solutions in a reasonable time for practical use but there is no guarantee of finding globally optimal solutions*. Figure 3.1 reflects the classification of the optimization methods.

3.2 Heuristic optimization methods

A heuristic method refers to discovery or problem-solving through repeated search and evaluation [45]. Unlike exact methods, heuristic methods are capable of finding quality solutions for large-size problems in a reasonable time. However, the obtained solutions cannot be guaranteed to be optimal solutions, yet they can be regarded as rather easily reachable solutions. In the last two decades, heuristic methods have become popular for the following main reasons [46]: fast computation time, ability to deal with complex and large-scale problems, easy implementation and real-time problem-solving applications, scalability, and flexibility. For these reasons, heuristic algorithms have been applied in many areas such as engineering design, machine learning, planning and scheduling problems, and others [46].

Recently, metaheuristic methods[1] have been introduced as an improved version of heuristic optimization methods in terms of efficient, practical, and quality solutions. Explicitly speaking, metaheuristic algorithms have two essential features: exploration and exploitation, which give them an edge over other optimization methods [45]. Exploration means exploring the global search space through a diverse set of (generated) solutions, while

[1]Moreover, it can be noted that the terms metaheuristic and heuristic can be used interchangeably as there is no consensus on their definitions [45]. Note that in this dissertation, we have used the terms algorithm and method interchangeably.

exploitation refers to exploiting the local search space through a set of existing solutions. The combination of exploration and exploitation greatly impacts the quality of the solutions by preventing them from falling into a trap in the local optimum and enhancing the diversity of the solutions. Hence, the combination of these features in heuristic methods enhances the possibility of reaching optimal solutions and desired objectives. Further, based on the above-stated advantages and features, this dissertation employs four main heuristic methods. In the next subsections, we cover the implementation steps of heuristic methods based on the designed system model (Publications II–V) and briefly indicate their problem-solving advantages.

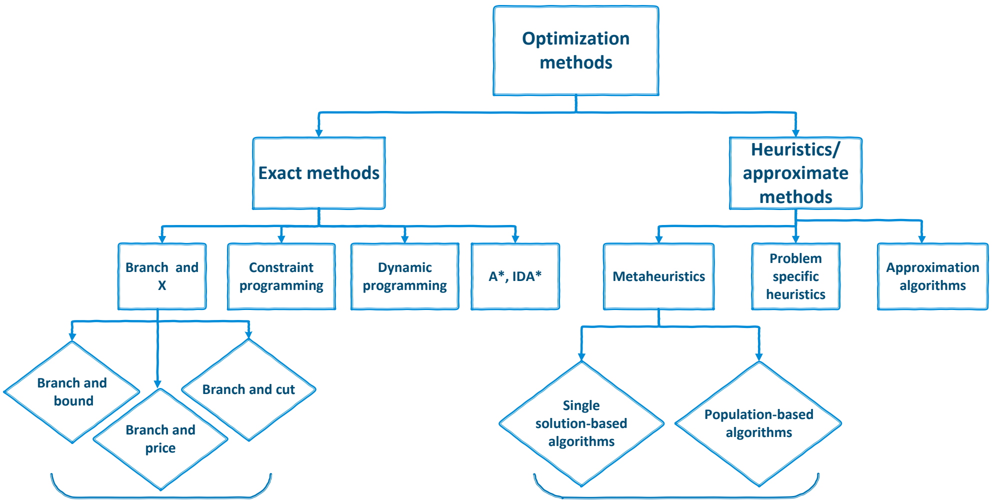

Figure 3.1: Classification of the optimization methods, A*, IDA*–iterative deepening algorithms [46].

3.2.1 Genetic algorithm

Genetic algorithm (GA) is a population-based heuristic algorithm and was first proposed by John and his colleagues between 1960 and 1970 [47]. The GA steps follow the biological evolution process, which is based on the famous *theory of natural selection* proposed by Charles Darwin [48]. Since then, numerous variants of GA have been derived and employed in many optimization problems ranging from discrete systems to continuous systems, graph theory to pattern recognition, and multiobjective optimization [45]. The GA optimization involves the following main steps: selection, crossover, and mutation. Initially, the population is generated randomly, and individuals in the population are selected for the evaluation, crossover, and mutation process. In the crossover, parents (two individuals) from the population swap their segments using the crossover probability with each other to generate a new individual (offspring) as shown in Figure 3.2. There are several variants of crossover steps (i.e., single point, two points, multiple points) to enhance the search efficiency of the GA. After crossover, the mutation process is applied by flipping the selected individuals based on the mutation probability. Similarly, mutation can be performed in many ways, i.e., for a single site and multiple sites; however, multiple site mutation may lead to a low convergence or even wrong solutions. Subsequently, modified individuals (solutions) are further evaluated and compared with existing individuals, and the best individuals (which performed better on the objective function) are selected in the generation while others are modified. This process continues until termination criteria (minimization of the objective function) are satisfied. It is worth noting that the choice of crossover and mutation process (crossover and mutation are often called stochastic operators) is essential to achieve the desired level of exploration and exploitation of the search space. The schematic representation of stochastic operators is shown in Figure 3.2. In this dissertation, GA is implemented to solve the optimization problem based on the following steps:

1) Population generation:
Initially, a set of individuals are generated randomly and transformed into a binary string such that $\mathrm{I_x} \in \{1\,\mathrm{if}\,\mathrm{P_0(x)} > 0.5, \mathrm{otherwise}\;\; 0\}$, $\mathrm{I_{xy}}, \mathrm{y} \in [1, \mathrm{L}]$, where $\mathrm{I_x}$ is the binary string in the population ($\mathrm{P_0}$), and L is the length of a vector indicating the status of appliances either ON or OFF during t. The following algorithm parameters are set initially: $\mathrm{P_0}$, crossover (C_{bt}), mutation (M_{bt}), and their probabilities P_c, P_m, respectively.
2) System inputs: The input values in Publications II–V and algorithm-specific variables are set with upper and lower bounds.
3) Evaluation: The objective function is evaluated as presented in Publications II–V with the set of constraints.
4) Updating $\mathbf{P_0}$: The set of individuals in $\mathrm{P_0}$ are modified/selected based on the tournament selection and go through crossover and mutation with a probability range between 0 and 1. In each iteration, *stochastic operators* are applied (until the *generations* reach a preset number) to achieve optimal solutions and minimize the objective function.

GA is the most commonly used optimization algorithm in various fields of engineering. The key advantages of the GA include dealing with complex engineering problems, parallel operation of the parameters, and exploration of search space in different directions (through stochastic parameters) and convergence characteristics. Besides its advantages, GA is sensitive toward the appropriate choice of algorithmic parameters, for example, crossover and mutation rate, selection parameters, and population size. Moreover, there are several variants of GA developed to improve its algorithmic features and formulate hybrid parameters utilizing the advantages of other heuristic algorithms.

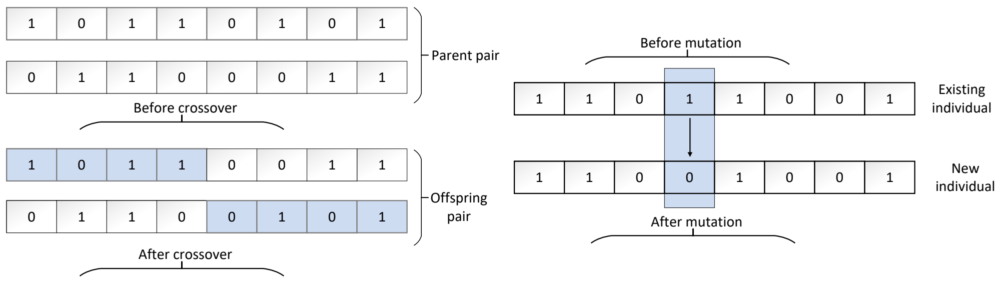

Figure 3.2: Schematic representation of stochastic operators: crossover and mutation [45].

3.2.2 Harmony search algorithms

The harmony search algorithm (HSA) is a new metaheuristic algorithm and was first proposed by Geem and his colleagues in 2001 [49]. The concept of HSA originated from musicians' improvisation actions, meaning that the musicians aim to look for the best possible (optimal) harmony state out of three possible states: playing a musical note from memory, playing a musical note by adjusting the pitch ratio, and generating a random note. To formalize these states in terms of the optimization process, HSA is classified into three main steps: initialization of the harmony memory (HM), improvisation, and upgradation of the HM. The initialization process starts with random generations of the population, and individuals in the population are analyzed based on the objective function. Next, an improvisation process starts, in which a new HM is created considering the following: HM consideration rate (HMCR), pitch adjusting ratio, and randomization. In order to effectively utilize the HM, the HMCR is assigned values between 0 and 1, which reflects on the convergence of the solution, for example, if the probability of the HMCR is low, then the selection is based on specific sets of HMs, which results in a slow convergence rate, and vice versa. Further, the pitch adjusting ratio and the randomization process are applied to improve the local search and enhance the exploration of the solutions in the HM, respectively. Finally, existing and new HMs are evaluated and compared based on the objective function, and the worst HM is replaced. This process continues until the termination criteria (minimization of the objective function) are satisfied. In this dissertation, HSA is implemented to solve the optimization problem based on the following steps [45]:

1) Population generation: Initialize the harmony memory (HM) size and other parameters of the algorithm, such as the HM consideration rate (HMc), the pitch adjustment ratio (Pa), and the minimum and maximum bandwidths (b_{min}, b_{max}). HM is generated using (3.1):

$$x_{i,j} = x_j^{min} + \mathrm{rand_i}(x_j^{max} - x_j^{min}) \tag{3.1}$$

2) Inputs: The input values in Publications II–V and the algorithm-specific variables are set with upper and lower bounds.
3) Evaluation: The objective function is evaluated as presented in Publications II–V with the set of constraints.

4) Updating HM size: The individuals in HM are updated based on (3.2). The new sets of harmony are further diversified using Pa according to (3.3).

$$HM = \begin{cases} HM \in HM_{old} \text{ with } P(HMc) \\ HM \in HM_{new} \text{ with } P(HMc - 1) \end{cases} \tag{3.2}$$

$$HM = \begin{cases} Yes \text{ with } P(Pa) \\ No \text{ with } P(1 - Pa) \end{cases} \tag{3.3}$$

In each iteration, the HSA operators $P(HMc)$ and $P(Pa)$ are applied to HM to strive for optimal solutions until the *generations* reach a preset number.

Moreover, it can be noted that the steps of HSA, i.e., pitch adjusting and randomization, show a resemblance to the crossover and mutation process of GA. However, unlike GA, HSA does not depend on binary encoding and decoding. Furthermore, the structure of HSA is easy to implement because of only a few mathematical requirements, and as it is insensitive to the algorithmic parameters, it can be applied to solve complex optimization problems regardless of objective function complexities, e.g., continuous, discontinuous, linear or nonlinear, and stochastic.

3.2.3 Binary particle swarm optimization

Binary particle swarm optimization (BPSO) is another class of heuristic algorithms developed by Kennedy and Eberhart in 1995 [50]. The BPSO follows the steps that mimic the social behavior of swarms. The swarm refers to the irregular or random movements of individuals/particles in the search space similar to *a flock of birds* or *school of fishes*. In BPSO, the particles adjust their velocities to achieve the best position (compared with the previous position) and the global best position. In each iteration, when particles find a better position (than the previous position), the search space is modified and particles with the better position are named as the current best particles. The main aim of the algorithms is to find the global best position $g^\star$ for the n particle considering the current best particles $c^\star$, and the algorithm repeats its steps in each iteration until an optimal–suboptimal solution is achieved. Next, we discuss in brief the basic steps of BPSO considering our designed joint optimization problem.

1) Population generation: Initially, particles in the swarm (S_0) are generated, and each particle has two features: (i) position ($\overrightarrow{ps_r}$) and (ii) velocity ($\overrightarrow{v_r}$). Equation (3.4) is used to generate ps_r of the particle r.

$$\overrightarrow{ps_r}(t) = \overrightarrow{ps_r}(t-1) + \overrightarrow{v_r}(t) \tag{3.4}$$

where $\overrightarrow{ps_r}$, $\overrightarrow{v_r} \in \mathrm{R^n}$ represent the position and velocity of the particles, and $\overrightarrow{ps_r}(t-1)$ is the prior position of the particle in S_0. The initial values of $\overrightarrow{ps_r}$ are opted between [0, 1].
2) System inputs: The input values in Publications II–V and algorithm-specific variables

are set with upper and lower bounds.
3) Evaluation: The objective function is evaluated as presented in Publications II–V with the set of constraints.
4) Updating S_0: The best particles (those which perform better on the objective) during the evaluation process are named as p_{best}. To update the S_0 for the optimal values, the particles in the S_0 are further refined/adjusted according to:

$$\begin{aligned}\overrightarrow{v_r}(t) = \overrightarrow{v_r}(t-1) + \alpha_1 \mathrm{rand}_1\Big(p_r - \overrightarrow{ps_r}(t-1)\Big) + \cdots \\ \alpha_2 \mathrm{rand}_2\Big(p_g - \overrightarrow{ps_r}(t-1)\Big)\end{aligned} \tag{3.5}$$

$$\overrightarrow{v_r}(t) = \begin{cases} \overrightarrow{v_r}_{\max} & \mathrm{if}\, \overrightarrow{v_r} > \overrightarrow{v_r}_{\max} \\ \overrightarrow{v_r}_{\min} & \mathrm{if}\, \overrightarrow{v_r} < \overrightarrow{v_r}_{\min} \end{cases} \tag{3.6}$$

where $\alpha_1.\mathrm{rand}_1$ and $\alpha_2.\mathrm{rand}_2$ represent random weights for p_r (local) and p_g (global) positions of the particles, respectively. $\overrightarrow{v_r}_{\max}$ and $\overrightarrow{v_r}_{\min}$ indicate the maximum and minimum velocities of the particle r at a random point, respectively, as calculated by (3.6). The updated particles in S_0 are further tested in the *evaluation* step to achieve the best values (until the *generations* reach a preset number).

BPSO is a swarm intelligence technique, and it has been applied to many engineering problems because of the following advantages over other optimization techniques: BPSO can achieve better solutions because of its ability to find the current best particles that help BPSO to converge faster, modify its search space, and improve diversification without discarding the worst solutions. Further, BPSO can be easily implemented because of the simple steps and few control parameters. In addition to these advantages, BPSO can still be modified in terms of memory, which means that BPSO does not record the movement (path) of each particle, making it memoryless, and hence, this aspect of BPSO can be further improved.

3.2.4 Differential evolution

Differential evolution (DE) was first developed in 1995 by Storn and Price [51]. DE is a population-based optimization algorithm applied in several engineering applications including signal processing, robotics, control systems, artificial intelligence, neural networks, and others [51]. Like any heuristic algorithm, the DE search starts with a randomly generated population followed by mutation and crossover cycles and selection. Initially, the algorithm generates a random population between upper and lower bounds using Equation (3.7). The individuals in the population are modified through mutation and crossover steps to obtain diverse and optimal solutions. The mutation process in DE follows two substeps, i.e., three random vectors, e.g, $v_{r1}, v_{r2},$, and v_{r3} are selected from the given population based on the target vector, and then their weighted difference is added to generate a mutant vector using Equation (3.8). The mutation process of DE provides an exploration of the given search space. After mutation, a new vector is formed, known as the trial vector by the crossover process. Typically, two main variants of the crossover process are suggested in [51]: exponential and binomial crossover. However, the binomial crossover is commonly explored, where the trial vector value is taken either from the target vector or the mutant vector in each iteration considering the crossover rate. Finally, the selection process is executed and the best individuals are selected based on the objective function. This process continues until the termination criteria (minimization of the objective function) are satisfied. In this dissertation, DE is implemented to solve the optimization problem based on the following steps:

1) Population generation: Initially, population P_1 is generated using (3.7) with p_e^U, p_e^L being the upper and lower bounds of P_1, respectively:

$$\mathrm{P}_1 = p_e^L + \mathrm{rand_i}(p_e^U - p_e^L) \tag{3.7}$$

where $\mathrm{P}_1 \in \mathrm{R^n}$, and $\mathrm{rand_i}$ is a uniformly distributed random number between 0 and 1.
2) System inputs: The input values in Publications II–V and algorithm-specific variables are set with upper and lower bounds.
3) Evaluation: The objective function is evaluated as presented in Publications II–V with the set of constraints.
4) Updating P_1: P_1 is updated through a mutation process using (3.8), and a new trial vector $\mathrm{T_v}$ is obtained by crossover using (3.9).

$$M_{de} = v_{r1} + F(v_{r2} - v_{r3}) \tag{3.8}$$

$$\mathrm{T_v} = \begin{cases} M_{de} & \text{if rand}(j) \leq \mathrm{c}r \\ \mathrm{P}_1 & \text{if rand}(j) > \mathrm{c}r \end{cases} \tag{3.9}$$

where F is a constant between [0, 2] and controls the amplification of search space, v_{r1}, v_{r2}, and v_{r3} are the vectors (randomly) chosen from P_1, and $r1, r2, r3$ are positive integers $\in \{1, 2, 3, 4...n\}$. Through crossover (cr), a new trial vector is generated according to (3.9). The updated individuals in P_1 are further tested in the *evaluation* step to achieve the best individuals until *generation* reaches a preset number.

DE is a popular optimization algorithm and well-suited for solving complex optimization problems in various disciplines of engineering due to its simple steps, few controlling parameters, and easy implementation. Apart from its simplicity, DE is still evolving and several variants of DE are established to improve its convergence speed and accuracy.

3.3 Summary

This chapter presented the research methodology employed in Publications II–V. A brief overview of the heuristic optimization methods was given; it was shown that heuristic methods are popular owing to their applicability in various fields of science and having a fast computation time for solving complex problems through easy implementation steps. In addition, heuristic methods have advantages over exact methods because of their two essential features: exploration and exploitation. Hence, in this dissertation, heuristic methods: GA, BPSO, HSA, and DE were implemented to solve optimization problems according to the designed system model in Publications II–V. The essential steps, working structure, and benefits and pitfalls of each algorithm were presented.

In particular, Publications II and III employed two well-known heuristic methods GA and HSA to solve the optimization problem for enabling cost-effective energy plans at smart homes under two main case studies: scheduling of HEMS and the impact of cyberattacks on the operation of the HEMS. Publications IV and V, in turn, employed an extended set of HOMs, BSPO and DE, to solve the joint optimization problem at smart homes to achieve minimization of the average aggregated system cost. Moreover, the simulation results obtained in Publications II–V indicate that the designed heuristic methods in various case studies perform efficiently by solving the optimization problem and accomplishing the desired objectives. In the next chapter, we provide a summary of Publications II–V.

4 Publication Summary

4.1 Publication highlights

This chapter provides a summary of the publications included in this doctoral dissertation. The summary covers the research aim and context as well as research contributions and sheds light on the research questions raised in the dissertation. Particularly, the dissertation is based on five main publications, which provide a broad overview of the EI framework and a heuristic-based energy management system for smart homes. The publications along with their titles and research questions are shown in Figure 4.1. In addition, the publications are summarized under the following headings: research aim and context, and research contributions. Besides the listed publications, this dissertation also includes collaboration work and book chapters that are related but not relevant to the focus of the studies.

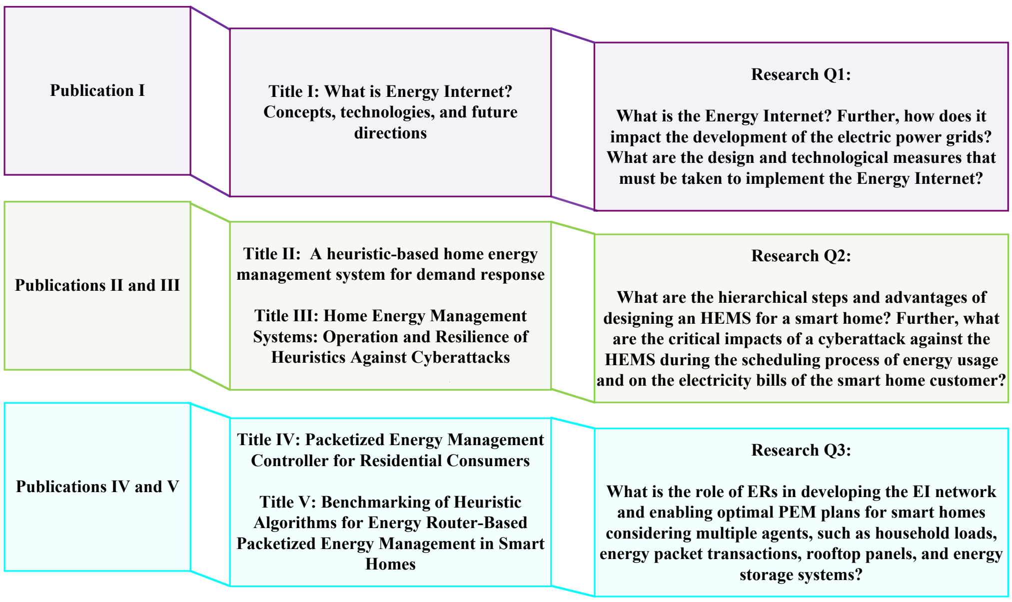

Figure 4.1: Publications I–V and their respective research questions.

4.2 Publication I

Title of Publication I: What is Energy Internet? Concepts, technologies, and future directions

4.2.1 Research aims and context

The EI is known as the next generation of power grids owing to its distinctive features of integrating multi-energy systems and internet-enabled ICTs to ensure flexible energy demand and supply. To understand the physical architecture and system design of the EI, we begin our research by reviewing the background of the EI in terms of different meanings and perspectives considering state-of-the-art works. It was discovered that previous studies have examined the technological features of the EI without focusing on the different interpretations and definitions of the EI, and hence, to present the concept of EI, its physical architecture, and system design aspects, the research question ***Q1*** is developed and addressed in Publication I:

Q1 *What is the Energy Internet? Further, how does it impact the development of the electric power grids? What are the design and technological measures that must be taken to implement the Energy Internet?*

Based on ***Q1***, Publication I comprehensively describes the background of the EI concept and its impact on the development of the modern grid in terms of the physical architecture and system design. As mentioned above, the EI is a broad concept that integrates multiple energy systems (e.g., PV, wind, heat, gas) to provide flexible, affordable, uninterruptible, and sustainable electricity. Previously, there have been different interpretations and perspectives of the EI without any agreement on its definition, e.g., the EI as a strong smart grid, the EI as a global energy internet, and the EI as a quantum grid. In this context, we examine the state-of-the-art works and combine the different understandings of the EI concept to propose a definition of EI in terms of the physical architecture and system design. The proposed definitions of the EI indicate the incorporation of large-scale DERs and DSDs and a tight coupling with other energy networks through cutting-edge technologies, such as internet-style communication, ER, SDN, AMI, and intelligent devices. This publication provides a brief description of the technological development of the EI and identifies the potential requirements and challenges, such as system complexity, system security, social acceptance, and policy-making.

4.2.2 Summary

The main contributions of Publication I—presented in Chapter 2—are summarized below.

- An extensive description of the EI concepts is presented including the existing and current perspectives based on the state of the art. Subsequently, a universal definition of the EI is proposed in terms of the physical architecture and system design.

- Technological development of the EI network that includes a brief overview of cutting-edge technologies, such as ERs, DERs, AMI, and SDN.

- Finally, the potential challenges and requirements of the EI network are highlighted based on system complexity, system security, social acceptance, and policy-making.

4.3 Publications II and III

Title of Publication II: A heuristic-based home energy management system for demand response
Title of Publication III: Home energy management systems: Operation and resilience of heuristics against cyberattacks

4.3.1 Research aims and context

The HEMS is an essential component of smart homes to monitor, control, and schedule smart home appliances to achieve objectives such as reducing the cost of electricity and scheduling energy consumption profiles. The HEMS also communicates with the utility grid through a smart meter to employ DR programs. Hence, we conducted a study to design a hierarchical structure of the HEMS and to investigate the scheduling operation of the HEMS and its resilience under an FDI cyberattack. The research question ***Q2*** is developed and addressed in Publications II and III:

Q2 *What are the hierarchical steps and advantages of designing an HEMS for a smart home? Further, what are the critical impacts of a cyberattack against the HEMS during the scheduling process of energy usage and on the electricity bills of the smart home customer?*

To answer ***Q2***, a comprehensive study is conducted in Publication II and Publication III, where the hierarchical steps of HEMS are described thoroughly including advantages of designing an HEMS, scheduling operation, and cybersecurity aspects of the HEMS. Particularly, Publication II presents fundamental building blocks of the HEMS and the impacts of a cyberattack against the HEMS during the scheduling process. Further, Publication III provides the design steps for the scheduling operation of household loads based on heuristic optimization methods. The main aspects of the system model are summarized below.

Classification of smart home loads

The smart home accommodates appliances that are categorized into two main classes: schedulable appliances and nonschedulable appliances. Schedulable appliances are flexibly controlled based on their energy usage, which means that their energy can be scheduled at various times when the price of electricity is high, and vice versa, whereas nonschedulable appliances, also known as fixed-power appliances, operate continuously, and their energy consumption cannot be scheduled, shifted, or delayed (e.g., TV and microwaves). We assume that $i \in \{1, 2, 3, ..., N\}$ that consume energy $e \in \{1, 2, 3, .., E\}$ time period $t \in \{1, 2, 3, .., T_0\}$. Let's assume U_t^i to be energy consumed by the appliance i at time t. The total energy consumption of all appliances N over T_0 is computed as

$$E_{T_0}^N = \sum_{t=1}^{T_0} \sum_{i=1}^{N} U_t^i \times \pi_t^i \qquad \forall \quad t \in \{t_1, t_2, t_3, .., T_0\} \tag{4.1}$$

where π_t^i is a binary parameter and denotes the operational status of the appliance i at time t, i.e., $\pi \in [0, 1]$, if $\pi = 0$, the appliance i is not consuming energy, and vice versa.

Electricity pricing model

The price-based DR is an essential feature of DR activities. The price-based DR includes various dynamic electricity schemes, e.g., ToU, RTP, CPP, and inclined block rates. These electricity pricing schemes together with the HEMS play a vital role to motivate consumers to adjust their energy usage, and as a result, provide the benefits of reducing the electricity bill and alleviating stress on the power grid. In Publications II and III, we employ the ToU pricing scheme, and based on that, the HEMS provides energy scheduling plans to shave the power peaks and reduce the energy cost. Mathematically, the cost of electricity is expressed as:

$$C_{T_0}^N = \sum_{t=1}^{T_0} \sum_{i=1}^{N} U_t^i \times \pi_t^i \times \gamma_t^i \qquad \forall \quad t \in \{t_1, t_2, t_3, .., \mathcal{T}\}. \tag{4.2}$$

Cyberattacks

In Publication III, we consider a cyberattack scenario where the adversary can compromise the pricing signal and inject tampered data with the aim to mislead the energy scheduling process of the HEMS. Thus, instead of the original pricing signal, the HEMS reshapes the load curve based on the fake pricing signal, which may lead to higher peaks and consequently, destabilize the operation of the power grid as well as increase the financial loss. To measure the resilience of the HEMS against such kinds of attacks, we mathematically express the resilience index as

$$\text{RI} = \left(1 - \frac{\mathcal{C}_{\mathcal{A}} - \mathcal{C}_O}{\mathcal{C}_O}\right) \times 100 \tag{4.3}$$

where $\mathcal{C}_{\mathcal{A}}$ shows the total cost of electricity when the system is under attack, and $\mathcal{C}_O$ represents the total cost with the HEMS.

Peak-to-average ratio

Peak-to-average ratio (PAR) is *the peak load demand and the average of total load demand over a day* [52]. PAR is related to the energy usage of consumers and the amount of energy generated by the power grid. Generally, the system operator monitors the PAR of the consumers to address the power peaks. The PAR is computed as in [53]:

$$D_{PAR} = \frac{G_{peak}}{G_{avg}}. \tag{4.4}$$

Here, G_{peak} and G_{avg} represent the maximum and average aggregated loads in time slot (t)

Problem formulation

Based on the above discussion, we consider $E^N_{T_0}$, $C^N_{T_0}$, and D_{PAR} to be the parameters to schedule the energy demand and minimize the bill of electricity. We formulate the electricity cost model for the EMS based on: (i) energy allocation of household appliances; (ii) electricity pricing schemes; and (iii) PAR. Thus, the objective function and constraints are formulated as follows:

$$Minimize \sum_{t=1}^{T_0} \sum_{i=1}^{N} C^N_{T_0} \tag{4.5}$$

$$E_{t,min} \leq E_t \leq E_{t,max} \tag{4.6}$$

$$D^{min}_{PAR,t} \leq D_{PAR,t} \leq D^{max}_{PAR,t} \tag{4.7}$$

$$\sum_{i=1}^{N} \sum_{t=0}^{T_0} x^i_t = H^N_{T_0} \tag{4.8}$$

Constraints (4.6) and (4.7) indicate the minimum and maximum values of the energy consumption and PAR during a time step t. Constraint (4.8) means that the scheduling process of the total energy consumption remains constant.

Research results and contributions

The simulation results are produced for single and multiple homes cases, and the energy consumption profile is obtained from [54]. The cost of electricity is computed based on the pricing signal from [55].
In Publication III, the simulation results are shown for a smart home in a single day considering the metrics: (a) scheduling of energy consumption; (b) PAR; and (c) electricity cost. The operation of the HEMS is also evaluated for the following scenarios: (a) single smart home user with a time resolution of one hour and 30 minutes and (b) multiple smart homes (30 and 50) with a time resolution of one hour and 30 minutes.

The result in Figure 4.2 represents cases with the HEMS (GA-HEMS and HSA-HEMS) and without the HEMS for the given metrics. It is evident from Figure 4.2 that a smart home with the HEMS (GA-HEMS and HSA-HEMS) attempts to schedule the energy usage of household loads to mitigate the power peaks and shifts the energy usage into off-

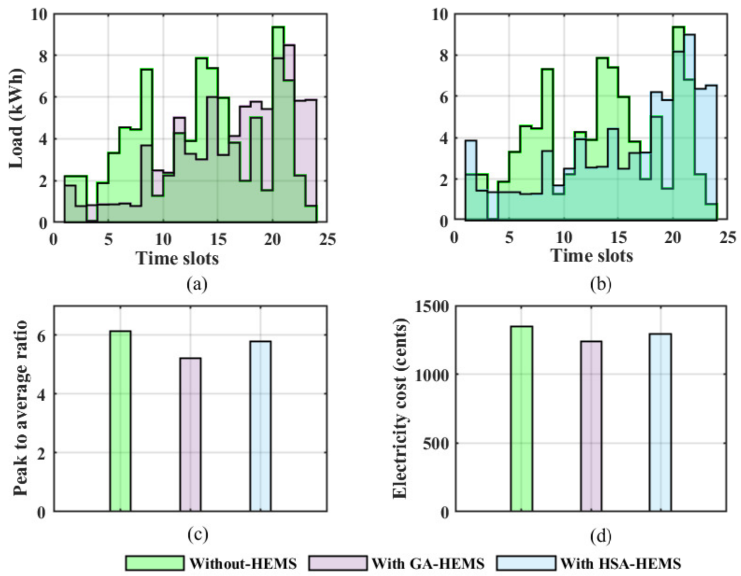

Figure 4.2: Unscheduled case without the HEMS and cases scheduled with the GA-HEMS and HSA-HEMS for: (a) energy consumption by appliances; (b) PAR; and (c) electricity cost.

peak hours, which reduces the PAR and also the cost of electricity. For example during peak hours (i.e., from 7 to 11 a.m. and from 5 to 7 p.m.) when the prices of electricity are high, 20.8 cent/kWh, the GA-HEMS and the HSA-HEMS shift the load to the off-peak time hours, and as a result, compared with the case without the HEMS, the PAR is reduced to 15% and 5.8%, and the cost of the consumer bill is minimized to 0.9% and 3.8% by the GA-HEMS and the HSA-HEMS, respectively. Importantly, the designed HEMS (GA-HEMS and HSA-HEMS) is scalable and optimizes energy consumption, reducing the PAR and the cost of the electricity in scenarios (a) and (b). A detailed statistical analysis of scenarios (a) and (b) in terms of the PAR and electricity cost is presented in Table 4.1.

In Publication II, the resilience of the designed HEMS (GA-HEMS and HSA-HEMS) is evaluated based on an FDI cyberattack on the electricity pricing signal. The cyberattacker aims to mislead the HEMS operation (which is based on heuristic algorithms GA and HSA) and manipulate the price signal with arbitrary peak prices, which leads to a demand and supply mismatch and economical loss of the power system. The RI metric for the designed HEMS (GA-HEMS and HSA-HEMS) is evaluated and shown in Figure 4.3. The result in Figure 4.3 shows that the designed HEMS performs reasonably well in the case of an attacked pricing signal and attains 99.8% and 97.8% values of RI, respectively.

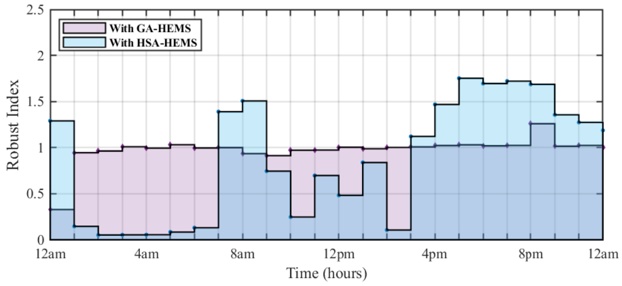

Figure 4.3: Resilience of the GA-HEMS and the HSA-HEMS represented by the resilience index.

Table 4.1: Comparative performance based on numerical results. The following symbols are used in the table: Rd is the reduction measured in %, PAR is the Peak-to-average ratio, $\mathbf{S}_{60}$ is the single user with a time slot of 60 minutes, $\mathbf{M}_{60}^{10}$, $\mathbf{M}_{30}^{10}$, $\mathbf{M}_{60}^{50}$, $\mathbf{M}_{30}^{50}$ are multiple users 10 and 50 with time slot 60 and 30 minutes, respectively.

	Without HEMS		**With GA-HEMS**		**With HSA-HEMS**	
Cases	Cost (¢)	PAR	Cost (¢ Rd)	PAR Rd	Cost (¢ Rd)	PAR Rd
$\mathbf{S}_{60}$	1347.9	6.13	0.9	15	3.98	5.8
$\mathbf{M}_{60}^{10}$	13479	61.36	0.71	14.6	1.37	11.94
$\mathbf{M}_{60}^{50}$	67394	306.79	0.98	17.41	1.83	12.02
$\mathbf{M}_{30}^{10}$	26569	15.34	1.41	6.51	1.67	12.05
$\mathbf{M}_{30}^{50}$	13285	76.70	1.36	11.86	1.64	10.52

4.3.2 Summary

The main contributions of Publications II and III are the following:

- First, the hierarchical structure of the HEMS is described comprehensively taking into account its key components and functionality, and the critical impacts of a cyberattack against the scheduling operation of the HEMS.
- The HEMS is designed based on heuristic optimization algorithms (GA and HSA) to provide efficient energy management plans, minimize the electricity bill for smart home users, and mitigate power peaks and the PAR. The scalability of the HEM is also evaluated in the scenarios of multiple smart homes and various time resolutions.
- The operation of the HEMS (GA and HSA) is tested under a cyberattack, particularly an FDI attack on the electricity pricing signal, and the performance of the

HEMS is evaluated in terms of the resilience index.

4.4 Publications IV and V

Title of Publication IV: Packetized Energy Management Controller for Residential Consumers
Title of Publication V: Benchmarking of Heuristic Algorithms for Energy Router-Based Packetized Energy Management in Smart Homes

4.4.1 Research aims and context

In the EI network, the energy router (ER) is the key component for merging various energy systems through real-time internet-enabled communication and performing packetized energy management (PEM). Therefore, we investigate the ER functionality in terms of PEM for smart homes, which consist of energy source elements (i.e., the utility grid and grid-connectible PV systems) and energy consumption elements, i.e., smart appliances (flexible or nonflexible) and energy storage systems. These elements in smart homes are often classified as agents. Hence, the ER-based PEM system aims to devise PEM plans for multiple agents at smart homes to minimize the average aggregate system cost. In this context, the research question ***Q3*** is formulated and addressed in Publications IV and V:

Q3 *What is the role of ERs in developing the EI network and enabling optimal PEM plans for smart homes considering multiple agents, such as household loads, energy packet transactions, rooftop panels, and energy storage systems?*

To answer ***Q3***, Publication IV presents a packetized energy management controller (P-EMC) for a single smart home based on heuristic optimization algorithms to accomplish minimization of the average aggregate system cost. Publication V extends the previous research work by defining the structure of the ER based on an extensive literature review. Subsequently, the ER-based PEM model is upgraded with a systematic integration of multiple smart homes and their associated attributes considering an extended set of heuristic optimization algorithms. The main aspects of the system model in Publications IV and V are summarized below.

Load modeling

In Publications IV and V, we present load modeling based on the following features: smart homes $j \in \{1, 2, 3, ..., M\}$ consist of loads $i \in \{1, 2, 3, ..., N\}$ that consume energy packets $e \in \{1, 2, 3, .., E\}$ in discrete time slots $t \in \{0, 1, 2, 3, ..., T_0 - 1\}$ in the energy ecosystem. The energy packets are characterized based on the following features: energy packet arrival time ($\varrho_t^{j,i}$), energy packet demand ($P_t^{j,i}$), scheduling time for energy packets ($\zeta_t^{j,i}$), length of energy packets ($\varsigma_t^{j,i}$), departure time of energy packets ($\tau_t^{j,i}$), and delay during the scheduling period ($d_{t,max}^{j,i}$). Based on these features, we assume $U_t^{j,i}$ to be the energy packets consumed by load i in smart home j at time t. The total energy packets consumed by N loads and M smart homes in the time period T_0 is given by

$$P_{T_0}^{M,N} = \sum_{j=1}^{M}\sum_{i=1}^{N}\sum_{t=0}^{T_0-1} U_t^{j,i} \times P_t^{j,i} \tag{4.9}$$

similarly, the scheduling delay experienced by N loads and M smart homes in time period T_0 is given by

$$\overline{d}_{T_0}^{M,N} = \frac{1}{M}\sum_{j=1}^{M}\sum_{t=0}^{T_0-1}\sum_{i=N}^{M} d_t^{j,i}, \quad 0 \leq \overline{d}_{T_0}^{j,i} \leq \overline{d}_{T_0,max}^{j,i}, \quad d_{t,min}^{j,i} \leq d_t^{j,i} \leq d_{t,max}^{j,i} \tag{4.10}$$

where $d_t^{j,i}$ is the scheduling delay experienced by load i in smart home j and can be computed as $d_t^{j,i} = \frac{\varsigma_t^{j,i} - \varrho_t^{j,i}}{d_{t,max}^{j,i} - \varsigma_t^{j,i}}$; considering (4.9) and (4.10), we assume $K_d(\overline{d}_{T_0}^{M,N})$ a cost function incurred due to $\overline{d}_{T_0}^{j,i}$ and hence, our goal is to minimize this cost $K_d(\overline{d}_{T_0}^{M,N})$.

Electricity pricing model

Typically, smart homes are equipped with a rooftop PV system, and they generate energy either to meet their energy demand only or to sell surplus energy. The buying and selling of energy apply an electricity pricing mechanism. Therefore, Publications IV and V present an electricity pricing model to provide flexibility for energy packet transactions between utility grids and smart home users via a packetized energy service provider (P-ESP). We assume that smart home j buys energy packets at the price of $K_t^{j,buy}$ and sells the energy packets at the cost of $K_t^{j,sell}$. $K_t^{j,buy}$ and $K_t^{j,sell}$ are computed as:

$$K_t^{j,buy} = H_t^{j,sell}\Big(P_t^{j,i} - (E_{t,pv}^{j} + E_t^{j,s})\Big), \quad if\ P_t^{M,L} > E_{t,pv}^{j} + E_t^{j,s} \tag{4.11}$$

$$K_t^{j,sell} = H_t^{j,buy}\Big((E_{t,pv}^{j} + E_t^{j,s}) - P_t^{M,L}\Big), \quad if\ E_{t,pv}^{j} + E_t^{j,s} > P_t^{M,L} \tag{4.12}$$

where $H_t^{j,buy}$ and $H_t^{j,sell}$ are the buying and selling prices of energy packets from/to the utility grid via a P-ESP, respectively. The P-ESP is an agent that provides energy trading (buying and selling) to the smart homes and the utility grid based on the following equations:

$$H_t^{j,buy} = \begin{cases} H_t^{j,sell} R_t^{DS} + J_t^{buy}(1 - R_t^{DS}) & \textit{if } 0 \leq R_t^{DS} \leq 1 \\ J_t^{sell} & \textit{otherwise} \end{cases} \tag{4.13}$$

$$H_t^{j,sell} = \begin{cases} \frac{J_t^{sell} J_t^{buy}}{(J_t^{buy} - J_t^{sell}) R_t^{DS} + J_t^{sell}} & \textit{if } 0 \leq R_t^{DS} \leq 1 \\ J_t^{sell} & \textit{otherwise} \end{cases} \tag{4.14}$$

R_t^{DS} in (4.13) and (4.14) represents the demand–supply ratio, positive values of R_t^{DS} indicate that smart homes have surplus energy that can be sold to the utility grid, and $0 < R_t^{DS} < 1$ show that the price of energy packets is dynamically adjusted between J_t^{buy} and J_t^{sell}, while $R_t^{DS} = 0$ means that smart homes have insufficient energy, and additional energy must be bought to meet the demand. Finally, (4.15) is represented as the energy packet transaction cost ($\overline{K}_t^{tx}$):

$$\overline{K}_{T_0}^{M,tx} = \frac{1}{M} \sum_{t=0}^{T_0-1} \sum_{j=1}^{M} \Big(K_t^{j,sell} - K_t^{j,buy} \Big). \tag{4.15}$$

The buying and selling criteria of energy packets are restricted to (4.16), which means that the scheduling process of the total energy packets remains constant, and (4.17) bounds the upper and lower energy packets. Similarly, the buying and selling processes of energy packets are restricted between the maximum and minimum limits.

$$\sum_{j=1}^{M} \sum_{i=1}^{N} \sum_{t=0}^{T_0-1} x_t^{j,i} = H_{T_0}^{M,N} \tag{4.16}$$

$$P_{t,min}^{j,i} \leq x_t^{j,i} \leq P_{t,max}^{j,i}, \quad 0 \leq H_t^{j,buy} \leq H_{t,max}^{j,buy}, \quad 0 \leq H_t^{j,sell} \leq H_{t,max}^{j,sell} \tag{4.17}$$

PV systems

Smart homes accommodate rooftop PV panels to generate electricity and meet their energy needs. The energy generated by PV systems of smart homes is as follows [56]:

$$E_{T_0,pv}^{M} = \sum_{j=1}^{M} \sum_{t=0}^{T_0-1} E_{t,pv}^{j} \tag{4.18}$$

where $E_{t,pv} = \eta_{pv} \times A_{pv} \times I_{ir}(1 - 0.005(K_t((t) - 25))$, η_{pv}, A_{pv}, and I_{ir} indicate the conversion efficiency, the area of the generator, and the solar irradiance, respectively. Further, 0.005 is the constant value employed for the (TCF) temperature correction factor, and K_t represents outdoor temperature. We assume that $E_{t,pv}^{c}$ is the amount of energy used from $E_{t,pv}$ in (4.19) considering the following constraints (4.20) and (4.21) as

$$E_{t,pv}^{c,j} = \min\Big\{ x_t^{N,M}, E_{t,pv}^{j} \Big\} \tag{4.19}$$

$$0 \leq E_{t,pv}^{j} \leq E_{t,pv}^{j} - E_{t,pv}^{c,j} \tag{4.20}$$

$$E_{t,pv}^{j} + E_t^{g} \in [0, \min\{S_{max}, E_{t,max}^{j,s} - E_t^{j,s}\}]. \tag{4.21}$$

(4.19), (4.20) state that the $E_{t,pv}$ can be delivered to the scheduled load first, and the remaining amount of energy $E_{t,pv}^{c,j}$ (if any) is then stored in the battery according to (4.21). In addition, the ER provides the optimal decision on whether to store (charged) or not store (not charged) energy in the battery considering joint optimization. The next subsection explains the operation of the energy storage system.

Energy storage systems

During time instant t, the energy storage system, i.e., the battery, can operate in three modes: ti can store charges (charging), discard charges (discharging), and remain inactive. The source of battery charging can be either a combination of PV energy and a P-ESP, or the battery can be charged independently from both sources. The battery discharges its energy to meet the energy packet demand, wheres during the inactive mode the operation of charging and discharging is halted. Equation (4.22) calculates the amount of energy currently in the battery.

$$E_{t+1}^{j,s} = \alpha_t E_t^{j,s} + \eta_t^{(+)}\left(E_{t,pv}^{j} + E_t^{g}\right) - \eta_t^{(-)}\left(k_t^{j}\right), \quad E_{t,min}^{j,s} \leq E_t^{j,s} \leq E_{t,max}^{j,s} \tag{4.22}$$

We assume that the battery only charges if $a_t^{(+)} = 1$ and $E_{t,pv}^{j} + E_t^{g} > 0$; otherwise, the battery does not store charge. Further, the total amount of charging at any time instant should not exceed the upper bound, i.e., $0 \leq E_{t,pv}^{j} + E_t^{g} \leq S_{max}$. On the other hand, the discharging amount of the battery is also constrained between the maximum and minimum values, i.e., $0 \leq k_t^{j} \leq k_{max}^{j}$. The battery starts the discharging mode if $a_t^{(-)} = 1$ and $k_t^{j} > 0$, where k_t^{j} is the amount of discharge by battery for a smart home j at time t. The charging and discharging modes of the battery incur a degradation cost and can be computed as [57], [58]

$$c_t^{j,(+)} = \frac{h_r}{h_t}\left\{\left(\frac{E_{pv}^{r,j}+E_r^{g}}{E_{t,pv}+E_t^{g}}\right)^{w_0} \times \exp^{w_1\left(\frac{E_{t,pv}+E_t^{g}}{E_{pv}^{r,j}+E_r^{g}}-1\right)}\right\} \tag{4.23}$$

$$c_t^{j,(-)} = \frac{h_r}{h_t}\left\{\left(\frac{k_r}{{k_t}^{j}}\right)^{w_2} \times \exp^{w_3\left(\frac{{k_t}^{j}}{k_r}-1\right)}\right\}. \tag{4.24}$$

Based on $c_t^{j,(+)}$ and $c_t^{j,(-)}$, the battery degradation cost for smart home j at t is computed by (4.25), and its average is expressed mathematically by (4.26).

$$K_t^{j,s} = a_t^{(+)} c_t^{j,(+)} + a_t^{(-)} c_t^{j,(-)}, \quad a_t^{(+)} + a_t^{(-)} \leq 1 \tag{4.25}$$

$$\overline{K}_{T_0}^{M,s} = \frac{1}{M}\sum_{j=1}^{M}\sum_{t=0}^{T_0-1} K_t^{j,s} \tag{4.26}$$

Problem formulation

We assume an energy flow vector $\theta_t \triangleq [E_t^{g}, E_{t,pv}^{c}, E_{t,pv}^{r}, k_t^{j}]$ and indicate the control actions for smart homes at time slot t. The objective of the study is to find an optimal policy $\{\theta_{T_0}, d_{T_0}^{M,N}\}$ and minimize the average aggregated cost of the system, which is based on the scheduling delay cost of the energy packets ($K_d(\overline{d}_{T_0}^{M,N})$), the transaction cost of the energy packets ($\overline{K}_{T_0}^{M,tx}$), and the battery storage cost ($\overline{K}_{T_0}^{M,s}$). Hence, the problem is for-

Table 4.2: Comparative performance based on numerical results; HOMs (heuristic optimization methods), Red (reduction), PEC (packetized energy cost), ASC (average system cost).

HOMs	$\overline{d}_{T_0}^{i}$ vs $\overline{d}_{T_0,max}^{i}$	%Red PEC (procured)	%Red ASC
P-EMC with GA	53.09	37.65	4.7
P-EMC with BPSO	42.60	7.5	5.14
P-EMC with DE	44.60	11.5	1.35

mulated as:

$$\underset{\{\theta_{T_0}, d_{T_0}^{M,N}\}}{\text{minimize:}} \quad K_d(\overline{d}_{T_0}^{M,N}) + \overline{K}_{T_0}^{M,tx} + \overline{K}_{T_0}^{M,s} \tag{4.27}$$

where $d_t^{j,i} \triangleq [d_t^{1,1}, d_t^{2,2}, ..., d_t^{M,N}]$, and $K_d(\overline{d}_{T_0}^{M,N}) \triangleq [K_d(\overline{d}_{T_0}^{1,1}), K_d(\overline{d}_{T_0}^{2,2}), ..., K_d(\overline{d}_{T_0}^{M,N})]$. The above cost function (4.27) and its constraints are formulated as joint optimization problems to obtain optimal energy control in terms of energy scheduling and energy transactions. The joint optimization problem is solved by employing a heuristic optimization method. The heuristic optimization method is exhaustively discussed in this section.

Table 4.3: Hyperparameters of the HOMs

HOMs	Hyperparameters	Selection I	Selection II	Selection III	Selection IV
GA	C_{bt}	1	2	3	4
	M_{bt}	1	2	3	4
	P_c,P_m	[0.9, 0.1]	[0.8, 0.2]	[0.7,0.5]	[0.5,0.4]
BPSO	$\overrightarrow{v_r}_{\max}, \overrightarrow{v_r}_{\min}$	[4,-4]	[6,-6]	[8,-8]	[10, -10]
	$\alpha_1 = \alpha_2$	1	3	3	5
	$\overrightarrow{v_r}$	2	3	4	8
DE	F	0.7	0.8	0.9	0.5
	P_{ce}	0.9	0.8	0.7	0.5
	$p_e^{L,u}$	$[30, 100]$	$[60, 150]$	$[70, 200]$	$[100, 300]$
HSA	HMc	0.9	0.8	0.7	0.5
	$Pa_{\min,\max}$	$[0.01, 1]$	$[0.05, 1]$	$[0.5, 1]$	$[0.05, 1]$
	$b_{\min,\max}$	$[0.001, 1]$	$[0.002, 1]$	$[0.004, 1]$	$[0.02, 1]$

4.4.2 Research results and contributions

The following datasets are used for the simulation results: (i) the power ratings and classification of the household loads are described in [59]; (ii) for the computation of PV generation, the parameters solar irradiance and temperature of a specific day and time horizon T_0 are obtained from [60]; (iii) the bilateral trading and transaction of energy buying or selling are computed using data from [61]; and (iv) the energy storage parameters are acquired from [58]. We also assume hyperparameters of the HOMs ((heuristic optimization methods)) as presented in Table 4.3.

The simulation results in Publication IV evaluate the minimization of the average aggregated cost of the system for a smart home based on the HOMs: GA, BPSO, and DE. The aggregated cost system consists of the load scheduling delay cost, the energy packet transaction cost, and the battery degradation cost. The relative performances of the HOMs (GA, BPSO, and DE) are evaluated and summarized in Table 4.2.
The scheduling of the energy packets incurred $\overline{d}^{i}_{T_0}$; the greater value of $\overline{d}^{i}_{T_0}$ means that scheduled energy packets can be delayed, which, in turn, reduces the average system cost and consequently, the user QoS is compromised. The scheduling process of the HOMs (GA, BPSO, and DE) impacts the transaction cost of the energy packets, i.e., when the HOMs are employed, the packetized energy cost (buying) is reduced in comparison with the unscheduled case (without the P-EMC). This shows that the P-EMC based on HOMs efficiently solves the joint optimization problem of energy packet scheduling, energy packet transactions, and battery management and minimizes the average aggregated cost of the system.

Publication V is an extension of the previous work and provides simulation results for multiple smart homes based on the joint optimization of energy packet scheduling parameters and storage system management. As stated above, smart homes equipped with an ER-based PEM system are responsible for providing PEM plans by managing MAs considering their respective attributes and constraints. Hence, we evaluate the performance of the ER-based PEM system to address the average aggregated cost. The average aggregated cost is based on the scheduling delay cost, the energy packet transaction cost, and the battery degradation cost. Therefore, a joint optimization problem is formulated and solved by employing HOMs (GA, BPSO, DE, HSA) and their hyperparameter selection in Publications I–IV. The results show that the ER-based PEM system provides cost-effective PEM plans for a smart home and an energy community of multiple homes, and in general, reduces the cost of the system. The statistical analysis of the ER-based PEM system including performance metrics is presented in Table 4.4. It is worth noting that during the unscheduled case, i.e., when the optimization process is not applied, the energy packet transactions are unidirectional, which simply means the smart homes only procure energy packets. On the other hand, the HOMs enable two-way energy packet transactions and empower smart home users not only to manage their energy demand but also sell excess energy packets. Consequently, the ER-PEM system based on the HOMs provides efficient management plans for smart home users and flexible and economical

Table 4.4: Average energy transactions between smart homes and the P-ESP. The symbol H'sS represents the hyperparameters' selection and the cost of the energy is computed in dollars.

HOMs	H'sS	$\overline{d}^i_{T_0}$ vs $\overline{d}^i_{T_0,max}$	P-ESP Energy (buy)	P-ESP Energy (sell)	Daily bill	Monthly bill
Unscheduled	–	–	1.90	–	1.90	57
GA Scheduled	I	30.05	1.79	0.61	1.18	35.4
	II	33.05	1.46	0.61	0.85	25.5
	III	33.10	1.55	0.61	0.94	28.2
	IV	31.29	1.62	0.72	0.90	27
BPSO Scheduled	I	33.10	1.85	1.04	0.81	24.3
	II	35.02	1.53	1.13	0.40	12
	III	34.2	1.49	1.13	0.36	10.8
	IV	33.36	1.46	1.19	0.27	8.1
DE Scheduled	I	31	1.83	0.51	1.32	39.6
	II	33	1.62	0.51	1.11	33,3
	III	33	1.65	0.51	1.14	34,2
	IV	32.09	1.63	0.61	1.02	30.6
HSA Scheduled	I	32	1.99	0.89	1.1	33
	II	33.2	1.69	0.89	0.8	24
	III	32	1.66	0.89	0.77	23.1
	IV	32	1.64	0.91	0.73	21.9

energy packet transactions. Moreover, the performance metric $\overline{d}^i_{T_0}$ vs. $\overline{d}^i_{T_0,max}$ indicates that when the values of the maximum allowable delay ($\overline{d}^i_{T_0,max}$) are relaxed, the value of the average experienced delay ($\overline{d}^i_{T_0}$) is increased and reflects the sublinear relationship. It is noteworthy that the average of $\overline{d}^i_{T_0}$ can be controlled between extreme values to achieve flexibility and QoS. However, it impacts the average cost of the system because of the trade-off relationship between $\overline{d}^i_{T_0}$ and the average cost of the system. In addition, the performance of the designed ER-based PEM is evaluated and validated for three different days over a time horizon T_0: winter–summer–spring in terms of the average aggregated system cost.

4.4.3 Summary

The main contributions of Publications IV and V are the following:

- An extensive literature review is conducted to compare the state of the art with the designed ER-based PEM systems in terms of research methods, research contributions, and research gaps.

- A comprehensive ER-based PEM system model is designed for single and multiple smart homes including MAs, i.e, energy packet scheduling parameters, energy packet transaction parameters, PV systems, and energy storage systems. The joint optimization problem is presented based on MAs with their associated characteristics and constraints.

- The ER-based PEM addresses the joint optimization problem by implementing well-known HOMs: GA, BPSO, DE, and HSA. The performances of the HOMs and their associated hyperparameters are evaluated in terms of the average aggregated system cost, i.e., energy packet transaction cost, scheduling delay cost, and battery degradation cost. The performance of the ER-based PEM system is validated for smart home users with varying weather conditions to provide efficient PEM plans and minimize the average aggregated cost of the system.

5 Conclusion and future work

This chapter presents the conclusion of the doctoral dissertation by summarizing the investigations carried out on the research questions, state-of-the-art research works, and the key scientific contributions.

5.1 Summary

The dissertation gives a comprehensive description of the EI concepts and energy management models for smart home users to provide efficient scheduling of energy usage and cost-effective plans. The dissertation raises three research questions, ***Q1***, ***Q2***, and ***Q3***, and answers them by reviewing the state-of-the-art research methods and bridging the research gaps. Subsequently, energy management models are developed and case studies are presented at the end of the chapters to summarize the research and demonstrate the contributions of the study. The contributions of the dissertation are summarized as follows:

- A universal definition of the EI is put forward based on an exhaustive study of the state-of-the-art research. Particularly, the impacts of the EI are comprehensively described in the context of the physical architecture and system design. The physical architecture of the EI integrates multiple energy networks, such as distributed energy networks, heat networks, and gas networks, and interconnects them through prominent technologies, e.g., ICTs, ER, AMI, SDN, HEMS, and PEM. These technologies play an essential role in establishing an EI; however, they also pose several potential challenges in terms of system complexity, system security, social acceptance, and policy-making.

- Following a description of an EI infrastructure, this dissertation investigates energy management systems at the residential level in terms of HEMS and ER-based PEM systems. Initially, a comprehensive modeling of an HEMS is described including hierarchical structure, key characteristics, DR activities, and HOMs-based scheduling operations. The scheduling operation of the HEMS is performed based on well-known HOMs. HOMs are widely used optimization methods for the following reasons: fast computation time, ability to deal with complex problems, easy implementation, and essential features, i.e., exploration and exploitation. This dissertation focuses on four HOMs: GA, BPSO, HSA, and DE and presents the essential steps, working structure, and benefits and pitfalls of each method. In particular, the scheduling operation of the HEMS is designed based on GA and HSA to achieve the following objectives: efficient energy management plans for smart homes, minimizing the electricity bill, and reducing the PAR. In parallel, the scheduling operation of the HEMS is tested under an FDI cyberattack, and the performance of the HEMS is evaluated without a cyberattack and with a cyberattack throughout the day considering the resilience index metric. The simulation results show that the HEMS is capable of achieving the key objectives as well as a high degree of resilience even during a cyberattack.

- Next, a comprehensive and unique approach to an ER-based PEM system is designed for smart home users to enable flexible, economical, and controllable consumption of household energy. An ER-based PEM system is modeled based on the joint optimization problem of household loads, energy price model, rooftop PV systems, and energy storage systems. Subsequently, the joint optimization problem is solved through HOMs (GA, BPSO, DE, HSA), and the performance of the HOMs is evaluated under various hyperparameters, i.e., Selections I–IV, varied seasonal conditions, i.e., summer–spring–winter, and constraints of the following parameters: load scheduling delay cost, energy procurement cost, and battery degradation cost. The simulation results demonstrate that ER-based PEM systems provide efficient PEM plans and minimize the average aggregated cost of the system.

5.2 Future work

This doctoral dissertation presents a broad overview of the EI paradigm and its applications, particularly in designing system models for the energy management of smart homes by employing optimization algorithms. The system model can, however, be further developed by incorporating various energy systems and exploring the technical, technological, and economic aspects in the energy community.

- **The generic role of the ER and its applications in the EI:** In Publication I, we described the EI and its architecture comprehensively based on the system design. However, the generic role of the ER in terms of interconnecting, controlling, and managing various energy systems can still be explored further. In addition, Publications IV and V provided an insight into the management aspects of the ER; yet, it is highly important to investigate the generic architecture of the ER, i.e., combined aspects of communication, power electronics, and management, to enable flexible services in the EI network.

- **Flexible integration of various energy systems:** In this dissertation, our main focus was to provide energy management for smart homes with limited integration of PV systems and energy storage systems. However, the future EI will integrate other energy networks, such as heat and gas networks to meet the needs of energy users. Hence, the joint optimization problem developed in Publication V can be updated to systematically integrate various energy networks and solve the optimization problem on a global scale.

- **Cybersecurity system:** The future EI will integrate ubiquitous Internet of Things (IoT) devices, ubiquitous energy sharing, and ubiquitous communication. Therefore, a cybersecurity systems model is an essential part of the EI network. In this dissertation, Publication III investigated the cybersecurity aspects of the smart home. However, we aim to extend our work by incorporating various kinds of cyberattack strategies, detection of cyber threats, and reliable and robust solutions for cyberattack challenges.

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Publication I

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What Is Energy Internet? Concepts, Technologies, and Future Directions

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ABSTRACT The climate change crisis, exacerbated by the global dependency of fossil fuels, has brought significant challenges. In the medium to long term, extensive renewable-energy-based electrification is considered to be one of the most promising development paths to address these challenges. However, this is tangible only if the energy infrastructure can accommodate renewable energy sources and distributed energy resources, such as batteries and heat pumps, without adversely affecting power grid operations. To realize renewable-energy-based electrification goals, a new concept—the Energy Internet (EI)—has been proposed, inspired by the most recent advances in information and telecommunication network technologies. Recently, many measures have also been taken to practically implement the EI. Although these EI models share many ideas, a definitive universal definition of the EI is yet to be agreed. Additionally, some studies have proposed protocols and architectures, but a generalized technological overview is still missing. An understanding of the technologies that underpin and encompass the current and future EI is very important to push toward a standardized version of the EI that will eventually make it easier to implement it across the world. In this paper, we first examine and analyze the typical popular definitions of the EI in scientific literature. Based on definitions, assumptions, scope, and application areas, the scientific literature is then classified into four different groups representing the way in which the papers have approached the EI. Then, we synthesize these definitions and concepts, and keeping in mind the future smart grid, we propose a new universal definition of the EI. We also identify the underlying key technologies for managing, coordinating, and controlling the multiple (distributed or not) subsystems with their own particular challenges. The survey concludes by highlighting the main challenges facing a future EI-based energy system and indicating core requirements in terms of system complexity, security, standardization, energy trading and business models and social acceptance.

INDEX TERMS Energy Internet, energy management, smart grid, Internet of Things, communication.

I. INTRODUCTION

Recently, the depletion of easily accessible traditional fossil fuels and growing concerns about the environmental repercussions of fossil fuel use have resulted in significant research focus on the development of alternative energy resources. Electricity generation has traditionally relied heavily on fossil fuels, which has resulted in environmental damage and increased atmospheric carbon dioxide (CO_2) levels [1], [2]. In addition, the traditional power grid faces other issues that hinder changes to a more sustainable energy system, e.g., (i) its centralized structure with one-way power flows, (ii) inadequate participation of consumers, (iii) weak market mechanisms, and (iv) other sustainability and economic challenges [3]–[5]. In attempting to address these issues, the concept of a smart grid has become a popular and highly researched paradigm [6]–[8]. A smart grid offers two-way energy and communication flow, incorporates consumers'

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decisions, and provides a platform to integrate distributed and automated systems that manage the energy flow [9]–[11].

Despite the considerable promise of the smart grid and its many attractive features, current research has indicated that it also has many shortcomings, e.g., inadequate utilization of energy forms like biomass, chemical and heat systems, a dependency on existing structures, which results in inefficient routing or scheduling, and security weaknesses [12]–[14]. Following the trend of smart grids and in view of the significant technological progress of the (data) internet, the concept of an energy internet (EI) has been advanced. A preliminary conceptual example of the EI was discussed by the prestigious magazine *The Economist* in 2004 [15], where an intelligent grid—called the "EI"—anticipates two-way flow of (various forms of) energy and information using internet-oriented technologies that leverage real-time data, improved power line qualities, and various sensors and micro-power sources. More systematic research with the EI as its core started in the late 2000s. For example, Tsoukalas and Gao [16], [17] presented the basic assumptions, architectural requirements, and prototype implementation for building an internet-type of "energy network". In [16], the basic assumptions of an EI are summarized as: virtual storage, dynamic pricing capabilities, and architectural requirements, including smart metering infrastructure, load and price forecasting, etc. The work also examined resemblances between the internet and electric networks. However, the authors did not undertake analyses of the technological aspects and key equipment required, such as energy routers having the plug-and-play services needed to implement the technology.

Around the same time, E-Energy (Internet of Energy) was initiated by the Federal Ministry of Economics and Technology, Germany. The E-Energy model mainly focuses on sustainable energy systems that are digitally connected throughout the entire power system—from generation to transmission, distribution, and consumption—using information and communication technologies (ICTs) (see Table 1 for a complete list of acronyms.) [18]. In 2010, in the US, the future renewable electric energy delivery and management (FREEDM) system center proposed an initial implementation plan to construct an EI. The FREEDM system aimed to incorporate numerous pivotal technologies as essential features of the EI, e.g., plug and play interfaces, large-scale distributed generation and storage units, and information and power electronics technologies [19]. Later, in 2011 and 2013, preliminary researches were conducted in China to develop a future electric power grid with the integration of new technologies in an EI [20], [21] (respectively). And shortly afterward, in 2015, a Chinese organization, the "Global Energy Interconnection Development and Cooperation Organization" (GEIDCO), founded the first dedicated organization to promote and encourage the sustainable development of a global EI [22].

In previous researches and scientific literature, the conceptual basis and implementation requirements of an EI have been investigated by considering features and sub-components, such as the architectural design, large-scale integration of ICTs, and the key components and design

TABLE 1. Nomenclature.

Abbreviation	Meaning
AMI	Advanced metering infrastructure
ADMM	Alternating direction method of multipliers
BEMS	Building energy management system
CPS	Cyber-physical system
CSR	Core server
DSM	Demand side management
DR	Demand Response
DERs	Distributed energy resources
DGI	distributed grid intelligence
DoS	Denial-of-service
EI	Energy internet
ER	Energy router
EH	Energy hub
EIAE	Energy internet access equipment
EMP	Energy management problem
E-Energy	Internet of energy
FREEDM	Future renewable electric energy delivery and management
GGL	Global grid level
GHG	Green house gases
GEIDCO	Global energy interconnection development & cooperation organization
HEMS	Home energy management systems
ICTs	Information and communication technologies
ICN	Information communication network
IEDS	Integrated energy distribution system
IoE	Internet of energy
IoT	Internet of Things
IEM	Intelligent energy management
KMS	Key management system
MESs	Multiple energy systems
MTC	Machine type communication
MPC	Multi-port converter
MILP	Mix integer Linear programming
MGs	Micro grids
PEM	Packetized energy management
PLC	Power line communication
PSU	Power sharing unit
PID	Proportional integral derivative
QGR	Quantum grid routers
QR	Quantum grid
RERs	Renewable energy resources
SERs	Sub energy routers
SST	Solid state transformer
SCADA	Supervisory control and data acquisition
SDN	Software-defined network
SDNEI	Software-defined energy internet
TDM	Time-division multiplexing
TCL	Thermostatically controlled load

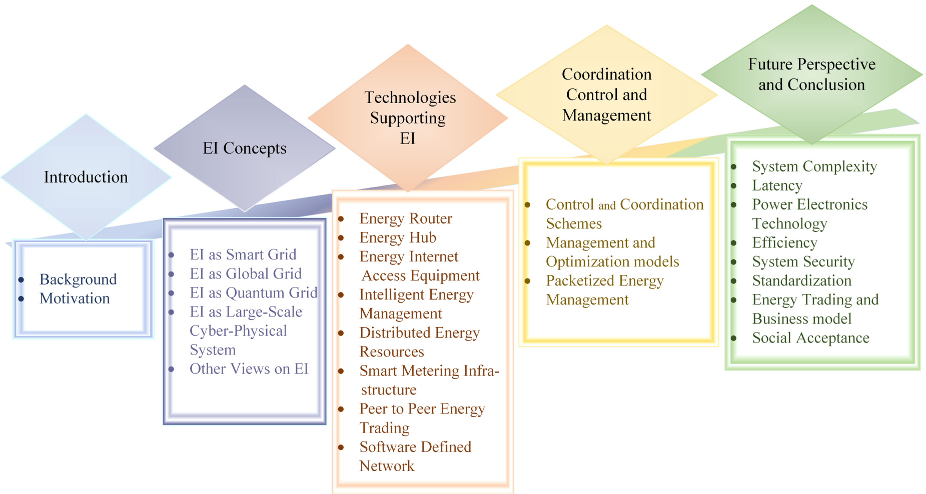

FIGURE 1. Overview of the structure of the paper and the technological challenges reviewed.

challenges [23]–[26]. Initially, some of the early researchers, such as Cowan and Daim [24], viewed the EI in terms of a smart grid; however, as the EI concept developed, more recent researchers have started to approach the EI as an independent paradigm different from the smart grid and the *EI is now described as an enabler of the smart grid*. Some works, for example, [25], [26], have explicitly highlighted the key differences between the smart grid and the EI. In [25], the authors identified the communication challenges and standards required to build an EI framework. The same group of researchers in [26] outlined the architecture of an EI based on the FREEDM system, along with a description of the design of EI components—particularly energy routers—and presented key challenges to the EI. These works examined the EI framework, but the management of EI resources and the controlling methods required remained unaddressed. In another work, [27], the EI concept is considered with a focus on smart grid applications integrated with the Internet of Things (IoT). Other researches, such as [28], have focused on the communications devices and architectures within the EI and have examined specific components of the EI, for example, the energy router architecture.

Today, the EI has become a topic of extensive ongoing research. Nevertheless, no coherent and comprehensive definition of the EI exists, and consequently, many different interpretations and conceptualizations of the EI can be found in the literature. In this paper, we try to systematize the existing literature to map the differences and similarities of existing contributions to the definition of the EI. As shown in Fig. 1, we first examine the many different meanings and definitions of the EI concept as a ''smart grid'', ''global grid'', ''quantum grid'', and other miscellaneous viewpoints. We present our comprehensive universal definition of the EI as a ''cyber-physical system,'' and elaborate on this conceptual basis of the EI, its main characteristics, the core technologies needed to construct the EI framework. In consideration of coordination and management of EI resources, we briefly describe different control schemes, management strategies and optimization models. Additionally, we highlight the key requirements and challenges facing the EI with the aim of exploring further development of the EI concept.

The remainder of the paper is structured as follows. Section II provides a classification of different contributions concerning IE. In Section III, we comprehensively describe the technical features and key technologies of the EI. Section IV introduces the control methods and coordination schemes needed for the optimal use of EI resources, and the concluding section, Section V, highlights the requirement and challenges in EI infrastructure. Finally, Section VI concludes this article.

II. EI CONCEPTS

As noted in Section I, no consensus exists on a definition of what constitutes an EI, and researchers have examined the EI idea using different definitions, interpretations, and perspectives. In this section, we will discuss the most common definitions of the EI.

A. EI AS A SMART GRID

In the past decade, most research efforts have explained the EI in terms of a smart grid. For example, [24], [41]–[46] refer explicitly to the EI as a smart grid or consider the EI an essential feature of a smart grid, and some papers interpret the EI as a web-based smart grid [47]–[52]. Tsoukalas and Gao [16] described the EI as follows: ''An implementation of smart grids is EI where energy flows from suppliers to

TABLE 2. Distinguishing features of smart grid and the energy internet (EI).

Features	Smart grid	Energy internet	Remarks
Transmission	Two-way flow of information and communication	Multi-way flow of information, communication, and energy	The EI enables the multi-way flow of information, communication, and energy whereas smart grid has information and communication flow only [25], [29].
Technology	Dominated by ICTs	Dominated by ICTs, Internet, or web technologies	The dominant technology in the EI is internet-based communication with ICTs and features like plug and play services and others while smart grid relies mainly, or solely, on ICT's [19], [26], [30].
Metering and routing equipment	Smart meters, sensors, home energy management systems	Energy routers, smart meters, intelligent energy management softwares, residential energy routers, etc.	The energy router together with smart meters is a unique feature of the EI; it not only measures and manages the data but also enables other features, such as converting the voltage level, communicating with other ER, and combining renewable energy resources (RERs) [31]–[33].
Network topology	Mainly centralized with the involvement of renewable energy sources	Decentralized with large-scale involvement of distributed renewable energy resources	The EI paradigm is highly reliant on power networks, distributed RER networks, storage networks, etc., while the smart grid is based on a centralized approach with some involvement of renewable generation [34].
Functionality	Grid monitoring, management, and data processing	Processing and analyzing of data and energy, grid management	The EI is based on multi-agent and intelligent systems that processes and analyzes the data and energy simultaneously, whereas the smart grid mainly focuses on data management and monitoring [28]
Available standards	International standards are available. e.g., DNP3, CEN-TC294, and IEC 61850	A few communication protocols are being established, such as ISO/IEC/IEEE/1880	In the smart grid, some international standard communication protocols are available and others are being developed, e.g., DNP3, CEN TC294, and IEC 61850 [35], [36]. On the other hand, the EI communication protocols IOT-G230MHZ and TD-LTE230 are beig discussed in [37], [38], but more standardized communication protocols are required.

customers like data packets do in the Internet.'' In their work, they investigate the assumptions underlying the EI, the prerequisites to restructure the delivery of energy, and the infrastructure needed to construct an internet-type energy network. Similarly, the EI is viewed in [53] as an advanced form of smart grid and the analogy between internet networks and energy networks is highlighted, as can be seen in (Fig. 2).

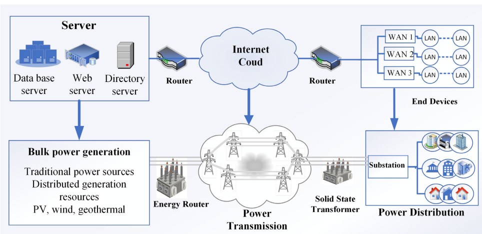

FIGURE 2. Comparison of energy flows in internet and power system networks [53].

However, interpreting the EI as a smart grid is not the only approach to its definition. In [26], for example, the EI is described in terms of how its characteristics differ from a smart grid. The EI system is considered to have three main components [25]—energy subsystem, network subsystem, and information subsystem—that are interconnected with ICTs. The work explores various technologies and core components of the EI in comparison to the smart grid. Among them is the energy router, which is a fundamental component not only responsible for connecting subsystems in real-time but also for enabling two-way communication and energy flow, as shown in Fig. 3. Wang *et al.* [54] similarly expounded the physical structure of the EI and categorized it into three levels, in this case; trans-regional, regional, and user level. A key difference with the smart grid mentioned in the work is the consolidation of various forms of energy, such as electricity, heat, peat, and gas at a regional and user level through an intelligent component known as an integrated energy distribution system (IEDS). In addition, the other key differences discussed in two articles ([25], [54]) and in [24], [27], [28] are summarized in Table 2.

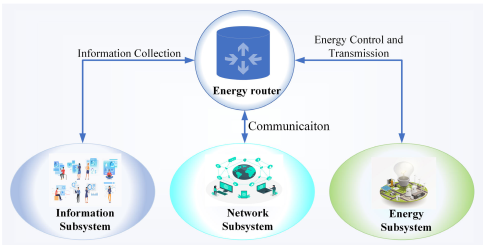

FIGURE 3. Overview of the subsystems of an EI defined in [25].

B. EI AS A GLOBAL EI

A promising idea explored by Liu *et al.* in [55] is the EI as a global energy internet (GEI) and a ''strong'' smart grid on a much larger scale. The GEI would interconnect RERs globally (including solar, wind, hydro, and geothermal), assure optimal management and coordination of these resources, and consequently ensure a clean, sustainable, and secure energy network across the globe. The authors put forward three aspects requiring further research: the system dynamics model, simulation methods, and multiagent game theory. The construction of a GEI is, however, a major undertaking and requires investigation of many areas, e.g., investment planning, investment decision making, coordination and/or interaction between countries and technical considerations.

Accordingly, in [56], the authors investigated the technological aspects of GEI and proposed an economic dispatch framework that is practically verified in South Asian countries. The framework focused on technical problems related to a GEI and explored reinforcement of the share of RERs while simultaneously handling uncertainty constraints and power regulations. The work additionally proposed an algorithm, the alternating direction method of multipliers (ADMM), to protect sensitive information of the countries involved and to enable reliable exchange of energy and communications.

C. EI AS A QUANTUM GRID

A unique approach to describing the EI is presented in [57] where the EI is viewed in the context of a quantum grid (QR). The so-called quantum grid integrates internet revolutionized communication and resembles the electrical power grid in certain aspects. For example, power transmission is attributed as energy packets similar to data packets, and power transmission lines and nodes are allocated addresses just like the internet network (IP addresses). In addition, the power nodes are referred to as quantum grid routers (QGR) and their functions are: (i) to optimize and control the energy generation resources, such as distributed energy resources, bulk power generation, and consumption; and (ii) to achieve quick restoration and self-healing. The basic layers of the QR network comprise a power plan, routing and control plan, and business plan. These plans are fully connected by leveraging the ICT, which thereby enables the QGR to exchange information in various layers by means of energy packets based on routing and control plans.

Other concepts similar to the QR include packetized energy management [58], the digital power grid [59], the physical energy packet transmission [60], and the local area packetized network [61]. The relationship between the different forms of packetized energy management and the EI is considered in [62] and deeply explained in IV-C.

D. OTHER MISCELLANEOUS VIEWS ON EI

Some research studies have elaborated the EI in a different way. For example, Energy + Internet is studied in [63], which compared the challenges inherent in the business model and management of integrated energy resources, services, and policies in a traditional energy system and a new Energy+Internet system.

In [64], Feng and Xiaoli explored the EI as ''people oriented'' that anticipated the wellbeing of the users by establishing communication channels between the users and energy systems. They argued that an economical and environment-friendly ''best energy service'' is the ultimate demand of the users. Seen from the technology point of view, the communication, information, and processing technologies used must connect the energy production systems with the consumer/prosumer and provide intelligent management and optimization of energy resources.

E. EI AS A LARGE-SCALE CYBER-PHYSICAL SYSTEM

After examining the various interpretations of the EI, it can be seen that the EI is a broad concept merging numerous energy-based networks (heat, gas, electricity, etc.) to provide a unified platform for better coordination and sharing of the energy resources. Consequently, development of the EI architecture is complex and multidisciplinary. In this article, we investigate the EI framework from the perspective of energy delivery and transactions in the electricity network and analyze complementary technologies.

Our proposal is a natural extension of the idea of the EI as a quantum-like grid enabled by packetized energy management, detailed in Section II-C. We argue that the EI is most accurately and universally represented as a software-defined ''energy network of networks,'' such as power generation networks, storage networks, data management networks, and distributed generation networks, as shown in Fig. 4. Each network is interconnected through three layers, i.e., energy, communication, and information. The core component responsible for organizing the three layers at the local level are the sub energy routers (SERs). Further, we argue that the EI can be most clearly approached using the idea of ''discrete or packetized energy,'' as emphasized in [62], [65]. The SERs communicate with each other through (discrete) energy packets that are akin to the data packets in the internet network. The SERs also exchange the obtained information with the core server (CSR). The CSR is the heart of the whole system and it performs the following functions: (i) accumulation of all information resources; (ii) control and coordination of the SERs; and (ii) packetized energy management (PEM) by leveraging information from SERs and making real-time optimal decisions for the distribution of resources.

Seen in the way described above, the EI can thus be viewed as a cyber-physical system (CPS), since it it comprises the features of physical systems and cyber systems simultaneously. Physical systems like electricity generation resources must be controlled and managed according to the instructions received from the cyber-systems, i.e., the SERs, CER, smart meters, sensors, and embedded systems. Thus, we define the EI as follows: ***a cyber-physical system in which physical energy infrastructures and physical distributed RERs are interconnected and managed via a software-defined cyber energy network using packetized energy management techniques***. Such a comprehensive definition and architecture cannot be designed without the integration of cutting-edge technologies including real-time communication technologies, control systems, information processing, smart metering infrastructure, and software-defined network. Moreover, it is also essential to organically deploy such technologies with management and planning strategies while taking into account EI requirements and challenges.

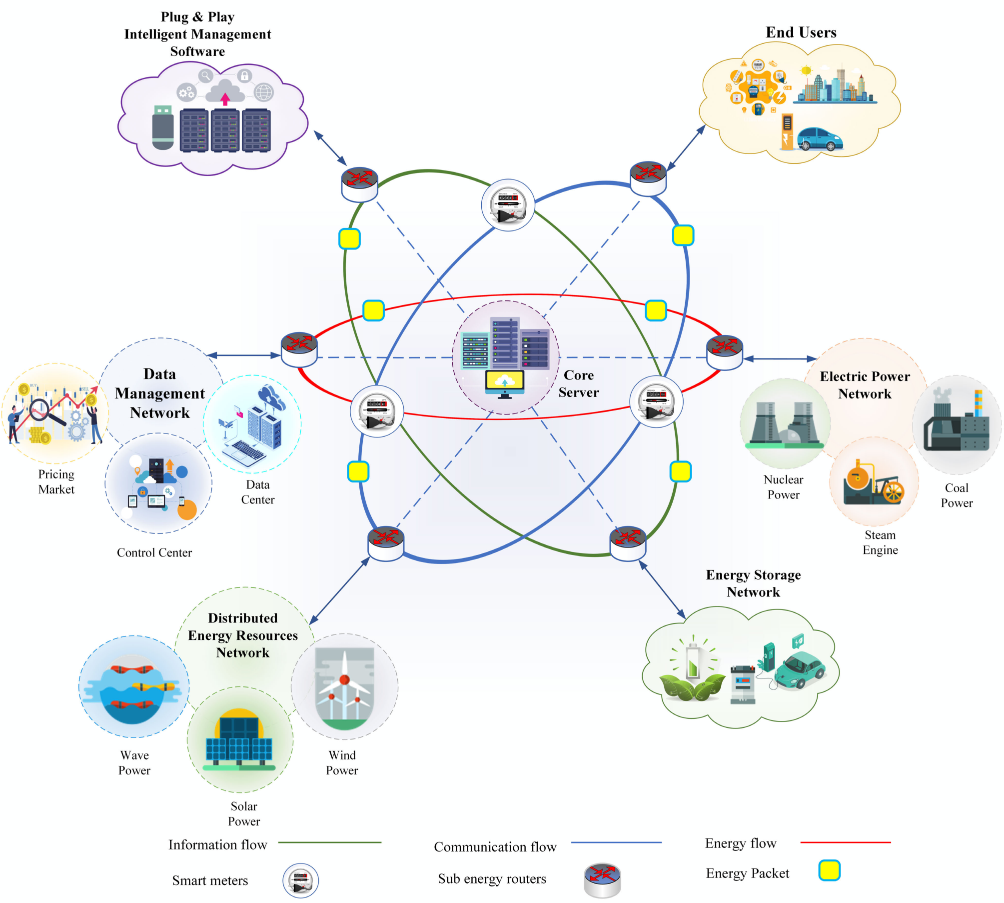

FIGURE 4. Basic structure of an EI comprising multiple networks, such as a distributive energy resources network, energy storage network, data management network, and internet and communication networks with features, like Plug and play, intelligent soft ware, sub energy routers, and smart meters.

F. SUMMARY

The overall concept of an EI was discussed based on definitions and uses that have been presented in the literature. The main studies on the topic are summarized in Table 3, where their reasoning is indicated. It is worth mentioning that none of the surveys consider the EI as a large-scale CPS enabled by a PEM system. Such a definition is, however, of importance for the technologies used. In the next section, we will present the key technological enablers of the EI.

III. SUPPORTING TECHNOLOGIES FOR EI

In this section, we discuss pivotal technologies that can contribute to the implementation of the EI.

A. ENERGY ROUTER

The energy router (ER) is essential equipment for realizing a functioning EI infrastructure. The ER concept was first proposed by FREEDM [19] and included features such as conversions of forms of energy and voltage levels, high power quality, and plug and play interfaces. The former two services provide flexible and optimal utilization of energy and ensure reliability of the system, and the latter ensures ease of operation. The ER proposed in FREEDM was based on a solid-state transformer (SST), and its architecture comprised three layers: physical control (power and energy), distributed grid intelligence (DGI), and communication layer.

The first layer is designed to provide flexibility in the physical system and to manage conversion, for example,

TABLE 3. Summary of the relevant research work.

Focus of the study	Survey (s)	Publication year (s)	Remarks
EI sustainability in terms of communication design, requirements, and standards	Kun et al. [25]	2017	The survey compares the EI with smart grid technologies and explains the EI architecture based on FREEDM including communication framework and standard protocols. Open challenges with proposed requirements are also described.
EI architecture in terms of four key features with complementary technologies including challenges and requirements	Kun et al. [26]	2018	Authors in [26] extend their previous work [25] and describe the communication infrastructure with potential key technologies in the EI. In addition, the article also presents an overview of the EI components including FREEDM system, etc. However, the control methods and management of key resources remain unidentified.
IoT applications explored in the smart grid, smart cities, and the EI	Yasin et al. [27]	2019	The work views the EI and smart grid as the same concept and mostly focuses on IoT applications in the smart grid, without considering the key communication technologies (e.g., the ER) of the EI.
EI treated as a part of smart grid with some key equipment including benefits and hindrance	Suhail et al. [28]	2019	The basic architecture of the EI (based on FREEDM) is discussed including the ER and its types, benefits, hindrances, and requirements. However, technical solutions for the management of various EI resources are not analyzed.
Internet of energy (IoE) described as a potential solution to address the energy management in buildings	Mahammad et al. [39]	2018	The work focuses on IoE applications in building energy management systems (BEMS). The principal aim is to improve the energy efficiency in building or offices while incorporating renewable resources and considering implementation challenges.
A tool proposed to leverage EI applications including both hardware and software implementations and challenges	Leeng et al. [40]	2019	The study comprehensively investigates the hardware equipment in the EI and proposes novel concept of EIAE, its design, technical features, and implementations at the user level.
Various concepts of the EI presented and a universal definition proposed; key supporting technologies, coordination, and management schemes discussed	Our Survey	-	Our survey examines various concepts of the EI and proposes a universal definition. Based on the definition, key supporting technologies are described, considering control and coordination methods. Potential bottlenecks including important requirements are explained to implement the EI in the future.

from high voltage alternating current (AC) to direct current (DC) as rectification, DC to DC (different voltage levels) as a chopper, and DC to AC as inversion, and also to provide low-level voltage for the AC bus. The second layer is the communication layer, which regulates the bidirectional flow of information and communication and uses technologies such as Ethernet, wireless LAN, and fiber optics. Lastly, the DGI layer utilizes information from the communication layer and coordinates other SSTs to enable optimal decision making and improve energy efficiency and utilization. Critical features of the SSTs are plug-and-play services, flexible power control and optimal energy flow [68].

Three types of ER based on SST, multiport converters (MPC), and power line communication (PLC) are described in [31], [66], [67]. The authors expounded a similar functionality of SST as proposed by FREEDM, i.e., the transformation of various forms of energy and regulation of voltage and current levels using power electronics devices. The MPC is specifically designed for the low-level voltage distribution network, i.e., for homes and buildings, and it manages the subsystems, including generation resources and storage systems, to maintain and balance the energy supply.

The PLC layer is a key layer in an ER and responsible for the simultaneous flow of energy and information by leveraging time division and multi-path transmissions. It is noteworthy that PLC is economical as it uses the same power line for energy and communication flow; however, it has shortcomings as regards bandwidth requirements, low data rates, and signal attenuation. Many researches have tried to address these shortcomings and improve the efficiency and reliability of PLC. For instance, the authors in [67], [69], [70] considered the electrical network similar to a data network; the energy is split into energy packets like data packets in the internet network. The energy packets are transmitted using transmission techniques such as time-division multiplexing (TDM). In TDM, the energy packets are tagged with header (source of generation) and footer (source of consumption) information and multiplexed over the transmission network. When these packets arrive at the load side, the ER distributes the packets to the final destination address. To improve energy efficiency of the transmission network, it is also important to utilize interference mitigation techniques. The architecture of the three types of ER is presented in Fig. 5.

B. ENERGY HUB

Energy hub (EH) was an important concept in the project Vision of Future Energy Networks [71]. The EH is a system that combines various energy networks, including electricity, heat, and gas to meet the demand of the end users. The EH offers two key features: flexibility and reliability; that is, it has the flexibility to utilize energy from different energy networks, and thus, it is not dependent on a specific energy source. This, in turn, increases the reliability of the system, particularly from the consumers' perspective. In addition,

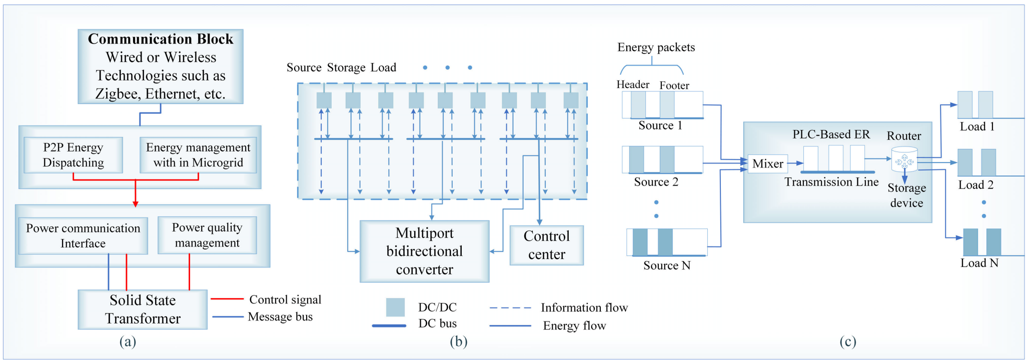

FIGURE 5. Types of energy router: (a) Solid-state-based energy router, (b) Multi-port converter-based energy router, and (c) Power-line-communication-based energy router adopted from [31], [66], [67].

the authors explored the feasibility of the combined transmission of different energy forms and proposed a device known as an energy interconnector. Combined transmission of different energy forms improves the system efficiency. A simple example would be that any heat losses in the electrical system could be used for regulating the temperature in the heat or gas network, which ultimately reduces the overall system losses. However, studies have shown that in such a combined network, common mode failures could result in a catastrophic collapse [72].

EH concepts are described more comprehensively in [73] that compares four key components of an EH—(variety of) energy inputs, storage systems, converters, and optimal output of EH models. Drawbacks in existing EH models are also discussed and methods are suggested for the management of EHs; features that would improve the sustainability of future energy systems are also proposed. Using a similar approach, Parisio *et al.* [74] described the EH model in a control-oriented manner and optimized the energy scheduling problems using mixed-integer linear (MIL) formulation. Wang *et al.* [75] applied MIL programming using a graph theory approach for the optimal planning of multiple energy systems (MESs) in EH.

C. ENERGY INTERNET ACCESS EQUIPMENT

In the EI infrastructure, the various energy generation networks, energy storage networks, and distributed energy resources (DERs) are connected to provide fully and flexible energy supply. In addition, the electricity market facilitates energy trading with the energy suppliers or between prosumers by adopting effective demand response strategies. To enable these services, energy internet access equipment (EIAE) is proposed in [40] as a way to connect and monitor energy usage and energy supply in real-time. Three prominent features of such EIAE are the following: (i) EIAE as end users' cyber-physical terminal media act as interfaces and measure, observe, and control all DER-using devices; (ii) EIAE enables interactions between end users and energy generation and supplies components in the EI using measurements, observations, and controlling methods; and (iii) EIAE is possibly the final execution component/device in the EI that provides all the aforementioned services. The authors highlight the differences between ER and EIAE to emphasize the novel features of EIAE. These novel features are succinctly summarized as follows: "EIAE should have cascading capabilities that enable bidirectional circulation of information flow and energy flow as well as aggregation and re-transmission." The other technical features of EIAE are perceptibility, controllability, autonomy, unified access, and cyber-physical capability. The key differences among ER, EH, and EIAE are presented in Table 4.

D. INTELLIGENT ENERGY MANAGEMENT

The EI infrastructure relies on fast and reliable information, leveraging smart and intelligent energy management systems. In this context, FREEDM [19] proposed an intelligent energy management (IEM) software that interacts with DERs, storage systems, and end users and enables plug and play features. Unlike a supervisory control and data acquisition (SCADA) system, the IEM has a distributed and flat architecture that makes it scalable and sustainable. IEM provides optimal utilization of RERs and cooperates with the storage system under contingencies or when grid power is not available. In essence, IEM performs multi-objective tasks and adapts the load demand curve, minimizes the operational costs and circuit losses (in SST), and regulates the voltage. In order to achieve these objectives, IEM requires recognition and incorporation of renewable distributed resources, on-time energy and power dispatch, and most importantly, a robust algorithm to control and distribute tasks efficiently.

E. DISTRIBUTED ENERGY RESOURCES

The envisioned EI has to be highly flexible to accommodate DERs while maintaining sustainability and availability of power generation. The EI encompasses numerous DERs that, along with other complementary technologies

TABLE 4. Distinguishing features of the energy router (ER), energy hub (EH), and energy internet access equipment (EIAE).

Features	ER	EH	EIAE
Aim and function	Acts as a core component in the EI and aims to combine MESs using conversion technologies, ICTs, and internet technologies	Acts as a part in the EI and aims to combine MESs and storage systems with mainly conversion technologies and ICTs	Acts as a key component in EI and aims to control and optimize energy usage (from various resources) at end users
Transmission	PLC-based ER used for the energy and information flow	Energy and information flow with a specific device such as an inter-connector	Not intended for transmission; however, acts as a medium to access DERs and other resources
Information & communication process	Collects information directly from MESs and enables bidirectional communication	No bidirectional flow of communication and information	Allows bidirectional flow of communication and information
Control system means	Responsible for control of energy, information, and communication simultaneously through distributed grid intelligence	Responsible for control and management of energy resources of MESs in the EI	Responsible for control of energy scheduling of MESs at end users' level
Main focus	Mainly accumulates energy and information from MESs and organizes the optimal resource allocation in the EI	Mainly accumulates MESs to improve reliability and availability in the EH	Mainly facilitates the economics and comfort of end users

such as storage systems, play an important role to optimize energy management. However, the controllability and management of DERs and storage systems face numerous challenges and sustainability issues, including high computational burden, frequency design requirements, communication topologies, etc. Yazdanian and Mehrizi-Sani, [76] reviewed distributed control and management techniques that can potentially improve computational capabilities and cooperation between growing numbers of DERs, power grids, and end users. In the same vein, Ding *et al.* [77] discussed a novel strategy—"event-triggered communication"—for optimal control between communication devices in DERs. Their proposed strategy considered the communication complexity and attempted to enhance coordination between DERs, which, in turn, improves the reliability and flexibility of the energy management. The authors also described trade-offs between communication resources and control performance. Choi *et al.* [78] designed a hierarchical distributed architecture and agent-based smart management that facilitates cooperation between homes and energy generation resources. The designed hierarchical architecture acts as a cloud and provides information and processing, data acquisition, and communication while the edge network makes autonomous decisions through an intelligent agent. Other research works have employed a fractional order proportional integral derivative (PID) controller with robustness [79]; explored test-beds for two levels of energy management and control systems [80]; and examined agent-based controlling techniques [81].

F. SMART METERING INFRASTRUCTURE

Smart and intelligent sensing devices are of great importance in the EI. Smart devices such as smart meters provide accurate data measurement, control, and predictions. As an essential component of advanced metering infrastructure (AMI), smart meters collect real-time information of energy generated from various sources and the energy consumed by the end users. Based on this information, smart meters together with demand-side management (DSM) and demand response (DR) offer potential benefits to end users and energy suppliers. For instance, from the end users' point of view, smart meters allow the end users to know about their electricity consumption, pricing tariffs, and real-time updates through a user interface often known as ''home energy management system (HEMS)." This information helps consumers to manage energy usage and to achieve reductions in their electricity bills. Seen from the point of view of the utility companies, the peak load can be curtailed, shifted, or predicted by implementing DR programs, thereby improving the energy efficiency of the system [82].

Alahakoon and Yu [83] studied smart meters, their framework, and potential applications. They found that the information received by smart meters such as power generation, consumption, and power quality can be used to enhance system stability and reliability. Their proposed framework identified prospective features of smart meters in terms of data analytics capability, technological perspectives, and stakeholder applications, and the work also detailed the limitations of existing smart metering infrastructure. However, future requirements and challenges such as communication latency, bandwidth, real-time processing, security, and privacy need to be addressed effectively. To focus on the communication aspects of smart meters, Fan *et al.* [84] examined the smart meter communication framework, the current challenges, technological solutions, and areas requiring further research, e.g., scalable inter-networking, interoperability, self-organization, and DR applications. In addition, the authors emphasized the need for the standardization of information and communication strategies for the deployment of smart meters and other devices to enable efficient and reliable energy transactions in smart grids.

Recently, the security concerns of AMI and smart meters are much more demanding and researchers have given serious attention to this topic. For example, Ghosal and Conti [85] investigated the key management system (KMS) of the AMI and discussed the role of defensive approaches to provide a secure communication and management system. The security challenges in AMI systems are, for example, consumer privacy preservation, potential cyberattacks against system resiliency, and electricity theft. Similarly, the authors in [86] proposed an information-centric network and key management scheme to ensure data integrity, confidentiality, and authentication of widespread smart meters. To tackle these threats and enable an efficient KMS, it is essential to deploy standardized ICTs, intelligent softwares, and potential solutions such as key graph technique, authentication (based) technique, and hybrid approaches [85], [87].

G. PEER-TO-PEER ENERGY TRADING

The EI is an interconnected, open, smart, and user-centric system that makes secure and reliable peer-to-peer (P2P) energy transactions and delivery feasible. As such, P2P allows prosumers to take part in the electricity market by selling their excess energy [88] or reducing their energy demand [89]. By doing so, the prosumers can make full use of DERs and consequently reduce electricity costs. P2P energy trading has many potential benefits, such as reducing peak (demand), lowering overall operational and investment costs, lowering reserve capacity requirements, and improving energy efficiency and power system reliability [90]–[92]. It is, therefore, important to investigate the technical and energy market requirements of P2P energy trading and an effective way to encourage customers to take part in the trading.

The architecture of P2P energy transactions is explored in [93], which investigates both the physical layer responsible for the transmission of electricity and the virtual layer providing secure transmission communication for energy trading between prosumers. The work examined the challenges faced by both layers including security concerns, dynamic pricing market, and cost reduction. To address these challenges, relevant technical approaches, such as constrained optimization, game theory, auction theory, and blockchain are essential to designing P2P architecture. In the same fashion, Zhang *et al.* [94] designed a four-layer model for low voltage (LV) microgrid through the ''Elecbay'' platform leveraging the game theory approach. Alam *et al.* [95] developed a P2P energy trading approach at the microgrid level among smart homes. Their objective was to incorporate storage systems and microgrid trading and distribute the energy cost equitably ensuring Pareto optimality.

H. SOFTWARE-DEFINED NETWORK

To meet the diverse communication demands and utilize the interconnected technologies efficiently, the adoption of a software-defined network (SDN) has emerged as an innovative networking approach. The SDN aims to improve routing strategies by establishing resources programmable software networks. The SDN and EI have been studied in [96]–[98]. Zhong *et al.* [96] investigated software defined EI (SDEI) architecture from three perspectives: energy flow plane (EP), data plane (DP), and control plane (CP). These planes function independently and incorporate new technologies to upgrade their infrastructure. The EP is responsible for the physical flow and control of energy. The DP collects and analyzes the information from various energy sources and services, including generation data from DERs and consumption data from households. The CP is the key layer and is responsible for dynamically controlling and configuring the DP and EP layers by enabling flexible cooperation between them; maintaining a balance between demand and supply; and programming ER optimally. The ER, on the other hand, supports P2P communication and energy flow and is classified into three categories: the ER at transmission (ER-T), the ER at distribution (ER-D), and the ER at consumption (ER-C). The authors discuss the interesting example of EVs to demonstrate the application of an SDEI in a mobility management system and to illustrate the potential challenges facing energy service providers. A similar approach for an SDN was developed in [97], where the SDN architecture was split into three layers. The infrastructure layer accommodates various energy networks, including network equipment such as the ER and switches. The middle layer, or the control layer, controls the data obtained from the infrastructure layer and is interlinked with the top layer known as the application layer. Additionally, the authors highlighted the concept of an intelligent energy controller (similar to the IEM in FREEDM) that receives data from multiple energy sources and sorts the data before sending it to the control or data center. Another interesting study [98] explores an SDN for the communication architecture of the EI at two levels, microgrid level (ML) and global grid level (GGL). In the study, the proposed communication architecture is evaluated based on the reliability, security, and latency features. Test bed cases of the proposed framework for the ML and GGL were presented, and it verified low latency and improved reliability results.

I. SUMMARY

This section introduced the main technological enablers of the EI identified in the literature. Table 5 lists the technologies, their main features and existing challenges, and presents some observations about the technologies. In the following section, we will discuss how these different elements can be used to coordinate and manage the distributed resources that lay the foundation for an EI.

IV. COORDINATION CONTROL AND MANAGEMENT

In an EI, various generation resources, storage components, consumption devices, and other elements must interact to maintain the stability and sustainability of the electricity infrastructure. Consequently, a robust and effective coordination and control scheme is necessary to ensure seamless operation of the EI. In this section, we will discuss coordination control and management strategies in the EI.

TABLE 5. A summary of the key technologies in EI.

Technologies	Reference(s)	Features	Challenges	Remarks
ER and EH	[68], [31], [69], [71], [73]	– Plug and play interfaces – Bidirectional flow of communication – Real time scheduling and management – Quick fault-detection restoration	– Real time control and protection – Management of MESs – Standard communication and information protocols	To enable EI and EH features, a standard network infrastructure, modeling of MESs, and multidisciplinary cooperation is essential
IEM	[19], [26]	– Optimal energy management – Addresses the load demand curve – Cooperation among MESs	– Tight coupling of EI components – Intelligent energy management software security and management	To control energy flow and enhance the efficiency of power system, power, voltage, and frequency control methods should be incorporated extensively.
DERs	[76]–[81]	– Improves the flexibility and reliability of the EI – Environment friendly	– Complexity in load management and forecasting problems – Intermittent nature – Reliable communication and power conversion requirements	To counter intermittency of DERs, storage network and management strategies need to be devised while monitoring the power quality factor.
Smart meters & EIAE	[82]–[85]	– Real time exchange of information – Assistance to manage energy utilization with DSM and DR	– Communication media – Real time processing, latency, and bandwidth – Security and privacy requirements	To establish reliable and flexible communication among end users and system operators, it is important to ensure data integrity, confidentiality, and authentication of widespread smart devices
P2P energy trading	[88], [93]–[95]	– Reduces stress on the power system – Improves the economic efficiency	– Network topology and optimal cost distribution – Voltage and capacity constraints	To facilitate active participation in P2P energy trading, new business and trading models should be included in the energy infrastructure; prosumers should be encouraged to sell their excess energy
SDN	[96]–[98]	– Provides efficient routing strategies – Programmable resources – Enhances energy control and communication efficiency	– Real time information processing and energy control with low latency – Computing capacity and efficient protocols for fast communication among ERs	To achieve the advantages of SDN technology, coordination among other SDNs and scalability are key problems to be identified and understood.

A. CONTROL AND COORDINATION SCHEMES

As we have seen, the EI structure is anticipated to be decentralized with the dominant integration of DERs accompanied by (AC or DC) microgrids (MGs) and microgrid clusters. Both AC and DC MGs are the essential units of the future EI, providing prominent benefits, such as improved reliability and stability of power grids, enhanced energy usage efficiency, and others listed in [99], [100]. However, MGs face many challenges including proportion power sharing and voltage regulation [101]. A great amount of research has been reported to control power-sharing proportion through multi-agent theory [101]–[103] and voltage (frequency) regulation through secondary control schemes [104]–[106]. Correspondingly, the authors in [107] have demonstrated a coordination and controlling scheme that provided insight on energy sharing among MGs incorporating energy, storage networks, and DERs, and maintaining a stable operation of the power system simultaneously. To accomplish better coordination, Sun [108] *et al.* analyzed a hybrid strategy and proposed a power-sharing unit (PSU) aiming to make full use of DERs in MGs with the help of a modified droop control approach using single-phase back-to-back converters. However, it is pertinent to note that droop-control schemes have shortcomings in terms of voltage synchronization, power sharing tradeoffs, and dependencies of load frequency and voltage [108], [109]. Therefore, the authors in [110] came up with an interesting multi-agent-based consensus algorithm to enhance the coordination and controllability of the DERs in the EI. The useful results of the researches can be summarized as follows:

- The synchronization of the voltages of various DERs, storage networks, and other EI elements with the main grid enables the EI to operate as a *spinning reserve system*;
- Coordinated control of the EI elements decreases energy costs; and
- Using MA systems, the EI infrastructure can flexibly achieve the desired power sharing among DERs.

The authors in [111], [112] described improved droop controlled schemes, while centralized control schemes and a multi-agent-based system are described in [113] and [114], respectively. Furthermore, communication among MGs and other generation resources is another important issue that needs the development of comprehensive ICT infrastructure along with control methods. The methods investigated in [115]–[118] are event-based control and predictive control. Table 6 gives a brief summary of the controlling methods.

TABLE 6. A brief summary of the controlling methods.

Control and Coordination schemes	Reference(s)
Droop based control methods	For improving voltage or frequency restoration in microgrids: [111]–[113], [119], [120]
Multi agent based methods	For improving power sharing and keeping voltage synchronized: [99], [100], [110], [114]

B. MANAGEMENT AND OPTIMIZATION MODEL

Thus far, research has tended to focus on the EI infrastructure/architecture [16], [19], [26], [28], ER [66], [68], [70], and frequency or voltage control [121], [122]. However, an important aspect of the power system is the energy management problem (EMP) in which an energy management system should be setup to achieve the goals of the EI. Typically, an EMP is designed as an optimization problem and solved using different approaches such as centralized, decentralized, or distributed methods. The centralized approaches provide global or near-optimal solutions. However, with the fast growth in DERs, many of these approaches do not always converge to an optimal point, while at the same time imposing strict conditions on the system, such as considerable computational complexity, and strict communication requirements. Distributed approaches, on the other hand, are robust, and enable fast computations and communication, and they are, thus, more popular.

The EMP for microgrids or smart grids has been explored widely in the literature [123]–[125]. The EMP with DSM has been analyzed for minimization of the cost of the system [126], [127] and the electricity bill of the consumer in the residential sector with a HEMS [128]–[131]. Subsequently, the problem has been approached using meta-heuristics, such as PSO [132], GA [133], HSA [134], and others [135]–[137], with the objective of optimally scheduling energy consumption and improving the reliability and stability of the power grid.

The EMP for an EI differs somewhat from the aforementioned methods because the EI is envisaged as an extensive collection of numerous energy generation networks, DERs networks, storage networks, etc., with large numbers of prosumers. Designing the EMP for the EI remains a major challenge because many of the previously studied smart-grid-based methods do not scale adequately. Nevertheless, some researches have attempted to tackle the EMP problem in the EI. For example, Sun *et al.* in [122] discussed EI features and proposed an innovative framework for energy management. Their model is complicated and incorporates other networks, including heating and gas. Therefore, the authors introduced a distributed-consensus-ADMM algorithm to solve the EMP problem. The proposed algorithm optimally manages the energy demand/output, taking into account customers' participation in the energy market. In the same context, other works [70], [138], [139] have attempted to manage and optimally allocate multi-energy sources such as PV, wind, and storage using intelligent ERs. Guo *et al.* [70] explored the hierarchical optimization method for the EH and ER in an EI to preserve privacy and information. The authors' approach comprised two levels: a lower level and an upper level. In the lower level, the optimal dispatch of energy is accomplished by providing the operation plans and integrating DERs in EH. In the upper level, on the other hand, the ER is employed to ensure secure and effective communication among other EHs and ERs. Chen *et al.* [138] designed a novel ER that enables bidirectional power flow, optimizes energy reallocation, and integrates other energy generation resources such as PV, wind, and storage. The proposed ER solution is easily scalable, capable of providing plug and play services, and improves the power quality by addressing the load-energy fluctuations. Gao *et al.* [139] modeled the ER based on probabilistic approaches aiming for energy trading and energy scheduling using a cloud computing tool.

C. PACKETIZED ENERGY MANAGEMENT

PEM is an interesting approach toward energy management and coordination of energy generation. The PEM concept is analogous to data transmission in a communication network; just like data is broken into packets, energy can also be broken into discrete packets. In this sense, energy packets or chunks represent a fixed power for a certain time duration, e.g., 1 kW in 1 minute (i.e., 0.0166 kWh of energy). Using PEM, the energy demand and supply can be aligned with the dynamic generation and consumption resources. Moreover, PEM brings benefits such as flexible decision-making, fairness, responsiveness, and scalability [58].

Recently, efforts have been made to implement PEM using physical [58] or virtual energy packets [61]. Takahashi *et al.* [60] claim that power distribution through discrete or PEM can be a game-changing approach toward energy management, energy control, and energy wastage reduction. In their work, they designed the ER such that it dispatched power packets with a destination address attached to each packet. Moreover, the power packets from distinct sources are distributed and transmitted through routers and delivered to the end users as per the attached address. The power packets-based distribution network also integrates storage capability and is a feasible solution for PEM. However, packet congestion is still problematic and requires economical solutions.

Zhang and Baillieul [140] developed a packetized direct load current solution for a thermostatically controlled load (TCL). They employed queuing theory to provide effective control of TCL, reduce power peaks, and smooth energy consumption oscillation. The authors extended their earlier work in [141] where they presented a model based on energy packet requests and withdrawals, which considers the total waiting time and mean waiting time of appliances. To achieve maximum utilization of power packets and meet urgency requirements, Ma *et al.* [142] adopted a deferred acceptance technique with heuristics algorithms to solve the scheduling problem. More recently, Zhang *et al.* proposed a protocol for P2P energy packets dispatched in a "local area packetized power network " using the branch-and-bound (BB) method with dynamic programming [143]. In [144], the authors demonstrated a PEM for DERs and proposed a macro model that considers the Markov chain and deferrable loads like electric vehicles and imposes the criteria of accepting and rejecting active energy packets during the state of charging and discharging. They analyzed the quality of service (QoS) guarantee and the accuracy of the model.

At the same line, Nardelli *et al.* [62] examined the implementation of the EI concept through PEM for residential sector loads. Their work considers a cyber-physical domain where flexible loads request energy as virtual energy packets from servers or a common inventory. The inventory is then responsible for the optimization and management of resource allocation based on prioritization, etc. To achieve QoS, the authors emphasized the role of massive machine-type communication (MTC) with ultra-reliable low latency. Nardelli and his group further extended their work in [145] and proposed PEM for flexible loads in the residential sector. Their work considers a cyber-physical system in which three types of loads send requests as virtual energy packets to the energy server through a residential energy router. The energy server can accept or reject the requests based on the energy available and prioritization rule/algorithm used. The proposed management algorithm addresses the peak load consumption and coordinates energy demand efficiently.

V. FUTURE PERSPECTIVES

Although the EI combines many promising features and versatile technologies, it requires co-ordination and co-operation between numerous energy, information and communication networks, which raises a number of challenges, such as system complexity, system security, efficiency, standardization issues, social acceptance, and energy trading and business models. We will now discuss the challenges (Fig. 6) that should be addressed in future researches.

- **System complexity:** An EI structure is built on multiple systems, which makes design, control, and optimization of the entire multi-level system comprising communication, information, and energy infrastructure very complex. On the one hand, the EI potentially offers exciting features based on latest technologies in communication and information but, on the other hand, reliability, efficiency, and robustness remain key issues hampering its implementation. Gungor *et al.* [146] used a three-layer division to discuss the communication requirements of potential smart grid applications to ensure flexible utilization of energy sources with advanced technologies: the application layer, power layer, and communication layer. A wide range of technologies is analyzed and the work also investigates the management of communication and information processing independently for each layer. Another interesting work [147] has investigated an energy-efficient infrastructure for communication and information for three cases: home area networks, neighborhood area networks, and wide-area networks.
- **Latency:** Latency is defined in [148] as "the time between when the state occurred and when it was acted upon by an application." To enable plug and play services and fully utilize the energy at all times, latency requirements have to be very strict. For example, in an electric substation, the communication latency for protection information is 8–12 ms, and for controlling and monitoring purposes is 16 ms [98]. These requirements could be even stricter in the case of MTC, as discussed in [149], and in the EI.
- **Power electronics technologies:** With the unprecedented integration of energy resources into the existing power system, EI components such as the ER, EH, and EIAE must provide robust conversion of energy resources as well as desired frequencies and voltages. In AC/DC MGs, power electronics-based devices are the leading technologies for power sharing and voltage restoration, as mentioned in IV-A. Achieving high-quality power supply in terms of efficiency and reliability is another challenge that needs to be overcome by leveraging efficient power electronics technologies (e.g., wide band-gap power semiconductors) and conversion systems.
- **Efficiency:** A core objective of the EI is to achieve improved efficiency compared to traditional power grids and smart grid. However, this is not easy because the aim of EI is to incorporate massive utilization of RERs. Indeed, it is important to manage, control, and optimize all RERs efficiently. The multiple energy vectors in an EI provide flexibility to accomodate and optimize the energy flow in an efficient manner to some extent. Furthermore, the two main drivers for improving efficiency in the EI are; the scheduling or management methodology in the physical energy delivery infrastructure, and in the ICT system. Both of them are briefly discussed below.
- **Energy scheduling and management:** To maintain flexible demand and supply, special attention should be given to the EMP due to the multi-layer architecture of the EI. Thus far, a few researches have discussed some control and management schemes, particularly centralized and distributed management. However, better and smarter energy management strategies must be employed for the optimal scheduling of energy resources. This also has the knock-on effect of

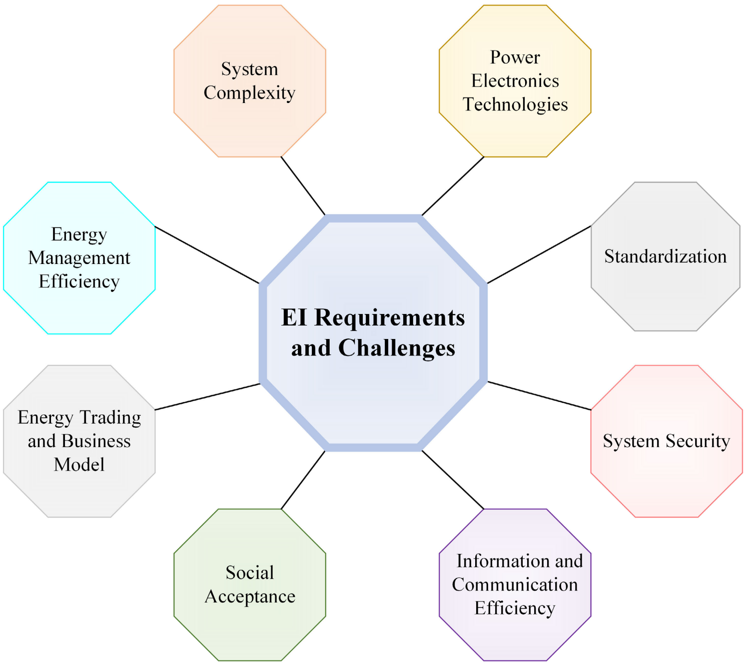

FIGURE 6. Challenges and requirements for advancing the energy internet (EI) technologies; future researches can focus on addressing these challenges.

encouraging prosumers to take part in the energy transactions using DR and DSM. Moreover, the efficient management of the storage network could also benefit both consumers and suppliers and lead to an overall economic and stable power grid.

- **Information and communication network:** The information and communication network (ICN) layer is the key for realizing a high-functioning EI. A fast and robust ICN network allows quick and seamless co-ordination and control of the complex EI network. However, it is still challenging to efficiently process and quickly communicate big data from different RERs and to improve the system performance. Some studies such as [150], [151] have discussed the information layer and its transmission in the EI. Another work [98] proposed an SDEI as an advanced approach to meet the demands and requirements of ICN. However, this is still an emerging research area that requires standard and efficient protocols for ICN. As discussed in [62], the development of the fifth generation of mobile systems (5G) and other solutions, such as edge computing for vertical applications, point toward a promising pathway to realize the EI in a more cost-effective manner.
- **System security:** In the EI, the multiway flow of information and communication is monitored and controlled by widespread and heterogeneous devices including the ER, smart meters, etc. These ubiquitous devices bring many security concerns for the ICN and energy network [152]. The issue of system security deserves great attention because inadequate security can pose a severe threat to system reliability, stability, and efficiency. Generally, the EI architecture relies strongly on the ICN to control, predict, manage, combine, and coordinate the energy resources. However, ICNs are vulnerable to cyberattacks that can jeopardize EI operations. Cyberattacks that could threaten system stability include denial-of-service (DoS) attacks, malware injection, and fake energy pricing [153]. To secure the stability and safety of the entire infrastructure, appropriate control system approaches and security detection techniques should be utilized.
- **Standardization:** To promote and implement the EI in a comprehensive manner, a set of well-defined standards should be established with global-level collaborations among governments, regulatory authorities, and industries [154]. Since the EI represents a comprehensive

multi-layer system that combines power generation, transmission, and consumption with ICN and internet technology, standard protocols and standardization are necessary to fast-track worldwide implementations using best practices. Many interoperability and communication standard protocols are already available for the smart grid, such as IEEE P2030, IEEE P2030.1, and IEC 60870 [146], [155], and a few of them are applicable to the EI, e.g., ISO/IEC /IEEE1880, IOT-G230MHZ, and TD-LTE230. Nevertheless, there is a great need to establish further standard protocols [25], [38].

- **Energy trading and business models:** To support and strengthen the EI applications, new policies for energy trading and innovative business frameworks are an urgent and critical requirement. The business potential of EI-enabled smart grids should be investigated as a way to engage energy users to perform trading and decision making. Governments and policymakers have an important role in facilitating energy market participation. Zhou *et al.* [156] considered a three-layer business management module for the EI. The module is associated with big data analytics from MESs and numerous services and applications to perform business management operations and tasks. To be able to develop an effective business model for the EI, stakeholders such as energy providers, regulators, operators, and prosumers must deepen their collaboration and facilitate cooperation on a larger scale.
- **Social acceptance:** The EI can only be realized by involving energy users fully and by making the best possible use of advanced technologies. Social awareness should be promoted extensively through the following steps: (i) improving or changing users' perceptions of modern technologies; (ii) promoting or publicizing the EI concept; and (iii) involving users in decision making. Recently, the social acceptance of various renewable technologies, such as PV or wind energy, has achieved considerable attention [157], and there is a similar need for tailored policies, business models, and open interactions to advance EI development.

VI. CONCLUSION

In this paper, we have reviewed the current definitions and conceptual basis of the EI given in the scientific literature; analyzed and categorized the scientific literature into broad categories; and proposed a modern universal definition that broadly captures the concept of the EI and its scope of applications. Further, we have also reviewed the technologies underpinning the EI paradigm and its implementations. We have presented the requirements that need to be fulfilled before our envisioned EI is implemented to its fullest extent and definition. And finally, we have explained the challenges that need to be overcome for the EI to be a successful technology in the future.

The EI is a technological paradigm whose promise is based on the ongoing remarkable advances in ICTs, power electronics technologies, and artificial intelligence methods. However, as indicated in this review, several challenges need to be addressed before the EI becomes a reality. These challenges can be broadly summarized into three categories as follows:

- Technological challenges related to the technological maturity and efficiency of the distributed devices in the network, ICT infrastructure, cyber-security and privacy, management algorithms, etc.
- Policy challenges such as the need for standardization, modernized constructive regulation, and incentivization of private- or public-sector participation.
- Social challenges such as the need for public acceptance, improving societal welfare, etc.

Currently, tremendous progress is being made to overcome these bottlenecks, and some versions of the EI have been practically implemented, for example, by using packetized energy concepts [158]. The EI has steadily grown to gain acceptance and become a popular research topic with significant practical benefits. Thus, the EI clearly has tremendous potential to radically transform the energy distribution technology and business, especially in the electricity sector. Indeed, the EI concept promises to make the electricity grid a truly intelligent grid.

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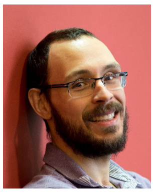

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Publication II

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A Heuristic-based Home Energy Management System for Demand Response

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***Abstract*—The so-called Internet of Things (IoT) and advanced communication technologies have already demonstrated a great potential to manage residential energy resources via demand-side management. This work presents a home energy management system in that focused on the energy reallocation problem where consumers shall shift their energy consumption patterns away from peak periods and/or high electricity prices. Our solution differentiates residential loads into two categories: (i) fixed power appliances and (ii) flexible ones. Therefrom, we formulate our problem as constraint optimization problem, aiming to reduce the electricity cost based on day-ahead prices and the peak-to-average ratio. To solve this problem, two well-known heuristics, the Genetic Algorithm (GA) and the Harmony Search Algorithm (HSA), are employed. These two approaches are compared to the case where no reallocation happens. Our numerical results show that both methods; GA and HSA can effectively reduce the electricity cost by 0.9%, 3.98 %, and PAR by 15%, 5.8%, respectively.**

***Index Terms*—demand-side management, heuristics, genetic algorithm, harmony search algorithm**

I. Introduction

Smart grid technologies, smart meters and demand response have enabled consumers to know their demand profile in more details, while helping the system operator to improve the efficiency and reliability of the power system [1]. In particular, demand-side management (DSM) has great impact on grid operation by, for example, facilitating the incorporation of renewable resources, and by allowing the consumers to actively participate in electricity dispatch. As part of this broader concept, demand-response (DR) is defined as [2]: "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized".

In this context, DR can categorized into two aspects, viz. incentive and price-based programs [3]. Incentive based programs involve customers' participation to reallocate their energy consumption in off peak hours in response to which a reward (bill credit payment) is given to them for their participation in the program. Incentive programs are direct load control (DLC), curtailable load, demand bidding & buy back, emergency & demand. On the other hand, price-based programs involve various pricing signals at different times to reduce energy consumption by providing monetary benefits to the consumers. It includes time of use, real time pricing, inclined block rate, critical peak pricing and day ahead pricing [4]. In a recent research, price-based DR has been studied widely in residential sector, particularly, in home energy management system (HEMS). For instance [4]–[8], various HEMS models in the context of DR have investigated to achieve optimal energy consumption of household appliances using optimization model, aiming to reduce electricity cost, balance energy demand, and improve energy efficiency.

In general, HEMS plays a significant role in energy management of residential sector and allows exchange of energy consumption information with the utility to improve energy profile as well as the reliability of power grid. The work in [4] comprehensively described HEMS architecture, DR programs, smart grid technologies, communication protocols, and various decision making algorithms like artificial intelligence (AI) and heuristic scheduling algorithms. These algorithms are considered as an essential part towards the energy optimization and load shifting operations in HEMS. Fan-Lin and Xiao-Jun in [5], designed a residential energy usage framework using genetic algorithm (GA) which attempts to maximize re-trailer's profit. The home appliances are classified in two groups (shift able and curtail able) and hourly energy usage is predicted in accordance with the electricity price and temperature signal. In another work [6], a multi-objective problem is applied to control energy consumption of household micro-grid and hybrid differential evolution is used to solve the scheduling problem. In a similar context with a recent work [7] authors have been explored the HEMS based on hybrid optimization technique to manage energy consumption of smart appliances in *24* hours time slots depending upon pricing tariffs and coordination among appliances. In [8], authors extended their previous work and incorporated various time slots, peak to average ratio (PAR), and multiple homes scenarios with much improved hybrid technique bacterial flower pollination algorithm (BFPA).

Kai Ma et al. further developed an optimization problem in [9] and investigated the trade-off between electricity cost and discomfort cost. In [10], a generalize HEMS discussed based on GA to schedule energy consumption and minimize operational cost of electricity considering user satisfaction constraints. Similarly, reference [11] adopted GA based on DSM (GA-DSM) strategy to distribute the power in industrial area effectively. In an other contribution [12], authors interested to analyze scheduling mechanism in domestic sector using binary particle swarm optimization (BPSO) to optimize energy consumption of household in pre define time intervals.

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Different from GA and BPSO, authors in [13] have been proposed an improved algorithm binary backtracking search algorithm (BBSA) to balance energy usage and effectively control cost. The simulation results of BBSA and BPSO are compared which shows effectiveness of BBSA. In the same fashion authors in [14], [15] introduced practical pricing and green energy scheduling plan with an aim of minimizing overall electricity cost while applying different approaches such as, non linear programming and game theory algorithm, respectively. In the same sense, but with different approach, we develop here an efficient DR strategy to lessen the cost and the peak-to-average ratio of energy usage, which is expect to contribute towards the green house emissions and fuel wastage.

Our goal here is to explore the energy consumption behaviour for residential consumer in order to shift some specific loads trying to shape the load curve, accordingly. This paper proposes an optimization model for scheduling energy consumption of various kind of appliances, which are classified into two groups based on their features and parameters, namely fixed power and flexible power appliances. We compare the performance of three different approaches: optimization via GA, optimization via harmony search algorithm (HSA), and no optimization (i.e., no load shift is performed). Our results compare the cost and the peak-to-average ratio in the three scenarios, showing that designed algorithms have the best performance. Our contributions are summarized as:

- We develop DR strategy to address the peak load shaving problem and flexibly control the household appliances specifically, at times when prices of electricity are high.
- To address the problem, we develop system model considering the household appliances and classifying them into two types; fixed power and flexible power appliances. The energy consumption of the appliances are managed and controlled considering the time of use pricing model.
- In order to solve the problem, we establish optimization model along with two well known heuristics; GA and HSA.
- We analyze three different scenario: Without HEMS, With HEMS-GA, and With HEMS-HSA. For example, with HSA-HEMS the cost and PAR are reduced to 3.98% and 5.8 %, respectively.
- We demonstrate the proposed solution is scalable for various scenarios by testing the designed algorithm with multiple users case i.e., 10 users and 50 users considering different time resolutions (60 minutes and 30 minutes).

The rest of the paper is organizes as follows. Section II states the system model used here, including the problem formulation, its input parameters and the optimization methods used. Section III presents the numerical results and the performance evaluation of the three different scenarios. Section IV conclude this paper and propose some potential future work.

II. System Modeling

In this work, we investigate the energy reallocation problem of peak hours based on DR strategy. We consider home energy management environment where each home is equipped with HEMS with the function of optimizing energy consumption of household appliances based on different input parameters as electricity price and type of load. The two way of communication between HEMS and utility enabled the consumers to alter the energy usage based on electricity price signal. The electricity price depends on the demand of energy, higher the demand the higher will be the electricity cost and vice versa. The demand information of energy is transmitted by smart meters to utility via IoT network. The peak energy demand (of home appliances) can be controlled appropriately by addressing the PAR. So that, we assorted home appliances into two types based on their features and priorities, namely, fixed and flexible loads [16], [17].

In order to support the communication infrastructure, advance metering infrastructure (AMI) is an essential element in smart grid. AMI combines multi-way communication, data management system and particularly, smart metering system. This enables smart meters (SM) to measure and collect the information of energy consumption in an accurate and precise way. Moreover, this information is also exchanged between HEMS and utility industry simultaneously in a real time scenario. The communication between HEMS and utility industry also enables the user to take part in DR strategies and manage the energy demand effectively. On the other side, users in home can monitor the information such as available energy, energy consumption, price of energy in the next hour, etc., using various interfaces e.g., smart phones, computers etc., and adjust energy consumption based on a DR strategy.

A. Appliances classification

Appliances are classified here into two types, namely fixed power and flexible power appliances, as discussed next.

1) Fixed power appliances: $(\mathcal{A}_{\mathcal{S}}^{fixed})$ fixed power appliances are ceiling fan, lamp, or TV, these have fixed power consumption profile and operational time and due to continuous power supply HEMS will not schedule fixed power appliances i.e., $\mathcal{A}_{\mathcal{S},h}^{fixed} = E_{fixed}$

2) Flexible power appliances: $(\mathcal{A}_{\mathcal{S}}^{F})$ Flexible power appliances can be controlled and their energy consumption profile are scheduled by HEMS. Their operation is attributed as incentive-based $(\mathcal{A}_{\mathcal{S},\mathcal{I}}^{F})$ and price-based $(\mathcal{A}_{\mathcal{S},\mathcal{P}}^{F})$. The energy usage of $(\mathcal{A}_{\mathcal{S},\mathcal{I}}^{\mathcal{F}})$ is curtailed considering DR strategy. Various pricing signals can be adopted to reallocate the load demand from peak to off-peak hours to achieve cost reduction. The price based flexible appliances are of two types (i) non-interruptible and (ii) interruptible. The operation time interval of non-interruptible appliance must not be halted during their operating time by HEMS such as, washing machine and iron. Interruptible appliances can be interrupted in any time period like, during the peak demand or high cost of electricity generation e.g., air condition and water heater. The energy usage of interruptible appliances are presented below: $E_{flex_{min}} \leqslant E_{flex} \leqslant E_{flex_{max}}$. The power rating (PR) and operational time interval (OTI) are shown in the Table I

B. Electricity pricing model

Pricing tariff refers to various pricing scheme for designated time frame. DR based pricing tariff plays important role to allow active participation of consumer in residential sector. Among various pricing tariffs discussed in the literature [3], [4], [17], we opted time of use pricing model in our simulation results. It is briefly discussed below:

Time of use: Time of use (TOU) pricing scheme reflects price of electricity in different time of interval including, off peak, mid peak, and peak hours. TOU tariff imparts the average electricity cost of power generation during different time periods and allows the consumers to manage their energy usage voluntarily instead of being forced by utility. In the same way, consumers have the flexibility either to use the electricity in peak time interval (which yields higher cost) or off peak (lower cost due to less stress on generation resources). Typically, TOU is spreading widely and used in many countries for residential sector consumers. For instance, TOU tariff is implemented in USA, Canada, and Ireland, and customers pay their bill according to fixed prices in different time periods i.e., during off , mid, and peak hours [3], [18], [19]. We have used TOU taken from [20]. An example of TOU is given in Fig. 1.

The total cost of electricity can be expressed using ToU pricing γ, and states of the household appliances π as:

$$\mathcal{C}_T(t) = \sum_{t=1}^{\mathcal{T}} \mathcal{E}(t) \times \pi(t) \times \gamma(t). \tag{1}$$

C. Cost function and energy demand

Let $\mathcal{A}_\mathcal{S}$ represents set of appliances and $\mathcal{P}_{fixed}(t)$, $\mathcal{P}_F(t)$ denote the energy consumption of fixed and flexible power appliance in time (t). The total energy consumption $(\mathcal{P}_T(t))$ in each time period $t \ \epsilon \ \mathcal{T}_\mathcal{S}$={1,2,....$\mathcal{T}$}, then considering this definition total energy usage during $t \ \epsilon \mathcal{T}$ can be calculated as $\mathcal{E}(t) = \sum_{\mathcal{A}=1}^{\mathcal{A}_\mathcal{S}} (\mathcal{P}_T(t))$. The overall cost is expressed mathematically as:

$$E_T = \sum_{t=1}^{\mathcal{T}} \sum_{\mathcal{A}=1}^{\mathcal{A}_\mathcal{S}} \bigg(\mathcal{E}(t) \times \pi(t) \times \gamma(t) \bigg). \tag{2}$$

In above equation, the first term on the right side computes the cost of electricity in each time slot t; the second term computes amount of energy used in t-th hour of the day; π is the decision variable that represents ON and OFF states of the appliances. As we are interested in reducing electricity cost, nevertheless the reallocation of energy into off peak hours is also an imperative step to improve the functionality of the grid. Therefore, PAR is computed as:

$$PAR = \frac{G_{peak}}{G_{avg}} = \frac{\mathcal{T}\underset{t\epsilon\mathcal{T}_\mathcal{S}}{max} \ \mathcal{E}(t)}{\sum_{t=1}^{\mathcal{T}} \mathcal{E}(t)}, \tag{3}$$

where G_{peak} and G_{avg} indicate the maximum and average aggregated load in any time slot (t).

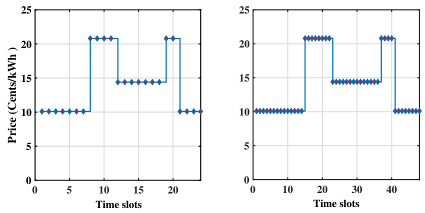


Fig. 1: TOU electricity price tariff, left to right side: price for one day with time slots 60 and 30 minutes.

D. Objective function

In general, the focus of this work is to jointly minimize the cost of energy and PAR. To accomplish the objective, HEMS is considered to schedule the energy usage of $\mathcal{A}_\mathcal{S}$ using optimization problem.

$$\text{Objectives} \begin{cases} \text{Cost minimization} \\ \text{PAR} \\ \text{Energy optimization} \end{cases}$$

The E_T represents the total energy usage cost; PAR is the ratio of maximum aggregated energy consumed and mean value of the total energy. The constraints related to objective are as follow:

$$\sum_{t=1}^{\mathcal{T}} \Psi_{With-HEMS} \leqslant \sum_{t=1}^{\mathcal{T}} \Psi_{Without-HEMS} \tag{4}$$

$$\gamma_{i,t} = \begin{cases} 1, \ \forall \quad t \in OTI \\ 0, \ otherwise \end{cases} \tag{5}$$

$$\sum_{t=1}^{\mathcal{T}} \Upsilon_{\mathcal{A}_\mathcal{S},t} = \Upsilon_{OTI} \ \ \forall t \in \mathcal{T}_\mathcal{S} \tag{6}$$

$$PAR_{SCH} \leqslant PAR_{UNSCH} \tag{7}$$

$$0 \leqslant \mathcal{E}(t) \leqslant \mathcal{G}_\mathcal{T} \tag{8}$$

The equations (4) to (8) represents the constraints of the designed model. The constraint (4) illustrates the total cost of the energy "With-HEMS" must be less or equal to "Without HEMS". Constraint (5) shows appliances states, "1" indicates ON and "0" OFF state. The constraint (6) means the OTI of each appliance should be completed before and after scheduling. The constraint (7) reflects that PAR should be remained less or equal to case (Without-HEMS). The last constraint describes that energy consumption of household should not exceed the total available energy.

E. Optimization techniques

1) Genetic Algorithm (GA): is meta heuristic algorithm and inspired by the theory of natural evolution. GA is one of the most applied algorithm in various field of computer science and engineering due to the fast computational time and easy implementation of many complex problems. Among them GA is one of the most applied algorithm in various field of computer science and engineering [21]. GA is influenced by biological evolution process which is based on genetic inheritance and natural selection. GA is population based heuristic algorithm and starts with the initialization of population then each candidate in the population (known as genes) is evaluated using objective function. To select better candidate for the next iteration, we introduce tournament selection. The role of selection is to select best individuals (parent) for recombination and replacement process. Usually, recombination (crossover) and replacement (mutation) are the main driving agents to modify the population and provide diverse search space. In our designed model, we implemented GA that is associated with binary representation where “0" indicates the OFF and “1" shows ON state. Then, each candidate in the population is tested by objective function. Two point crossover and uniform mutation are introduced to achieve better results. After crossover and mutation the new set of candidates again evaluated and compared with previous candidates. The stopping criteria is maximum number of population size, and the allocation is the best candidate that satisfies the objective function.

2) Harmony Search Algorithm (HSA): is a popular meta heuristic algorithm inspired from musical improvisation process [22]. It is developed with an aim to search best state of harmony. This (best) harmony in the music is similar to optimization process to find global optimal solutions for a given objective function. HSA is an idealising mapping from the qualitative improvisation into quantitative formulation, and hence transforming musical harmony into optimization process. The HSA steps are given in the following.

Step 1: In the beginning, HSA parameters are initialized such as, size of harmony memory (HMS), harmony memory consideration rate (HMCR), bandwidth distance (BW), pitch adjustment rate (Par), harmony memory (HM), and total improvisations (NI).

Step 2: In the second step, initial random population is generated using Eq (4). This uniformly random distributed population is stored and analyzed in HM then evaluated using objective function.

$$A_{i,j}^{0} = X_j^{min} + B_j(X_j^{max} - X_j^{min}), \tag{9}$$

where X_j^{max} and X_j^{min} are the upper and lower limits and j=1,2,3,..HM.

Step 3: In this step, a set of new vectors known as harmony vectors are generated based on the criteria, HMCR, (1-HMCR), and Par. The stored values in HM are then selected with HMCR and Par probability or it can be opted randomly from HM with the probability of (1-HMCR). In the designed model, it is important to select the best set of candidates from HM in order to effectively minimize objective function. The

TABLE I: Appliances' characterization

Appliance	Class	PR (kWh)	OTI (hours)
Ceiling fan	fixed	0.075	14
Lamp	fixed	0.1	13
TV	fixed	0.48	7
Oven	fixed	2.3	6
Washing machine	flex	0.7	8
Iron	flex	1.8	7
Air conditioner	flex	1.44	10
Water heater	flex	4.45	8

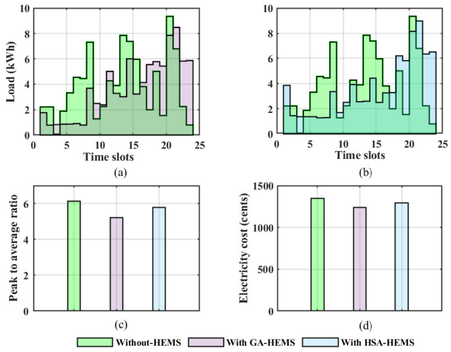


Fig. 2: Single user, Legend: (a) and (b) Energy usage profile for 60 minutes time resolution (c) PAR (d) Electricity cost

above discussion can be mathematically expressed as [23]:

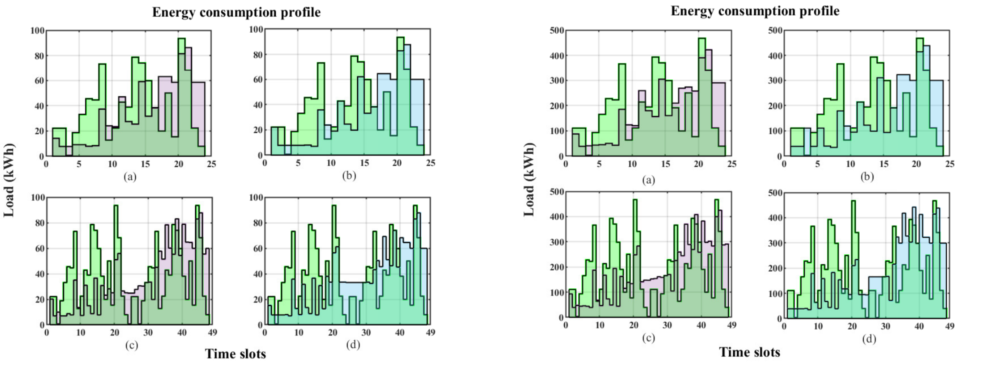
$$A_{new} = \begin{cases} A\epsilon\{a_{1i}, a_{2i}, a_{3i} \dots a_{HM}\}, \; With \quad P(HMCR) \\ A\epsilon\{a_1, a_2, a_3 \dots A_N\}, \quad With \quad P(1-HMCR) \end{cases} \tag{10}$$

$$A_{new} = \begin{cases} YES, \quad With \quad P(Par) \\ NO, \quad With \quad P(1-Par). \end{cases} \tag{11}$$

In each iteration this process searches new best harmony (solution) and replaces the worst individual in HM. The process is terminated when stopping criteria (total number of improvisation) is met.

III. Simulation and experiment results

In this section, we conduct the simulation results based on metrics energy consumption, electricity cost, and PAR. To present the performance of optimization algorithms, we investigate the experimental results of particularly eight appliances including; four fixed power, two non-interrupt-able, and two interrupt-able flexible power appliances. The fixed power appliances consume fixed power and cannot be scheduled by HEMS (e.g., fan, lamp, TV, and oven). However, non-interrupt-able appliances operate on fixed power and can not stop their operation during scheduling time period (e.g., washing machine and iron) we assume that HEMS will schedule the iron operation after washing machine. While, interrupt-able



(a) (b)

Fig. 3: Energy consumption information (a) 10 users with time slots of 60 minutes and 30 minutes (b) 50 users with time slots of 60 minutes and 30 minutes

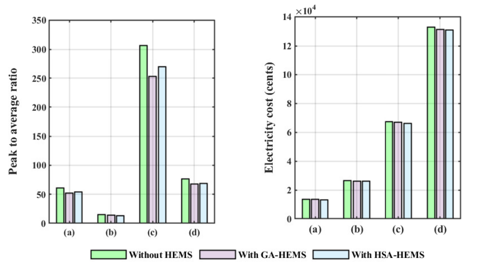


Fig. 4: PAR and electricity cost information. Legend: (a)10 users with timeslot 60 minutes (b) 10 users with time slot 30 minutes (c)50 users with time slot 60 minutes (d) 50 users with time slot 30 minutes

appliances (air condition and water heater) can be controlled and scheduled based on the pricing signal in any time period. To present our results, we consider energy consumption of household appliances for one day with time resolution of one hour (t) (starting from 12 am to the next day 12 am) and the TOU pricing tariff for Winter season (November 1, 2018 - April 30, 2019). Moreover, we also demonstrate that above scenario can be used for multiple users and various time resolutions such as; 10 users with time resolution 60 and 30 minutes and 50 users with time resolution 60 and 30 minutes.

As mentioned earlier, energy scheduling is one of the core motivation of this work, therefore, HEMS is designed based on the optimization algorithms; GA and HSA. Fig. 2 represents load profile (a and b), PAR (c) , and electricity cost (d) in one day. It is seen in Fig. 2 that each algorithm attempts to schedule energy profile in off peak time (i.e., 21-th hour evening time to 7-the morning time) when the price of energy is low (6.5 cents/kWh). While in peak hours (7 to 11 and 5 to 7 (am)) with price 13.2 cents/kWh, the maximum energy is consumed 8.72 kWh by "Without HEMS" whereas, GA-HEMS and HSA-HEMS accounted for 8.67 kWh and 7.14 kWh, respectively. On the other hand, Fig. 3a and Fig. 3b illustrate the energy consumption of the household appliances for 10 and 50 users with time horizon of 60 and 30 minutes. The maximum energy consumption is 9.35 kWh for single user and 93.5 kWh for 10 users with time span of 60 and 30 minutes while these consumption are flexibly control and shifted to off-peak times in order to reduce the electricity bill. Furthermore, the maximum consumption in case of 50 users (both time interval) are also optimized by GA-HEMS and HSA-HEMS by 9.82 % and 6.20 %, respectively.

The effectiveness of designed HSA-HEMS and GA-HEMS is also evaluated by the PAR, defined as the maximum aggregated load (i.e., peak load) to average load used by consumer. The PAR values is reduced to 15% and 5.8% by GA and HSA, respectively, compared to the scenario i.e., "Without HEMS". Moreover, in Fig. 4 (left side) , we demonstrate the PAR for scenarios ;multiple users (10 and 50) with the time resolution of 60 and 30 minutes. Out of all maximum reduction of PAR is 17.41 %, which can be seen for 50 homes with time interval 60 minute. Thus, It shows that the energy consumption is shifted from peak to off- peak time period, proving that GA-HEMS and HSA-HEMS can manage energy consumption adeptly .

Fig. 4 (right side) presents the comparison of electricity. It can be observed that the deployment of HSA-HEMS and GA-HEMS reduces the cost in contrast to the case "Without HEMS". Since both algorithms attempt to reduce the cost of the electricity, however, among all (a), (b), (c), and (d) the maximum cost is reduced 1.83% by HSA-HEMS in case of 50 users and 60 minutes time slots. It is also seen that cost of energy is maximum (13285 cents for 50 users and 30 minutes time slots) for one complete day "Without HEMS", because most of the energy is used either in peak time or mid peak, while on the contrary, HSA-HEMS and GA-HEMS reduce the cost (1.64%) and (1.34%), respectively, in response to pricing tariff. The statistical analysis of the designed scenarios

TABLE II: Comparative performance based on numerical results. Costs are in cents (¢) and Red. means reduction.

	Without HEMS			With GA-HEMS			With HSA-HEMS		
Designed case	**Max E_H**	**Cost (¢)**	**PAR**	**% E_H Red.**	**% ¢ Red.**	**% PAR Red.**	**% E_H Red.**	**% ¢ Red.**	**% PAR Red.**
1 user; 60 min	9.35	1347.9	6.13	9.30	0.9	15	3.95	3.98	5.8
10 users; 60 min	93.50	13479	61.36	7.74	0.71	14.6	6.20	1.37	11.94
50 users; 60 min	467.50	67394	306.79	9.82	0.98	17.41	6.20	1.83	12.02
10 users; 30 min	93.50	26569	15.34	6.20	1.41	6.51	6.20	1.67	12.05
50 users; 30 min	467.50	13285	76.70	9.00	1.36	11.86	5.40	1.64	10.52

is provided in Table II.

IV. Conclusion

In this paper we designed heuristic model combing with DR strategies for optimizing energy consumption in residential sector. Considering HEMS environment, we modeled our optimization problem using various types of household appliances, electricity pricing tariffs, and energy demand. The results show that designed algorithms; GA and HSA can effectively optimize energy consumption, reduce electricity cost by 0.9 %, 3.98 %, and PAR by 15 %, 5.8 %, respectively. Also with the different number of users and timescales, the relative performance of both algorithms is effective and minimized the cost and PAR accordingly. As a result, efficient management of resources, peak shaving (power grid), and improve energy usage rate of power grid can be achieved. Simulation results illustrate that both heuristics illustrated the potential of those heuristics in terms of electricity cost and PAR. Besides, it is also shown that DR-based strategies encourage the consumer to manage their energy consumption by shifting the peak hours into off peaks.

In future works, we expect to include distributed energy resources and pollution emitted at time of electricity generation, then it would become multi-objective problem (cost and pollution minimization). We also plan to analyze the impact of cyber-attacks in the price signals used by the HEMS.

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Publication III

Hussain, H. M., Narayanan, A., Sahoo, S., Yang, Y., Nardelli, P. H., and Blaabjerg, F.
Home Energy Management Systems: Operation and Resilience of Heuristics Against Cyberattacks

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Home Energy Management Systems

Operation and Resilience of Heuristics Against Cyberattacks

by Hafiz Majid Hussain, Arun Narayanan, Subham Sahoo, Yongheng Yang, Pedro H.J. Nardelli, and Frede Blaabjerg

Internet of Things (IoT) and advanced communication technologies have demonstrated great potential to manage residential energy resources by enabling demand-side management (DSM). Home energy management systems (HEMSs) can automatically control electricity production and usage inside homes using DSM techniques. These HEMSs wirelessly collect information from hardware installed in the power system and homes with the objective of intelligently and efficiently optimizing electricity usage and minimizing costs.

However, HEMSs can be vulnerable to cyberattacks that target the electricity pricing model. The

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cyberattacker manipulates the pricing information collected by a customer's HEMS to misguide its algorithms toward nonoptimal solutions. The customer's electricity bill increases, and additional peaks are created without being detected by the system operator. This article introduces demand response (DR)-based DSM in HEMSs and discusses DR optimization using heuristic algorithms (HAs). Moreover, it addresses the possibilities and impacts of cyberattacks, their effectiveness, and the degree of resilience of HAs against them. This article also opens research questions and shows prospective directions.

Home energy management systems can automatically control electricity production and usage inside homes using DSM techniques.

Home Energy Management Systems

Smart grid technologies and smart meters have enabled customers to know their demand profiles in greater detail while helping electricity grid operators to improve the efficiency and reliability of the power system [1]. This encourages both customers and grid operators to modify load energy demand profiles to achieve different objectives, such as optimizing the usage of renewable energy, reducing peak loads, or moving some loads to off-peak times, such as nighttime and weekends. Such DSM has become important and popular recently because it facilitates the incorporation of renewable energy sources (RESs) into the power system by customers. At the same time, grid operations are significantly impacted by the active participation of customers in electricity dispatch. To implement DSM and optimize electricity usage, residential customers often employ HEMSs. These play a significant role in the energy management of the residential sector and allow the exchange of energy consumption information with the utility to improve the energy profile and reliability of the power grid.

An HEMS (Figure 1) is an information and management system to automatically (or semiautomatically) monitor and control the electrical energy production and usage within a household by processing the

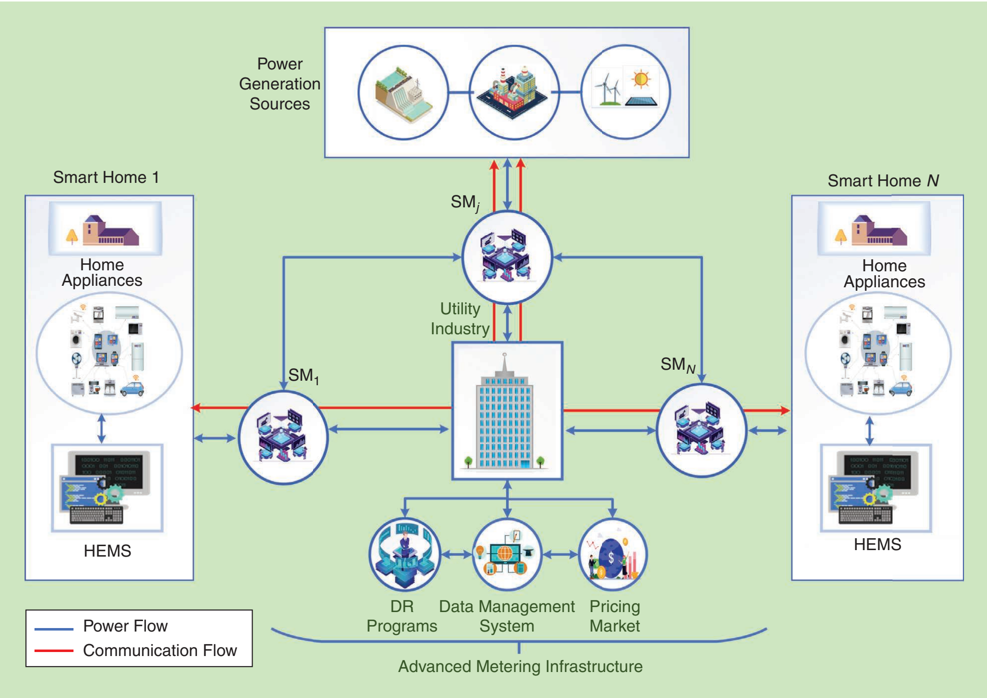

Figure 1. An HEMS in the electrical power system. SM: smart meter (subscript indicates $j = \{1,2,3..N\}$).

information collected from hardware installed in the electrical power system and household. The typical objective of an HEMS is to minimize the customer's costs. Bidirectional communication among the HEMS, smart meters, utility, and power grid enables the HEMS to meet its objectives by, for example, implementing a peak-shaving strategy while considering the electricity price signal.

An IoT network, along with an advanced metering infrastructure (AMI), supports the bidirectional communication and enables robust data management systems, strong network connectivity, and smart metering systems. The deployment of an AMI makes it possible for smart meters to measure and collect useful information, such as the energy consumption, available (generated) energy, or energy price in the next hour, in a precise and timely manner. Moreover, this information is exchanged between the HEMS and utility simultaneously in real time. As a result, customers can take part in DSM strategies and manage the energy demand effectively.

Figure 2 illustrates the operations of a typical HEMS. Four components—the data aggregator (DA), software and network management (SNM), appliance management system (AMS), and HA—interface with each other to form the HEMS. The DA receives energy pricing and production information and sends this to the SNM and HA. The AMS component collects data about appliances, such as energy consumption, operation time interval, data received from user interfaces, and so on, and exchanges them with the HA and SNM. Thereafter, the HA executes the scheduling task and sends the results (a new schedule and so on) to the SNM, which operates as the primary control and management component, managing the accumulated data of the DA, HA, and AMS components and processing the flow of instructions in the network.

HEMSs and their characteristics have been extensively investigated in the last decade, and a comprehensive description of HEMS architectures, DSM approaches, smart grid technologies, communication protocols, and various decision-making algorithms can be found in [2]. This article focuses on the operational aspects of HEMSs and assesses their resilience against a specific type of cyberattack. Such an attack is defined by fake price signals that are used as inputs to the HEMSs to alter their load schedule. To the best of the authors' knowledge, this important aspect has not yet been studied in the literature. Before we discuss the details of the proposed study, we briefly introduce the main ideas behind DR and the scheduling algorithms.

The continuous integration of RESs into the power system has made it important to enable effective DSM to match the power supply with the load.

Demand Response

The goal of an HEMS is to enable and support DSM to meet specific objectives, such as the minimization of customers' electricity bills, utility costs, or system costs. DSM is typically achieved by offering financial incentives to customers, inducing behavioral changes through education, using higher-efficiency loads, increasing diversity factors, using distributed energy resources, or other measures [3]. The continuous integration of RESs into the power system has made it important to enable effective DSM to match the power supply with the load.

DR methods, which offer financial incentives to customers, are popular and highly researched techniques to achieve DSM since they incentivize RES integration along with DSM. *DR* is defined as [4]:

> a tariff or program established to motivate changes in electric usage by end-users from their normal consumption patterns in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.

HEMSs nearly always employ DR methods to achieve their goals.

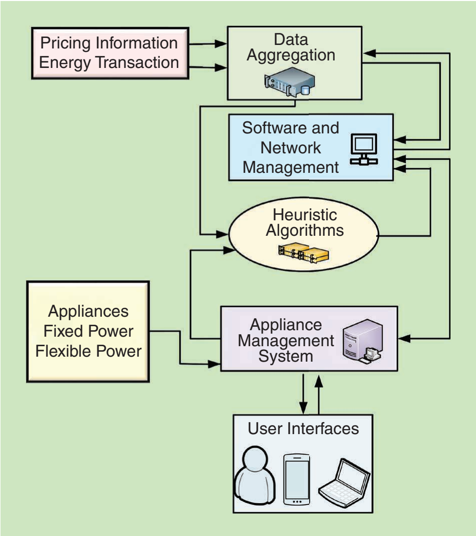

Figure 2. The typical operations of an HEMS.

DR can be categorized into two types: incentive- and price-based programs [5]. In an incentive-based program, customers participate by reallocating their energy consumption in off-peak hours, in response to which a reward (a bill credit or payment) is given to them. Incentive-based programs involve direct load control, load curtailing, emergency DRs, and so on.

On the other hand, a price-based program is a more indirect means of achieving DR. In this approach, different pricing signals are sent at varying times to customers. As a result, customers are induced to reduce their energy consumption at certain times to take advantage of possible monetary benefits. Price-based programs include time-of-use (TOU) tariffs, real-time pricing, inclined block rate, critical peak pricing, and day-ahead pricing [2], [6], [7]. In recent research, price-based DR has been widely studied in the residential sector, particularly in HEMSs.

DR methods, which offer financial incentives to customers, are popular and highly researched techniques to achieve DSM since they incentivize RES integration along with DSM.

For price-based DR, the price tariff scheme, i.e., the price bands for different designated time intervals, including off-peak, midpeak, and peak hours, is important. The TOU tariff scheme is widely used in many countries for customers in the residential sector. It provides the average electricity cost of power generation during different time periods, thereby enabling customers to manage their energy usage voluntarily. Customers have flexibility to use electricity either in the peak time interval (which yields a higher cost) or off peak (at a lower cost as a result of less stress on the grid).

Table 1. Home appliance characteristics: The type, power rating (PR), and operating time (OT).

Appliance	Type	PR (kWh)	OT (h)
Ceiling fan	Fixed	0.075	14
Lamp	Fixed	0.1	13
TV	Fixed	0.48	7
Oven	Fixed	2.3	6
Washing machine	Flexible (uninterruptible)	0.7	8
Iron	Flexible (uninterruptible)	1.8	7
Air conditioner	Flexible (interruptible)	1.44	10
Water heater	Flexible (interruptible)	4.45	8

In this case, DR algorithms depend on the flexibility offered by home appliances. An appliance is flexible if its energy consumption can be shifted in time within the boundaries of end-user comfort requirements while maintaining the total consumption [8]. Home appliances can be divided into two types based on their characteristics and priorities [9], [10]:

- Fixed-power appliances have a fixed power consumption profile and operating time, e.g., ceiling fans, lamps, and TVs.
- Flexible-power appliances can be controlled, and their energy consumption profiles can be scheduled by the HEMS. Their operation can be controlled by incentive- or price-based programs. These loads can be further categorized into two types—uninterruptible and interruptible—depending on whether their operations can be interrupted or not. Table 1 lists the appliance classes of fixed and flexible home appliances with their power ratings and operating times [9]–[11].

Heuristic Scheduling Algorithms

Many techniques have been explored to exploit the flexibility in home appliances and perform DR-based optimization. A typical approach is to cleverly adapt optimization techniques to solve linear and nonlinear objective functions. Recently, artificial intelligence (AI)-based methods have also become popular. Heuristic scheduling (HS) algorithms comprise an important group of techniques to realize energy optimization and load-shifting operations in HEMSs. Many HAs have been explored previously, depending on the problem setup and conditions [2], [7], [11]–[19]. Among the various optimization techniques, the genetic algorithm (GA) and harmony search algorithm (HSA) are two important ones that are particularly suitable for solving constraint-optimization-based scheduling problems and the flexible selection criteria of achieving an optimal (balanced) combination of exploration and exploitation [11], [20], [21].

Genetic Algorithm

GA is a widely applied algorithm due to its fast computational time and easy implementation of many complex problems [22]. It is a metaheuristic algorithm inspired by the theory of natural evolution and evolutional processes like genetic inheritance and natural selection.

GA is an iterative process in which a population of potential candidate solutions is first randomly generated. The population in each iteration is called a *generation*. All of the individual candidates (known as *genes*) in the population are then evaluated using a fitness function (i.e., the problem objective). The best candidates are stochastically selected from the current generation, and their genomes are modified by recombination (crossover) and replacement (mutation) to form a new generation of candidate solutions, which is then used in the next iteration. The stopping criteria for the algorithm are the maximum population size and best candidate allocation that satisfy the objective function.

Harmony Search Algorithm

HSA is a popular metaheuristic algorithm inspired by the musical improvisation process [23]. Consider a music orchestra that improvises to find and perform the most harmonious and melodious music. Each musician in an orchestra corresponds to a decision variable, and an instrument's pitch range corresponds to the set of possible values of the decision variable. The musical harmony produced by the musicians at a certain time can be considered as the solution vector for an iteration. An audience's aesthetic judgment of the music can be related to the fitness of the objective function. Just like a musical orchestra attempts to find (or play) the best music possible by improving it over time, the optimization algorithm aims to progressively find the optimal solution. Thus, HSA is an idealized mapping from qualitative improvisation into a quantitative formulation, where musical harmony concepts are applied to an optimization process.

Representative Simulations for Demand Response in Home Energy Management Systems

Some simulation results are now provided to demonstrate the performance of the optimization algorithms GA and HSA. As the household loads, the eight appliances listed in Table 1 are investigated with the given power ratings and operating time periods. Since the uninterruptible appliances cannot be shifted after they start operating, the HEMS schedules the operation of the iron after the washing machine. Interruptible appliances, on the other hand, are scheduled based on the pricing signal in any time period. The energy consumption of the household appliances for one day (starting from 12 a.m. to 12 a.m. the following day) with a scheduling resolution of 1 h (t) is considered. The TOU pricing tariffs for the summer (1 May to 31 October 2019) and winter (1 November 2018 to 30 April 2019) seasons are taken from [24].

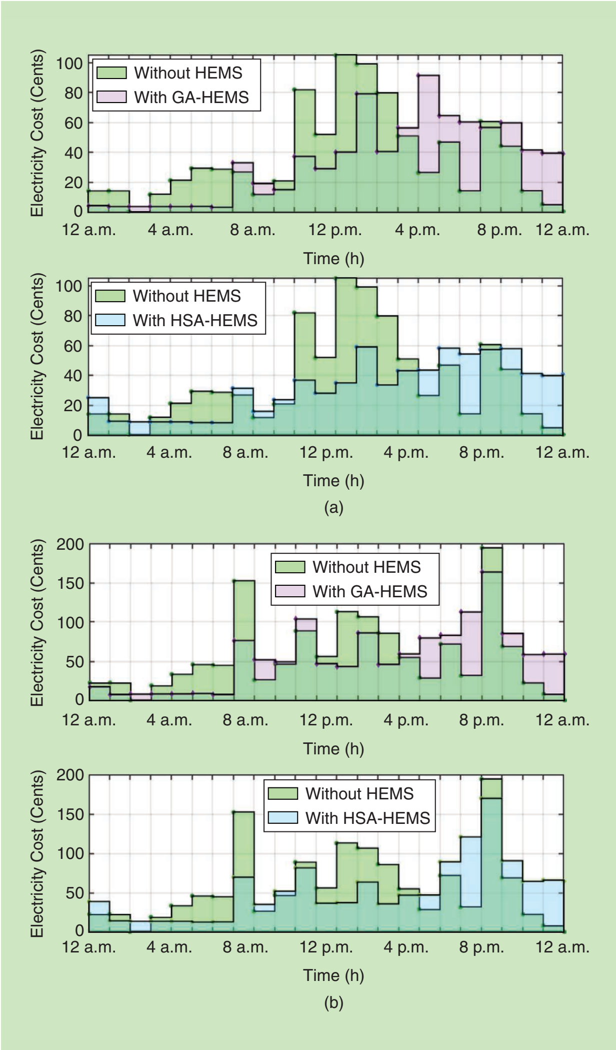

Figure 3. The electricity costs per hour under the TOU pricing scheme for a day each in the (a) summer and (b) winter seasons without and with the two Has: GA and HSA.

Figure 3 presents a comparison of the electricity costs for three cases—without an HEMS as well as with a GA- and an HSA-HEMS—in the summer and winter seasons. The deployment of an HSA- and a GA-HEMS led to lower total costs compared to the case without an HEMS. The energy cost was highest without an HEMS because most of the energy was used in either the peak or midpeak times. Between the two algorithms, the HSA-HEMS reduced the cost by 43.55% and 11.91% in the summer and winter seasons, respectively, while the GA-HEMS reduced it by 23.37% and 18.91%, respectively.

GA is a metaheuristic algorithm inspired by the theory of natural evolution and evolutional processes like genetic inheritance and natural selection.

Cyberattacks

In a smart grid, the real-time exchange of information, especially data collected from smart meters, electricity pricing markets, and utility companies, requires a secure and protective layer of the communication channel [25]. However, the complex structure of the smart grid and proliferation of smart devices make it vulnerable to cyberattacks. A typical cyberattack in a smart grid is the injection of false data into the system to distort the energy demand, grid network states, and electricity pricing signals [26], [27].

How Cyberattacks Work

Tan et al. [28] studied the impact of security threats on a real-time pricing system, which could destabilize the electricity market or even cause severe failures. They delineated defensive measures against two classes of data integrity attacks: scaling (the meter reads an amplified version of the actual prices) and delaying (the meter uses old prices). In [29], the authors systemically examined the arbitrary injection of pricing (data) signals and proposed countermeasures based on a cumulative sum control chart technique to identify the attacks. The injection of false data creates a disparity between the generated and consumed power, which subsequently leads to two major problems: 1) the instability of the entire system and 2) an increase in the operational costs by the addition of forged data to the electricity market [30]–[32].

Figure 4 depicts possible cyberattacks on a cyberphysical system comprising the communication infrastructure of various components associated with a smart grid connected to an end-user household. The utility collects information related to the energy demand (generation, consumption, and price) through the AMI and transmits this information to the smart meters and end users through an IoT or Wi-Fi network.

The hierarchical communication infrastructure shown is exposed to three kinds of cyberattacks [32]. First, an adversary can attack the utility's main system (computer devices) and change the pricing curve. Subsequently, this information is sent to the end users, and, based on the fake price, the HEMS schedules their loads. Second, an attacker can directly attack smart meters at or near the end-user household and tamper with the received (or transmitted) data. An adversary can also attack any access point in the Wi-Fi network, create a (fake) access point, and send false pricing data to the smart meter.

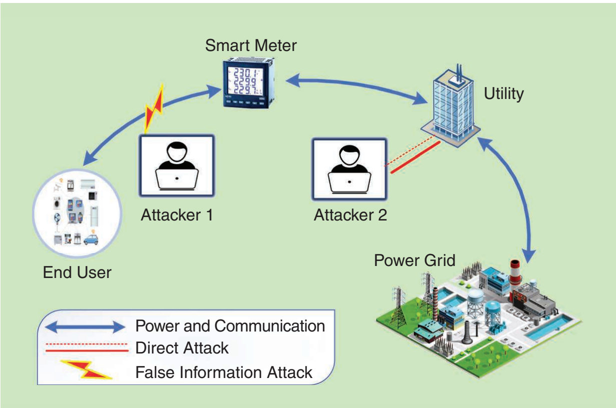

Figure 4. A cyberattack on a cyberphysical system: Attacker 1 attempts to inject the wrong pricing data or alter the energy demand information, and Attacker 2 attempts a direct attack on the utility to change the energy demand and/or production.

Cyberattack Scenario

Consider an HEMS that employs HS algorithms to perform DR-based optimization based on the received price signals. As discussed in [29], a smart meter or other receiver can often be hacked with minimum effort due to the lack of security measures. Let us examine a scenario where an attacker has the resources to hack into a smart meter and inject corrupted (price) information. The cyberattacker aims to mislead the heuristics to induce a higher electricity bill or peak demand by modifying the peak prices arbitrarily, which increases the mismatch between the generated energy and energy demand. For example, in the case of TOU tariffs in winter, the peak time prices of 20.8 cents/kWh occur from 7 a.m. to 11 a.m. and from 6 p.m. to 8 a.m. [23]. The attacker can now alter these peak prices by either shifting them to the off-peak time or simply directly lowering the prices, which, in turn, increases/decreases the electricity bill.

HSA is an idealized mapping from qualitative improvisation into a quantitative formulation, where musical harmony concepts are applied to an optimization process.

In such a scenario, how do the designed models using GA and HSA react when the system is attacked and forged pricing information is injected? To analyze this, assume that the adversary particularly targets the peak prices of the energy demand, i.e., from 7 a.m. to 11 a.m. and from 6 p.m. to 8 a.m. Figure 5(a) presents the electricity costs for a day in winter after a cyberattack has occurred. The GA-HEMS and HSA-HEMS attempt to schedule the energy consumption as before, but the electricity costs naturally increase. However, this increase is not very high: with the GA, the cost rises by 0.15% compared to the optimal cost achieved earlier without the cyberattack, and, with the HSA, the cost grows by 1.8%.

The resilience of any algorithm against cyberattacks can be characterized by measuring how much the forged pricing data affect the performance of the considered system metrics (here, electricity costs) in the designed scenario. A simple way to measure the resilience is by using a resilience index (RI) as follows:

$$\mathbf{RI} = 100 - \left(\frac{|C_A - C_O|}{C_O} \right) \times 100 \qquad (1)$$

where C_A and C_O represent the total electricity cost when the system is under attack and otherwise, respectively. In both cases, the total cost is optimized by using the HEMS. Thus, the RI gives a measure of accuracy of the HA against cyberattacks. $\mathbf{RI} \in [-\infty\, 100\%]$. $\mathbf{RI} = 100\%$ means that the algorithm is extremely resilient ($C_A = C_O$). As the amount of deviation from the optimal cost increases, the RI decreases from the maximum of 100%, and it becomes negative when $C_A > 2C_O$. A negative RI means that the algorithm's performance is poor; the new cost is more than twice the actual cost.

Figure 5(b) presents the RI for the designed model for a day. The GA-HEMS maintains a good and somewhat constant RI across the day, whereas the HSA sometimes has a poor RI. Further, the overall RI values for GA and HSA for the entire day were 99.8% and 97.8%, respectively. Thus, even though the cyberattacker

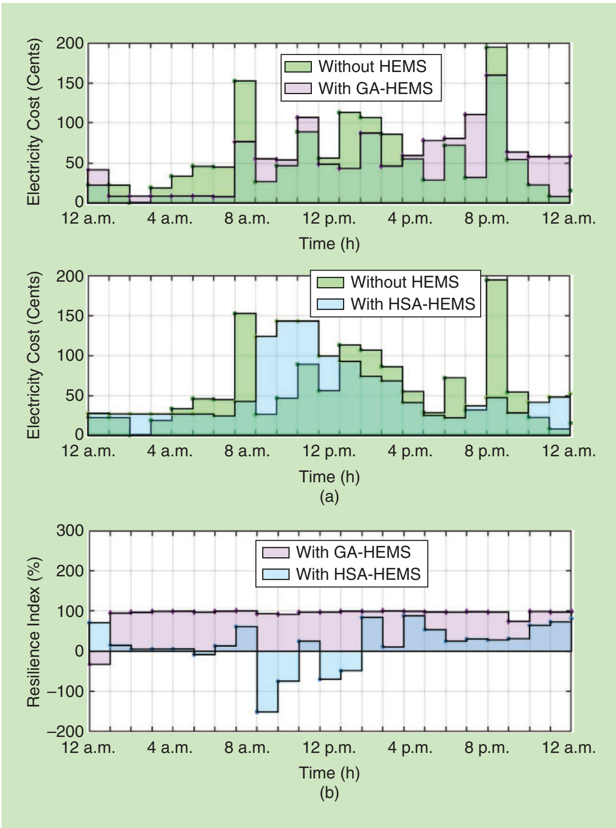

Figure 5. The impact on the electricity costs for a day when a cyberattacker changes the TOU pricing. Two heuristic optimization algorithms, GA and HSA, optimize the costs for the HEMS. (a) The electricity costs per hour under the cyberattack case. (b) The resilience of the GA-HEMS and HAS-HEMS—represented by an RI.

attempts to mislead the designed heuristic approaches with fake price information, both of the designed algorithms perform robustly against these attacks, providing a similar performance to the case without active management.

Conclusion: Cyberattacks and Future Power Systems

Modern power systems (MPSs) have added flexibility and coordination by utilizing information and communication technologies and AMI. MPSs have now gradually transitioned into a complex cyberphysical energy system (CPES). The cyber layer has made it possible for MPSs to not only become more responsive to faults and other systemic problems but also coordinate production and load energy by reacting faster and smarter to changes. Moreover, individual households are empowered to install HEMSs to manage their own production and load as well as interactions with the power system. The efficient transformation of an MPS into a CPES is doubly important today because global climate change issues have made it necessary to integrate large amounts of RESs into the power system.

However, this transformation comes with a price: vulnerability to cyberattacks. MPS control and operations are more visible to external actors, and the strong interactions between the cyberphysical layers in a CPES increase the MPS's vulnerability to cyberattacks. Moreover, power electronic converters, which are key enablers for integrating RESs into MPSs, are typically controlled by employing a hierarchical three-stage structure, namely, primary, secondary, and tertiary layers. This means that the MPSs have additional vulnerabilities and possible attack points in different layers of the system. A cyberattacker can take advantage of any software flaws or failures in any layer of the CPES and create harmful disturbances in the system.

How MPSs will deal with such cyberattacks in the future will be critical to ensure their stability and performance. Advanced and resilient technologies and mitigation measures have to be developed and implemented at every level. Hierarchical stages in MPSs enforce different timescales of operation, giving great flexibility to design mitigation techniques against cyberattacks. At the same time, these measures can also be cheated if the attacker has access to multiple points to design coordinated attacks [33]. Data-driven techniques are a computationally viable platform to identify such anomalies. Robust and resilient control strategies using watermarking [34] and state observers [35] could be smartly employed to infiltrate such cyberattacks in the primary and secondary control layer by guaranteeing faster action.

How MPSs will deal with such cyberattacks in the future will be critical to ensure their stability and performance.

For researchers and industry practitioners, the development of countermeasures to mitigate the impacts of cyberattacks, including financial and data losses, privacy invasions, and so on, is a fascinating and highly relevant area of investigation today. After all, a safe and secure electrical power system is an important part of a safe and secure society.

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SMC

Publication IV

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Packetized Energy Management Controller for Residential Consumers

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***Abstract*—In this paper, we investigate the management of energy storage control and load scheduling in scenarios considering a grid-connected photovoltaic (PV) system using packetized energy management. The aim is to reduce an average aggregated system cost through the proposed *packetized energy management controller* considering household energy consumption, procurement price, load scheduling delays, PV self-sufficiency via generated renewable energy and battery degradation. The proposed approach solves the joint optimization problem using established heuristics, namely genetic algorithm (GA), binary particle swarm optimization (BPSO), and differential evolution (DE). Additionally, the performances of heuristic algorithms are also compared in terms of the effectiveness of load scheduling with delay constraints, packetized energy transactions, and battery degradation cost. Case studies have been provided to demonstrate and extensively evaluate the algorithms. The numerical results show that the proposed packetized energy management controller can considerably reduce the aggregated average system cost up to 4.7%, 5.14%, and 1.35% by GA, BPSO, and DE, respectively, while meeting the packetized energy demand and scheduling delays requirements.**

I. INTRODUCTION

As a result of the high penetration of renewable energy resources (RERs) and modern communication technologies, power system operations have been improved considerably in terms of sustainability and economics [1]. The RERs have now become an alternative solution to replace fossil fuels and protect environmental concerns. Among RERs, photovoltaic (PV) energy with the storage system is the most feasible and fast-spreading technology due to storing surplus energy, improving energy efficiency, and enhancing the stability of the system. Though promising, energy generation from PV is stochastic in nature to time which affects the lifetime of the storage system due to the frequent charging and discharging rate and hence, becomes less successful to manage fluctuating peak load demand (PLD) [2]. Therefore, PV with a storage system may not be the simple solution for the PLD problem. In this regard, energy management techniques (EMTs) are the potential way to address optimally the PLD problem and reduce energy usage cost considering demand response strategies (DRS) and the exchange of surplus energy between smart homes and interconnected microgrids.

Recently, numerous EMTs have been exploited to determine economical and optimal energy allocation plans considering energy sources (like PV and grid energy) [1]–[4] and DRS with dynamic pricings [5]–[7] subject to the various household loads, quality of service [8], [9] and energy trading [10]–[12] constraints. For instance, the authors in [5], [6] studied energy scheduling of residential users to reduce the peak to average ratio (PAR) and minimize energy cost. Ahmed et al. [7] examined consumer behavior patterns for the prediction of future aggregated load and analyzed different user reference models, comfort, and control parameters of appliances in the context of activation delay. Some authors [8], [9] proposed packetized energy management (PEM) approach to address the demand of thermostatically controlled loads (TCL) and validate the quality of service (QoS). In contrast, the authors in [1]–[4], [10]–[12] focused on incorporating RERs together with battery storage system and management techniques. Shafie et al. [10] investigated energy cost minimization and consumer satisfaction level in home energy management system (HEMS) under demand response programs (DRPs), while Dinh et al. [11] conducted a study for optimizing energy consumption costs and participating in bilateral energy trading with the main (external) grid. Similarly, other authors [1]–[3], [12] proposed an HEMS model to reduce the peak load and energy usage costs, while Leithon et al. [4] considered joint optimization of energy scheduling at consumer and trading for profit maximization. Some of the former works [5]–[7] have addressed consumer-centric problems such as load scheduling and energy cost minimization, but they ignored the integration of RERs and bilateral energy trading. Others [8], [9] considered interesting PEM approaches, but they did not discus the role of energy retailers (*i.e.,* utilities) that coexist with consumers and provide pricing mechanisms. In subsequent works [1]–[4], [10]–[12], RERs with battery storage systems were incorporated in the system model, but the impacts of user inconvenience and PEM approaches have not been explicitly studied. Further, the above mentioned works have less thoroughly investigated bilateral energy exchange between the consumer and utility (except [10]–[12]). Moreover, most of the existing works (*e.g.,* [5]–[7] [1]–[4], [10]–[12]) have not been considered PEM approach specifically.

In this paper, we propose a packetized energy management controller (P-EMC) and present a joint energy scheduling and storage system management for PV system with the aim to minimize the energy packet transactions cost, load scheduling delays, and cost of the storage battery degradation. The battery can be charged from roof-top PV panels and an on-grid (external) power grid. For the PV system, we assume that energy generation from PV system will first serve the load, and the remaining energy is stored in the energy storage system. We consider three types of loads and characterized them based on arrival time, length of operation time, unit energy packets demand, and maximum allowable delay. For batteries, the constraints are related to the charging/discharging operation, and the resulting degradation costs.

The main contributions of the paper are:

- We propose a packetized energy management controller (P-EMC) for the household loads with the characteristics such as unit energy packets (EP), the cost of EP, and scheduling of the EP. We also model the internal pricing mechanism for the EP transactions considering the respective constraints.
- The internal pricing model provides a general criteria (subject to constraints) for bilateral energy trading between users and the energy packet service provider.
- The proposed P-EMC solves a joint stochastic optimization problem considering well-known optimization algorithms such as genetic algorithm (GA), binary particle swarm optimization (BPSO), and differential evolution (DE).

II. System Model

Consider a residential smart home connected with renewable and non-renewable energy sources, an energy storage system (*i.e.*, an energy storage battery), and collection of household loads as shown in Fig. 1. The energy generation sources include an external utility grid and a roof-top photo-voltaic (PV) system. A P-EMC is installed in the smart home to perform the following tasks: (i) communicate with the energy sources, storages and loads in the system; and (ii) devise and actuate optimal PEM schedules for the considered energy sources, storage and loads.

A. Load model

The smart home loads $i \in \{1, 2, ..., L\}$ are energy consumption elements that operate at discrete time slots $t \in \{0, 1, 2, ..., T_0 - 1\}$. Each load is characterized by different attributes as follows; Load arrival time (λ_t^i), Scheduling start time (S_t^i), Length of operation time (ρ_t^i), Maximum allowable delay ($\mathrm{d}_{t,max}^i$), Load departure time (γ_t^i), and Unit energy packets demand (E_t^i). Consider that load i consumes energy in the form of discrete value packets, and each discrete packet

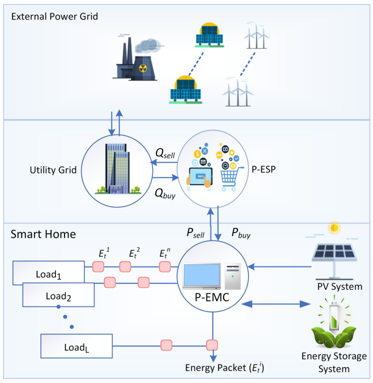

Fig. 1: Schematic diagram of the residential smart home

is denoted by E_t^i. Where, $E_t^i = \frac{E_j - E_{j-1}}{t_k - t_{k-1}}$, $\forall\, j \in \{1, 2, ..., J\}$ and $\forall\, k \in \{1, 2, ..., K\}$ as illustrated in Figure 1.

Let n_t^i be the number of unit E_t^i demanded by load i at time slot t. The total energy packets demanded by all the loads (L) over the entire scheduling horizon (T_0) is given by the following equation.

$$E_{T_0}^L = \sum_{i=1}^{L} \sum_{t=0}^{T_0-1} n_t^i \times E_t^i \tag{1}$$

Let d_t^i be the actual delay incurred by load i at time slot t after serving, such that,

$$d_t^i = \frac{S_t^i - \lambda_t^i}{d_{t,max}^i - \rho_t^i} \tag{2}$$

In (2), if $\lambda_t^i = S_t^i$ then d_t^i=0, and the load is immediately served. Otherwise, it is delayed as per (2). A greater value of d_t^i in (2) means downgraded comfort level of the end-user. Thus, (3) is formulated to imposed user QoS based lower and upper limits on d_t^i.

$$d_{t,min}^i \leq d_t^i \leq d_{t,max}^i \tag{3}$$

Following up on (2) and (3), the average experienced delay of a specific load i over the entire scheduling horizon T_0 is calculated as follows.

$$\overline{d}_{T_0}^i = \frac{1}{T_0} \sum_{t=0}^{T_0-1} d_t^i, \tag{4}$$

Finally, (5) is formulated to ensure that the user QoS based average bounds (0 and $\overline{d}_{T_0,max}^i$) on $\overline{d}_{T_0}^i$ are satisfied over the entire scheduling duration T_0.

$$0 \leq \overline{d}_{T_0}^i \leq \overline{d}_{T_0,max}^i \tag{5}$$

Let $C_d(\overline{d}_{T_0}^i)$ be the function to denote the cost incurred due to $\overline{d}_{T_0}^i$ under the assumptions that $C_d(.)$ is a non-decreasing continuous convex function and its derivative $C'_d(.) < \infty$. Thus, the objective here is to minimize $C_d(\overline{d}_{T_0}^i)$.

B. Internal price model

Smart home customers either have a deficiency or a surplus of energy packets. Energy deficient customers can buy energy packets from the external grid through an energy packet service provider (P-ESP) to meet their demand. Similarly, customers with surplus energy packets can sell them back to the external grid through the P-ESP to avoid energy wastage. Buying and selling of energy packets is carried through an internal pricing model of the P-ESP [13], which considers constraints of feed-in-tariff of the utility, and demand-and-supply ratio (R_t^{DS}) within the energy packet sharing zone. The P-ESP acts an agent for all the smart home prosumers. It buys energy packets from the prosumers in homes and utility grid at unit prices P_t^{buy} and Q_t^{buy}, and sells energy packets to them at unit prices P_t^{sell} and Q_t^{sell}, respectively.

$$P_t^{sell} = \begin{cases} \frac{Q_t^{sell} Q_t^{buy}}{(Q_t^{buy} - Q_t^{sell}) R_t^{DS} + Q_t^{sell}} & \textit{if } 0 \leq R_t^{DS} \leq 1 \\ Q_t^{sell} & \textit{otherwise} \end{cases} \quad (6)$$

It is evident from (6) that: (i) if $R_t^{DS} = 0$, the smart home prosumers do not sell energy packets and the required number of energy packets are procured from the utility at Q_t^{buy}; (ii) if $R_t^{DS} \geq 1$, the smart home prosumer has an energy packet surplus and this surplus is fed back to the utility at Q_t^{sell}; and (iii) if $0 < R_t^{DS} < 1$, the selling price is dynamically adjusted between Q_t^{sell} and Q_t^{buy}. On the other hand, internal energy packet buying price is defined in (7) considering internal energy packet selling cost, P-ESP's charge and utility's charge.

$$P_t^{buy} = \begin{cases} P_t^{sell} R_t^{DS} + Q_t^{buy}(1 - R_t^{DS}) & \textit{if } 0 \leq R_t^{DS} \leq 1 \\ Q_t^{sell} & \textit{otherwise} \end{cases} \quad (7)$$

In (7), $0 < R_t^{DS} < 1$ means that the total energy packet demand is greater than the total energy packet supply of the smart home prosumers in the energy packet sharing zone, and this energy packet deficiency is fulfilled by buying energy packets from the utility at Q_t^{buy}.

Based on the load and the internal price models in this article, the cost of buying and selling energy packets from and to the utility at time slot t via P-ESP can be expressed by (8) and (9), respectively, as follows.

$$C_t^{buy} = P_t^{sell}\Big(E_t^L - (E_t^{pv} + E_t^s)\Big) \;\; if \; E_t^L > E_t^{pv} + E_t^s \quad (8)$$

$$C_t^{sell} = P_t^{buy}\Big((E_t^{pv} + E_t^s) - E_t^L\Big) \;\; if \; E_t^{pv} + E_t^s > E_t^L \quad (9)$$

Thus, the average cost of energy packets transactions ($\overline{C}_t^{tx}$) can be calculated by the following equation.

$$\overline{C}_t^{tx} = \frac{1}{T_0} \sum_{t=0}^{T_0 - 1} \Big(C_t^{sell} - C_t^{buy}\Big) \quad (10)$$

The objective is to maximize the prosumer's energy packet revenue by minimizing the difference between total energy packets selling and buying. However, this buying and selling of energy packets is constrained by the following equations:

$$\sum_{i=1}^{L} \sum_{t=0}^{T_0 - 1} x_t^i = E_{T_0}^L \quad (11)$$

$$E_{t,min}^i \leq x_t^i \leq E_{t,max}^i \quad (12)$$

$$E_t^i - x_t^i \leq B_{max} \quad (13)$$

In the above, (11) implies that flexible loads can be scheduled to operate at other allowable time slots (x_t^i); however, in doing so, the total energy packet demand must be kept constant.

Similarly, (12) ensures that the scheduling of flexible loads (x_t^i) should not violate user's base energy packet demand ($E_{t,min}^i$) and the upper bound of supply capacity ($E_{t,max}^i$), Finally, (13) imposes a constraint on the feed-in energy packets when the utility prohibits selling of additionally generated energy packets (B_{max}) due to grid security issues.

C. PV system

The smart home prosumers are equipped with roof-top PV panels generating renewable energy. Adopting the model in [14], let E_t^{pv} be the amount of harvested energy from the PV source at t, such that,

$$E_t^{pv} = \eta_{pv} \times A_{pv} \times I_{ir}(1 - 0.005(T_a((t) - 25)) \quad (14)$$

where η_{pv} is conversion efficiency of the PV system A_{pv} is the area of the generator, I_{ir} is the solar irradiance at time t, 0.005 is temperature correction factor and T_a is the outdoor temperature. We assume that E_t^{pv} is firstly given to the scheduled load at t ($x_t^L = \sum_{i=1}^{L} x_t^i$), and the remaining ($r_t^{pv}$), if any, is stored in the energy storage system. Let the consumed portion of E_t^{pv} be c_t^{pv}, such that,

$$c_t^{pv} = \min\Big\{x_t^L, E_t^{pv}\Big\} \quad (15)$$

$$0 \leq r_t^{pv} \leq E_t^{pv} - c_t^{pv} \quad (16)$$

It is worth noting here that charging and discharging activities of energy storage battery incur a degradation cost in it. Thus, the decision to store the unused portion of E_t^{pv} (i.e., r_t^{pv}) in the battery is taken by the packetized energy controller installed in the smart home.

D. Energy storage system

Depending on the current energy packet demand and supply conditions, energy storage system can be characterized by three possible states: charging, discharging and idle. For instance, it can be charged from a roof-top PV system, or a P-ESP or a combination of both. Similarly, it can be discharged to meet the energy packet requirement of different loads. In an idle state, it is neither charging nor discharging. These state transitions are bounded by the following set of constraints.

$$0 \leq r_t^{pv} + E_t^g \leq H_{max} \quad (17)$$

$$0 \leq k_t \leq K_{max} \quad (18)$$

$$E_{min}^s \leq E_t^s \leq E_{max}^s \quad (19)$$

Specifically, (17) ensures that the total charging amount at time slot t ($r_t^{pv} + E_t^g$) does not exceed its upper bound (H_{max}). While, (18) limits the total discharging amount at t (k_t) by its upper bound (K_{max}), and (19) imposes minimum and maximum capacity constraints (E_{min}^s and E_{max}^s) on the current energy state of the battery (E_t^s). The dynamics of the current energy state of the storage battery evolve according to the following equation.

$$E_{t+1}^s = \alpha_t E_t^s + \eta_t^{(+)}\left(r_t^{pv} + E_t^g\right) - \eta_t^{(-)}\left(k_t\right) \tag{20}$$

In (20), α_t accounts for a decay rate in the battery with the passage of time, and $\eta_t^{(+)}$ and $\eta_t^{(-)}$ denote the charging and discharging efficiencies, respectively. Let $a_t^{(+)} \triangleq \{1, \text{ if } r_t^{pv}+E_t^g > 0; 0, \text{ otherwise}\}$ indicate whether a charging activity occurred ($a_t^{(+)} = 1$) or not ($a_t^{(+)} = 0$). Similarly, $a_t^{(-)} \triangleq \{1, \text{ if } k_t > 0; 0, \text{ otherwise}\}$ is defined to track the occurrence of a discharging activity. These charging and discharging activities incur degradation cost in the battery, denoted by $c_t^{(+)}$ and $c_t^{(-)}$, respectively. Based on extensive analyses of the authors in [15], the degradation costs in the storage battery at t can be modelled as follows.

$$c_t^{(+)} = \frac{h_r}{h_t}\left\{\left(\frac{r_r^{pv}+E_r^g}{r_t^{pv}+E_t^g}\right)^{w_0} \times \exp^{w_1(\frac{r_t^{pv}+E_t^g}{r_r^{pv}+E_r^g}-1)}\right\} \tag{21}$$

$$c_t^{(-)} = \frac{h_r}{h_t}\left\{\left(\frac{k_r}{k_t}\right)^{w_2} \times \exp^{w_3(\frac{k_t}{k_r}-1)}\right\} \tag{22}$$

In (21) and (22), if the actual cyclic depth-of-charge (i.e., $r_t^{pv}+E_t^g$) and depth-of-discharge (k_t) are kept at their rated values (i.e., $r_r^{pv}+E_r^g$ and k_r), then the lifetime of the storage battery is affected by current variations corresponding to their rated values. Thus, from (21) and (22), the battery degradation cost is modelled at t is given in (23) and its average over the T_0 duration is given in (24).

$$C_t^s = a_t^{(+)}c_t^{(+)} + a_t^{(-)}c_t^{(-)} \tag{23}$$

$$\overline{C}_{T_0}^s = \frac{1}{T_0}\sum_{t=0}^{T_0-1} C_t^s \tag{24}$$

Our aim is to minimize the average degradation cost in (24).

III. Problem Formulation

Let $\theta_t \triangleq [E_t^g, c_t^{pv}, r_t^{pv}, k_t]$ be a vector of energy flow control actions at time slot t. Here, our objective is to minimize an average aggregated system cost consisting of: (i) the cost of energy packet transactions (selling and buying) with the P-ESP ($\overline{C}_{T_0}^{tx}$), (ii) the cost of household load scheduling delays ($C_d(\overline{d}_{T_0}^I)$), and (iii) the cost of energy storage battery degradation ($\overline{C}_{T_0}^s$). Our aim is to find an optimal policy $\{\theta_t, d_t^I\}$ while minimizing the average system cost. Thus, the problem is formulated as follows.

$$\underset{\{\theta_t, d_t^I\}}{\text{minimize}} \quad C_d(\overline{d}_{T_0}^I) + \overline{C}_{T_0}^{tx} + \overline{C}_{T_0}^s$$

Subject to: (2),(3),– (9), (12), (13), (15) – (19), and

$$r_t^{pv} + E_t^g \in [0, \min\{H_{max}, E_{max}^s - E_t^s\}] \tag{25}$$

$$k_t \in [0, \min\{K_{max}, E_t^s - E_{min}^s\}] \tag{26}$$

Where, $d_t^I \triangleq [d_t^1, d_t^2, ..., d_t^L]$, and $C_d(\overline{d}_{T_0}^I) \triangleq [C_d(\overline{d}_{T_0}^1), C_d(\overline{d}_{T_0}^2), ..., C_d(\overline{d}_{T_0}^L)]$. Clearly, the above problem is a joint stochastic optimization problem between the three considered system costs. This joint scheduling makes the problem very difficult to solve by traditional mathematical optimization techniques [16]. Therefore, in the next section, we solve it through heuristic optimization techniques.

IV. Optimization Techniques

Heuristic algorithms are often used to solve joint stochastic optimization due to: (i) their ability to solve high dimensional and complex problems with a fast convergence rate, (ii) ease in implementation, and (iii) capable of avoiding local optima in pursuit of a global optima [16]. We solve the optimization problem in Section III via three popular heuristic algorithms: genetic algorithm (GA), binary particle swarm optimization (BPSO) algorithm, and differential evolution (DE) algorithm. Their brief description is given next (more details in [16]).

A. Genetic Algorithm (GA)

1) Generate an initial population of solutions (i.e., $\mathrm{P_0}$) randomly and binary encode it such that $\mathrm{X_a} \in \{1 \,\mathrm{if}\, \mathrm{P_0(a)} > 0.5, \mathrm{otherwise}\, 0\}$. Each binary coded individual $\mathrm{X_{ab}}, \mathrm{b} \in [1, \mathrm{k}]$ is a k-dimensional vector denoting ON and OFF states of a given load.
2) Use $\{E_t^g, E_t^{pv}, E_t^s, E_t^i, P_t^{sell}, P_t^{buy}\}$ as the inputs, and equations (2),(3),(5),(14),(20) to determine the objective function in Section III.
3) Determine the fitness of each individual in $\mathrm{P_0}$ with respect to the objective function in step 2 above.
4) Adopt the process of tournament selection and select the best individuals (who perform better on objective function) from $\mathrm{P_0}$, as parents.
5) Employ local crossover and bit-flip mutation with a probability between 0 and 1 to reproduce new individuals and update $\mathrm{P_0}$.
6) Repeat step 2 above until the individuals in $\mathrm{P_0}$ approach the optimal values or the total number of generations reach a preset number.

B. Binary Particle Swarm Optimization (BPSO)

1) Randomly generate an initial swarm ($\mathrm{S_0}$) in a pair $(\overrightarrow{ps_i}, \overrightarrow{v_i})$, where the vector $\overrightarrow{ps_i} \in \mathrm{R^n}$ represents the position of the particles and $\overrightarrow{v_i}$ corresponds to their velocity $\overrightarrow{v_i} \in \mathrm{R^n}$. Here, $\overrightarrow{ps_i}$ is computed with respect to $\overrightarrow{v_i}$ as follows.
$$\overrightarrow{ps_i}(t) = \overrightarrow{ps_i}(t-1) + \overrightarrow{v_i}(t) \tag{27}$$
where $\overrightarrow{ps_i}(t-1)$ is the previous position of the particle in the swarm.
2) Evaluate each particle in the swarm using the input values from $\{E_t^g, E_t^{pv}, E_t^s, E_t^i, P_t^{sell}, P_t^{buy}\}$ and equations (2),(3),(5),(14),(20) to determine the objective function in Section III. If the evaluated particle minimizes the objective function then remember the particle as p_{best}.

3) Update S_0 and $\overrightarrow{v_i}$ of each particle in the swarm using (28), while respecting the upper and lower bounds of $\overrightarrow{v_i}$ in (29).

$$\overrightarrow{v_i}(t) = \overrightarrow{v_i}(t-1) + \alpha_1 \text{rand}_1 \Big(p_i - \overrightarrow{ps_i}(t-1)\Big) + \cdots \alpha_2 \text{rand}_2 \Big(p_g - \overrightarrow{ps_i}(t-1)\Big) \tag{28}$$

$$\overrightarrow{v_i}(t) = \begin{cases} \overrightarrow{v_i}_{\max} & \text{if} \overrightarrow{v_i} > \overrightarrow{v_i}_{\max} \\ -\overrightarrow{v_i}_{\max} & \text{if} \overrightarrow{v_i} < -\overrightarrow{v_i}_{\max} \end{cases} \tag{29}$$

In (28), $\alpha_1.\text{rand}_1$ and $\alpha_2.\text{rand}_2$ are random weights for local and global positions (p_i and p_g) of the particle, respectively. And $\overrightarrow{v_i}_{max}$ and $-\overrightarrow{v_i}_{\max}$ are the maximum and minimum velocities of the particle at any point, respectively. Note that $\overrightarrow{ps_i}$ is bounded between [0,1].

4) Evaluate the updated swarm (S_1) by comparing it with S_0 using objective function in Section III and select the particles with lowest value of objective function and refer their position as pg_{best}.
5) Repeat step 4 above until particles in S_1, S_0 approach the optimal values or the total number of generations reach a preset number.

C. Differential Evolution (DE)

1) Generate an initial population $P_e \in R^n$ randomly using (30), where $P_e = [p_{e1}, p_{e2}, p_{e3}, p_{e5}, \cdots p_{en}]$.

$$\text{Pe} = p_e^L + \text{rand}_\text{i}(p_e^U - p_e^L) \tag{30}$$

p_e^U, p_e^L are the upper and lower bounds of P_e, respectively, and rand_i is the uniformly distributed random number between 0 and 1. Note that the individuals in P_e represent the operation states of appliances.

2) Generate a mutation (M_{de}) vector using equation (31) to determine the objective function in Section III considering values from $\{E_t^g, E_t^{pv}, E_t^s, E_t^i, P_t^{sell}, P_t^{buy}\}$ and equations (2),(3),(5),(14),(20).

$$M_{de} = v_{r1} + C(v_{r2} - v_{r3}) \tag{31}$$

Where C is a constant between [0,1], v_{r1}, v_{r2}, and v_{r1} are three vectors randomly picked up from P_e and $r1, r2, r3$ are positive integers $\in \{1, 2, 3, 4 ... n\}$.

3) Generate a new trial vector T_v through crossover between Pe and M_{de} using (32). Calculate objective function based on T_v. Step (2) and (3) are compared to achieve minimal value of objective function.

$$T_v = \begin{cases} M_{de} & \text{if rand}(j) \le \text{cr} \\ \text{Pe} & \text{if rand}(j) > \text{cr} \end{cases} \tag{32}$$

4) Repeat step 3 above until individuals in Pe approach the optimal values or the total number of generations reach a preset number.

V. Results and Discussion

Considering a scheduling horizon of one day (*i.e.,* 24 hours), let the PV system generate a maximum energy $E_{t,max}^{pv}$=9.62 kWh with η_{pv}=18%, and A_{pv}=0.5. For simulation purpose, the solar irradiance and temperature data are taken from [14]. The maximum battery storage capacity is set at 20 kW. In simulations, surplus energy packets are fed back to the utility via P-ESP with minimum and maximum P_t^{sell} are 0.06 cents and 0.57 cents, respectively [17]. Similarly, energy packets are bought from utility at P_t^{buy} which fluctuates between 0.6 cents/kWh and 3.7 cents/kWh [18].

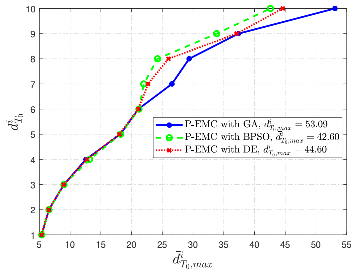

Fig. 2: Delay performance of GA, BPSO, and DE: $\overline{d}_{T_0}^i$ vs $\overline{d}_{T_0,max}^i$, $\forall i \in \{1,2,...,L\}$

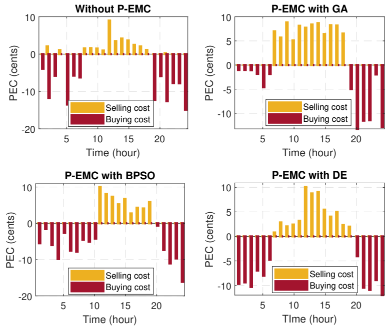

Fig. 3: Performance of GA, BPSO, and DE in terms of packetized energy transactions

Figure 2 illustrates the relative performance between the selected algorithms (GA, BPSO and DE) in terms of average experienced load scheduling delay against the maximum allowable delay. It can be seen from the figure that as the maximum allowable delay requirement of loads ($\overline{d}_{T_0,max}^i$) is relaxed/increased, their average experienced delay ($\overline{d}_{T_0}^i$) also increases. However, the increase in $\overline{d}_{T_0}^i$ is sublinear for all the compared algorithms as compared to the increase in $\overline{d}_{T_0,max}^i$. For example, GA has achieved $\overline{d}_{T_0,max}^i$=53.09, which is greater than BPSO and DE by 11.03 % and 19.03% , respectively. This means scheduled load can be delayed which in turn reduces the average system cost and consequently the user QoS is compromised.

Figure 3 depicts the relative performance of the selected algorithms (GA, BPSO and DE) employed in the P-EMC and a special case without the P-EMC in terms packetized energy transactions that involve both selling to and buying of energy packets from the utility. As shown in the figure, without P-EMC case has a selling cost of 34.9 cents and

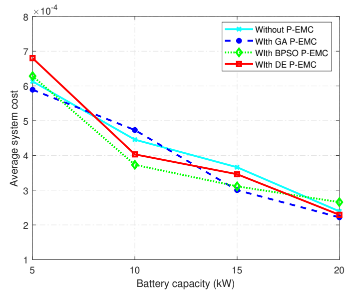

Fig. 4: Average system cost vs Battery capacity

a buying cost of 108.08 cents in a day. When optimization algorithms are employed, the selling costs are increased to 88.9 cents, 54.4 cents, and 57.9 cents for P-EMC with GA, with BPSO, and with DE, respectively. Similarly, the buying costs are decreased to 67.33 cents, 99.74 cents, and 95.51 cents for P-EMC with GA, with BPSO, and with DE, respectively. It is can be seen that GA has a higher selling cost than BPSO and DE, because GA tends to schedule the load in later time slots (achieves greater delay) and utilizes the harvested energy from the PV system and the storage system in a more efficient manner, thus it sells greater amount of energy to the utility. This means that the optimization algorithms help to allocate the energy resources effectively and also facilitate the user to sell back the surplus energy to the utility grid via P-ESP. Further, BPSO and DE moderately schedule the load at time slots when energy from PV system is less or not available. Hence, achieving a relatively lower selling cost than GA.

Figure 4 reflects the impact of battery capacity on the average system cost under the selected algorithms. It is evident from the figure that when increase in the battery capacity induces a decrease in the average system cost for all the selected algorithms including the unscheduled special case of without P-EMC. A higher battery capacity provides more flexibility in scheduling loads at low peak hours. Thus, resulting in reduced average system cost. The optimization algorithms reduced average system cost to 4.7%, 5.14% and 1.35% by P-EMC with GA, BPSO, and DE, respectively.

VI. Conclusion

This paper proposed P-EMC for a residential smart home considering household loads, energy transaction cost, PV energy generation and energy storage system. The proposed P-EMC employs the internal pricing model and solves the joint stochastic problem using optimization algorithms such as; GA, BPSO, and DE. Simulation results have shown that optimization algorithms are capable to schedule the load effectively and reduced the energy procurement cost to 37.65%, 7.5%, and 11.5% by GA, BPSO, and DE, respectively. Furthermore, the proposed P-EMC helps the consumer to sell surplus energy up to 88.9 cents, 54.4 cents, and 57.9 cents with the help of GA, BPSO, and DE, respectively. In the future, we aim to extend our case study for the different PV generation profiles and pricing signals and analyze the level of accuracy of each designed optimization algorithm.

Acknowledgements

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Publication V

Hussain, H. M., Ahmad, A., Narayanan, A., Nardelli, P. H., and Yang, Y.
Benchmarking of Heuristic Algorithms for Energy Router-Based Packetized Energy Management in Smart Homes

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Benchmarking of Heuristic Algorithms for Energy Router-Based Packetized Energy Management in Smart Homes

Hafiz Majid Hussain, Ashfaq Ahmad, *Member, IEEE*, Arun Narayanan, *Member, IEEE*, Pedro H. J. Nardelli, and Yongheng Yang, *Senior Member, IEEE*

***Abstract*—This article presents an ER-based PEM strategy for PV integrated smart homes to jointly optimize their load scheduling delays, energy transactions cost, and battery degradation cost. The proposed approach incorporates a MA case, where, the ER acts as a main selecting agent realized by all other system elements. This leads to a combinatorial optimization problem, which can be effectively solved by heuristic optimization methods (HOMs), namely, genetic algorithm (GA), binary particle swarm optimization (BPSO), differential evolution (DE) algorithm, and harmony search algorithm (HSA). Specifically, we investigate the impact of the hyperparameters of the HOMs on the designed ER-based PEM system. Simulations are carried out for multiple smart homes under varying weather conditions to evaluate the effectiveness of HOMs in terms of selected performance metrics. Results show that the ER-based PEM reduces the average aggregated system cost, ensures economic benefits by selling surplus energy, while meeting customers energy packet demand, satisfying their quality-of-service, and operational constraints.**

***Index Terms*—Energy Internet (EI), energy router (ER), heuristic algorithms, packetized energy management systems (PEMs).**

NOMENCLATURE

Abbreviations

DMS	Demand-side management.
EI	Energy Internet.
ER	Energy router.
PV	Photovoltaic.
EMS	Energy management system.
MAs	Multiagents.
PEM	Packetized energy management system.
P-ESP	Packetized energy service provider.
PEC	Packetized energy cost.
PLC	Power line communication.
RRs	Renewable resources.
QoS	Quality-of-service.
SDN	Software-defined network.

Indices and Superscripts

t	Time step.
$\max$	Maximum.
$\min$	Minimum.
—	Average.
$'$	Derivative.
i	Superscript for load from 1 to N.
j	Superscript for smart home from 1 to M.
t	Superscript for time period from 1 to T_0.
r	Subscript for particle in the swarm.

Main Symbols

C_{bt}	Crossover operator.
M_{bt}	Mutation operator.
$d_t^{j,i}$	Delay experienced by a load i in a smart home j at time t.
$E_{t,pv}^j$	Harvested amount of PV energy by a smart home j at t.
$E_t^{j,s}$	Battery state of energy of a smart home j at t.
$P_t^{j,i}$	Energy packets demand by a smart home j at t.
$P_{T_0}^{M,N}$	Total energy packets demanded by M smart homes of N loads over T_0.
E_t^g	Energy packets supplied by utility grid.
$H_t^{j,buy}$	Energy packets procured by a smart home j from E_t^g.
$H_t^{j,sell}$	The E packets sold by a smart home j to E_t^g.
$R_t^{DS,j}$	Demand-and-supply ratio at time t.
J_t^{buy}	$P_t^{j,i}$ procured by P-ESP from E_t^g at t.
J_t^{sell}	$P_t^{j,i}$ sold by P-ESP to utility grid at t.
$K_d\left(\overline{d}_{T_0}^{M,N}\right)$	Cost function based on average delay experienced by M smart homes M of N loads over T_0.
$K_t^{j,buy}$	Cost of $P_t^{j,i}$ buying by j from utility grid at t.

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$K_t^{j,buy}$	Cost of $P_t^{j,i}$ selling by j from utility grid at t.
$\overline{K}_{T_0}^{M,tx}$	Average cost associated with the transactions of energy packets for M smart homes over T_0.
$\overline{K}_{T_0}^{M,s}$	Average cost associated with charging and discharging activities for M smart homes over T_0.
$x_t^{j,i}$	Time slots available for scheduling of $P_t^{j,i}$.
$P_{t,\min}^{j,i}$	Lower bound of the $P_t^{j,i}$.
$P_{t,\max}^{j,i}$	Upper bound of the $P_t^{j,i}$.
$B_{\max}$	Upper bound of J_t^{buy}.
$E_t^{j,s}$	Amount of energy charged in a storage system of a smart home at t.
k_t^j	Amount of energy discharged from storage system of a smart home at t.
$E_{t,\max}^{j,s}$	Per slot upper bound on amount of energy charged in storage system by a smart home at t.
$k_{\max}^j$	Per slot upper bound on amount of energy discharged in a smart home at t.
$E_{\min}^{j,s}$	Per slot minimum required $E_t^{j,s}$ for a storage system.
$E_{t,pv}^j$	Amount of energy harvested from PV by a smart home.
$c_t^{j,(+)}$	Admission cost for the charging event of a storage system in a smart home at t.
$c_t^{j,(-)}$	Admission cost for the discharging event of a storage system in a smart home at t.
$E_{t,pv}^{j,c}$	Consumed portion of PV energy stored by j at t.
$E_{t,pv}^{j,r}$	Residual portion of PV energy by smart home in the battery at t.
$E_{T_0,pv}^M$	Amount of energy produced by PV panel for all smart homes M over T_0.
$S_{\max}$	Upper bound on the total amount of energy stored in a battery.

I. Introduction

OVER the past few decades, electric power system has been influenced greatly by the integration of large-scale RRs. The RRs (represented by solar panels and wind turbines) have become inevitable for alleviating energy prices and mitigating environmental concerns [1], [2]. Yet, energy generation from RRs is intermittent making them less reliable for a stable operation of the power system [3]. Recently, EI has been widely investigated to combat the intermittency in renewable generation through Internet-oriented technologies, such as ERs, plug and play services, and PEM [4], [5], [6].

In the EI paradigm, ER is an integral part, analogous to a router in an Internet network [7]. ER provides real-time communication among users and the utility grid and performs management of RRs, flexible and nonflexible household loads, rooftop PV panels, and storage system often classified as *agents* [8]. Thus, ER is regarded as an essential element that interfaces multiple agents (MAs) and enables energy resource allocation in smart homes exploiting demand-side management (DSM) [9], [10].

PEM as a part of the DSM can be utilized to meet energy packet demand of smart home customers by scheduling flexible energy packets while ensuring their QoS constraints [11]. In PEM, energy is delivered to the customer loads in the form of energy packets that represent fixed power consumed by the load during a predefined time interval, e.g., 1 kW in an hour [12]. In this sense, this article focuses on the ER-based PEM (ER-PEM) framework for smart homes and provides resource allocation of MAs operating at various times instants. In addition, ER-PEM enables cost-effective solutions for smart users considering QoS, energy transactions between ER and utility grid, PV energy, and storage system.

However, a limited amount of work has been done in the above context and most of the literature has either focused on communication and control aspects [5], [6], [7], [9], [13] or on energy management aspects of ER [11], [12], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23]. For instance, authorsin [5] and [6], described the role of the ER in EI networks, investigated design challenges in terms of communication typologies, governance models, and security concerns. Gao et al. [7] studied an ER-based system to investigate the communication and reliability of multiple ERs and energy trading for green cities in EI. Guo et al. in [9] proposed secure energy routing protocols for the optimal energy dispatch between energy hubs (EH) considering power transmission constraints in the EI. Tu et al. [13] proposed a modular-based ER strategy for connecting dc micro grid clusters with ac grids. The other references investigated the operation of ER based on the management aspects [11], [12], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], for example, authors in [11] and [12] evaluated the QoS metric for load allocation problem using PEM system. Li et al. [14] proposed an optimization-based strategy for the integrated energy system to minimize the cost of the EH using ER applications. In [15], the authors examined optimization problems for home energy management systems (HEMS) in the context of the EH, while the authors in [16] and [17] formulated an energy management solution for operational costs and CO_2 minimization considering contingency constraints in microgrids. Ahmad and Khan [18] solved the joint optimization problem through Lyapunov optimization considering renewable sources, loads, and energy procurement prices, whereas Carli et al. in [19] proposed scheduling algorithms for solving an online optimization problem in microgrids and daily cost minimization through the DSM was achieved. Demand response (DR) methods were proposed in [20] and [21] to control the peak to average ratio (PAR) and to reduce systems costs, while the authors in [22] and [23] investigated HEMS with DSM to reduce energy costs and peak power consumption, considering user's requirements over a finite time horizon.

It is suggested from the above literature review that most of the previous works have investigated energy management solutions e.g., [16], [17], [18], [19], [20], [21], [22], [23] or the control and routing aspects of the ER [7], [9], [15] without considering distinctive and key aspects of EI, such as ER, MAs, and PEM. Although authors in [11] and [12] have studied PEM-based solutions, however, their system model has not provided

TABLE I
COMPARISON OF THE STATE-OF-THE-ART WORKS WITH OUR DESIGNED SYSTEM MODEL

S.Nr	Ref.(s)	Method (s)	Energy premises	PEM System	Use of RRs	Contribution(s)
1	[7]	Hierarchical optimization strategy	Smart energy community	NO	YES	To minimize daily operational cost of EH considering the energy transaction of EHs in EI.
2	[9]	Markov decision process	Smart energy community	NO	NO	To control and verify the energy transmission and management of ER-based system.
3	[11]	Rule based optimization	Smart homes	YES	NO	To reduce peak shaving.
4	[12]	Controlled Markov chain	Smart home	YES	YES	To obtain QoS for managing RRs via PEM.
5	[15]	Probabilistic optimization approach	Smart home	NO	YES	To minimize the energy cost of the customer.
6	[16]	MINLP	Microgrid	NO	YES	To achieve the optimal day-ahead scheduling of energy resources.
7	[17]	Lightning search optimization algorithm	Microgrid	NO	YES	To minimize the aggregated operational cost of the system.
8	[18]	Lyapunov optimization technique	Smart building	NO	YES	To minimize the aggregated average operation cost of the system.
9	[19]	Model Predictive Control	Smart building	NO	YES	To minimize the daily cost of the energy from the main grid.
10	[20], [23]	Heuristic optimization algorithms	Smart home	NO	YES	To minimize the cost of the smart home and reduce PAR.
11	[21]	Artificial immune algorithm	Smart energy community	NO	YES	To maximize the net profit by decreasing the operating cost of the system.
12	[22]	Natural aggregation optimization algorithm	Smart energy community	NO	YES	To minimize one day cost of the smart home and reduce PAR.
14	*Our work*	Heuristic optimization algorithms	Smart energy community	YES	YES	To minimize aggregated average cost of system based on (a) energy packet transactions cost (b) load scheduling delays cost (c) battery degradation cost.

Research limitations in [7], [9], [11], [12], [15]–[23]: (i) The ER-PEM system including; the key attributes of EI such as ER, MAs, and PEM has seldom been explored in previous works [7], [9], [11], [12], [15]–[23]. (ii) Most of the studies have investigated the minimization of the system cost based on the various methods, however, their design system lack adequate analysis either on PEM system [15]–[23] or energy packets attributes e.g., arrival time, unit demand, scheduling start time, departure time, and allowable service delay [7], [9], [11], [12]. (iii) In addition, none of the previous works has provided comparative analysis of heuristic algorithms in the context of ER-based PEM system.

Research contributions: (i) This work presented a comprehensive ER-PEM system for multiple smart homes and their associated characteristics including energy packet attributes, delay constraints, PV energy generation, battery storage system, and energy packets transactions. (ii) ER-based PEM system solved the joint optimization problem of minimizing average aggregated system costs based on, energy packet transactions cost, load scheduling delays cost, and battery degradation cost (iii) The designed ER-PEM system also evaluated the comparative performance of heuristic algorithms and the impact of their hyperparameters on energy packet transactions and their associated service delays.

adequate analysis of design aspects of energy packets, for instance, arrival time, unit energy packet demand, scheduling start time, departure time, and allowable service delay. In contrast, the designed ER-PEM system is a unique architecture and incorporated distinctive design aspects of EI and ER-PEM system. Moreover, the designed ER-PEM system not only accomplished the objectives (i.e., to minimize average aggregated system costs based on, energy packet transactions cost, load scheduling delays cost, and battery degradation cost) but also carried a comparative analysis of the heuristic optimization methods (HOMs) in terms of different sets of hyperparameters and different seasons. Table I briefly summarizes the models in the previous work and also compares the previous models with the designed ER-PEM system in this article.

In the above context, we present an ER-PEM system for multiple smart homes to achieve optimal energy plans in terms of management of MAs based on heuristic optimization methods. Specifically, we account for key attributes of the smart homes, i.e., energy packet scheduling and pricing parameters, and constraints of roof-top panels and energy storage system in the context of ER-PEM system. The goal of ER-PEM is to minimize an average aggregated system cost by solving a joint optimization problem of load scheduling and storage management. The minimization of an average aggregated system cost is subject to constraints of energy demand, scheduling delay parameters, storage system management and energy procurement parameters. To this joint optimization problem, we employ HOMs: genetic algorithm (GA), binary particle swarm optimization (BPSO), differential evolution (DE), and harmony search algorithm (HSA). Finally, we present simulation results and analyze the relative performance of HOMs and the impact of their hyperparameters on the designed ER-PEM system.

The major contributions of this work are summarized below.

1) A comprehensive system model is presented for smart homes based on an ER-PEM system. The model consists of multiple smart homes and their associated characteristics including energy packet attributes and delay constraints, PV energy generation, battery storage system, and energy packets' transactions.
2) An energy pricing model ([24], [25]) is tailored for energy packet exchange (buy and sell) between smart homes and packetized energy service provider (P-ESP). The model provides flexibility for economic energy transactions while conserving the demand–supply ratio.
3) The joint optimization problem is solved by implementing four well-known HOMs—GA, BPSO, DE, and HSA—and their performance and suitability for the designed system model are benchmarked.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

4) A comprehensive case study is conducted to evaluate HOMs and their associated hyperparameters in terms average aggregated system cost parameters.

Note that this work is an extension of [26] and it contributes in the following ways.

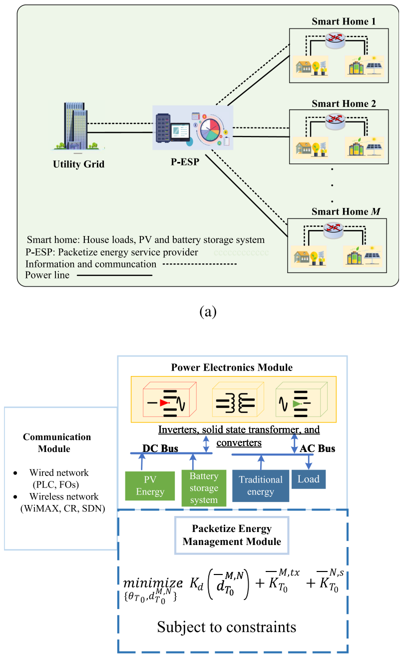
1) Literature review is extensively updated with state-of-the-art research methods in terms of their contributions and potential research gaps.
2) Unlike a single smart home in [26], the ER- PEM model in this article is upgraded with a systematic integration of multiple smart homes, their respective attributes and constraints considering an extended set of HOMs and varying weather conditions.
3) The relative performance analysis of HOMs is carried out based on the joint optimization problem of load scheduling and storage management in the ER-PEM system.

In addition, simulation scenarios are extended to investigate the impact of the HOMs' hyperparameters on energy packet transactions and their associated service delays.

The rest of this article is organized as follows. Section II formulates the problem and provides the system model. A brief overview of heuristic optimization is given in Section IV. Simulation results are presented in Section V. Finally, Section VI concludes this article.

II. System Model

Fig. 1 depicts conceptual overview of ER-PEM system. Where Fig. 1(a) shows the interaction of ER with MAs, utility grid, and P-ESP, and Fig. 1(b) represents three main building blocks of the ER: a power electronics module, a communication module, and a management-and-control module [7]. The power electronics module can be a solid-state transformer, inverters, and converters to provide circuitry-based active control of energy flows. The management module is responsible for allocating energy resources and providing optimal energy usage plans to satisfy users' demand and cost requirements. The power electronics and management modules are connected through a communication module that may consist of a wired network, e.g., PLC and fiber optics (FOs), a wireless network, e.g., WiMAX, cognitive radio (CR), and a SDN, or a combination of both [5]. Potentially, the ER can act like a plug-and-play interface for smart homes to connect to or disconnect from traditional energy sources, PV sources, battery storage systems, and electrical loads. In this work, we mainly focus on packetized energy optimization via an energy management module carrying the following tasks: 1) devise and manage schedules for energy packets transactions considering all connected sources, storage, and loads; and 2) coordinate with the P-ESP for economic energy transactions.



(b)

Fig. 1. (a) Illustration of the ER-PEM system. (b) Main modules of an ER.

A. Load Model

A set of smart homes $j \in \{1, 2, \ldots, M\}$ accommodate loads $i \in \{1, 2, \ldots, N\}$ that operate at discrete time slots $t \in \{0, 1, 2, \ldots, T_0 - 1\}$ in a local energy community. The loads are energy consumption elements in each smart home, and they are characterized by different attributes as follows.

1) Load arrival time ($\varrho_t^{j,i}$): The time slot at which a request for a given load arrives in a smart home j.
2) Unit energy packets demand ($P_t^{j,i}$): In a smart home, we consider the energy is consumed in the form of discrete value packets by load i and each energy packet is represented by $P_t^{j,i}$. Here, $P_t^{j,i} = \frac{P_e - P_{e-1}}{t_k - t_{k-1}}, \forall\, e \in \{1, 2, \ldots, E\}$ and $\forall\, k \in \{1, 2, \ldots, K\}$, as shown in Fig. 2.
3) Scheduling start time ($\zeta_t^{j,i}$): Time slot at which the load is actually scheduled.
4) Length of operation time ($\varsigma_t^{j,i}$): The number of time slots during which the load completes its operations.
5) Maximum allowable delay ($d_{t,\max}^{j,i}$): The maximum amount of delay (i.e., the number of time slots) that can be tolerated prior to the load being scheduled.
6) Load departure time ($\tau_t^{j,i}$): The time slot at which the load departs after completing its operation.

Let $U_t^{j,i}$ be the number of unit energy packets $P_t^{j,i}$ demanded by a smart home j of load i at time slot t. The total energy packets required by all smart homes (M) with loads (N) during scheduling horizon (T_0) is computed by

$$P_{T_0}^{M,N} = \sum_{j=1}^{M} \sum_{i=1}^{N} \sum_{t=0}^{T_0-1} U_t^{j,i} \times P_t^{j,i}. \tag{1}$$

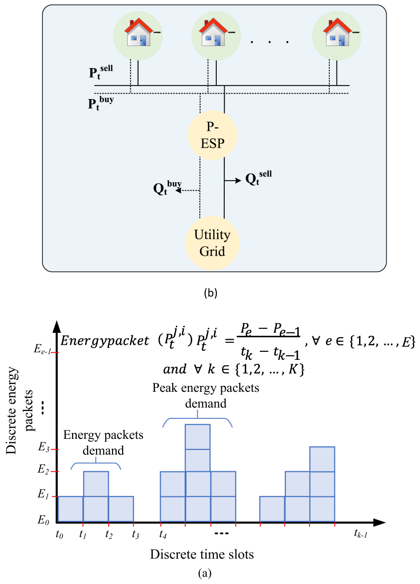


Fig. 2. Energy pricing under P-ESP. (a) Energy packet and (b) energy pricing model.

During appliance scheduling, the following user defined QoS constraint should be satisfied:

$$\varrho_t^{j,i} \leq \zeta_t^{j,i} + \rho_t^{j,i} \leq d_{t,\max}^{j,i}. \tag{2}$$

Equation (2) ensures that a given appliance i in a smart home j is scheduled at t without violating its delay requirement ($d_{t,\max}^{j,i}$), considering its arrival time ($\varrho_t^{j,i}$) and its length of operation time ($\varsigma_t^{j,i}$). During the scheduling duration (T_0), appliances with $d_{t,\max}^{j,i} > 0$ can be delayed from their respective arrival times ($\varrho_t^{j,i}$'s), thereby adding flexibility to the load scheduling process. However, this flexibility (i.e., load scheduling delay) may adversely affect user comfort, if it goes beyond a specific user-defined level. Let $\mathrm{d}_t^{j,i}$ be the delay experienced by load i in smart home j at t after serving [23], [27], such that

$$d_t^{j,i} = \frac{\zeta_t^{j,i} - \varrho_t^{j,i}}{d_{t,\max}^{j,i} - \varsigma_t^{j,i}} \tag{3}$$

in which, if $\varrho_t^{j,i} = \zeta_t^{j,i}$ then $d_t^{j,i} = 0$, and the load is served immediately; otherwise, delay is incurred. A greater value of $d_t^{j,i}$ in (3) reflects the downgraded comfort level of the smart home user. Thus, (4) is modeled to impose user QoS-based lower and upper limits on d_t^i

$$d_{t,\min}^{j,i} \leq d_t^{j,i} \leq d_{t,\max}^{j,i}. \tag{4}$$

Using (5), the average delay incurred of any load i in a smart home j during T_0 is obtained as

$$\overline{d}_{T_0}^{M,N} = \frac{1}{M} \sum_{j=1}^{M} \sum_{t=0}^{T_0-1} \sum_{i=N}^{M} d_t^{j,i}. \tag{5}$$

Finally, (6) guarantees that the user QoS-based average bounds (0 and $\overline{d}_{T_0,\max}^{j,i}$) on $\overline{d}_{T_0}^{j,i}$ are satisfied during scheduling horizon T_0

$$0 \leq \overline{d}_{T_0}^{j,i} \leq \overline{d}_{T_0,\max}^{j,i}. \tag{6}$$

From the above analysis, it is clear that load scheduling, if allowed to operate under user QoS-based allowable delay bounds, adds flexibility to the scheduling process. However, this flexibility may have a counter-productive effect on user comfort if it goes beyond the user QoS-based specifications. Let $K_d\left(\overline{d}_{T_0}^{M,N}\right)$ be a function to indicate the cost due to $\overline{d}_{T_0}^{j,i}$ based on the assumptions that $K_d(.)$ is a nondecreasing continuous convex function and its derivative $K'_d(.) < \infty$. Thus, here our objective is to minimize $K_d\left(\overline{d}_{T_0}^{M,N}\right)$.

B. Energy Price Model

Smart homes, equipped with ERs and energy sources, are either having insufficient or adequate energy packets. Energy-insufficient smart homes have a greater energy demand than their locally generated and stored energy, and smart homes which possess adequate energy packets have a smaller energy demand than their locally generated and stored energy. Energy-deficient smart homes can buy energy packets ($H_t^{j,buy} = [H_{t,1}^{j,buy}, \ldots, H_{t,i}^{j,buy}, \ldots, H_{t,I}^{buy}]$) from an utility grid through a P-ESP to satisfy their demand. On the contrary, smart homes with excess energy packets can sell ($H_t^{j,sell} = [H_{t,1}^{j,sell}, \ldots, H_{t,i}^{j,sell}, \ldots, H_{t,I}^{sell}]$) back to the utility grid through the P-ESP. This process of energy packets exchange (buying and selling) is conducted by an energy pricing model of the P-ESP, which is formulated based on the constraints of feed-in-tariff of the utility, and demand-and-supply ratio (R_t^{DS}) within the energy packet sharing zone. The P-ESP acts as an agent for M smart home prosumers. It can buy energy packets from smart homes and the utility grid at unit prices $H_t^{j,buy}$ and J_t^{buy}, and sells energy packets to them at unit prices $H_t^{j,sell}$ and J_t^{sell}, respectively [24]. This can be formulated as

$$H_t^{j,sell} = \begin{cases} \frac{J_t^{sell} J_t^{buy}}{(J_t^{buy} - J_t^{sell}) R_t^{DS} + J_t^{sell}} & \text{if } 0 \leq R_t^{DS} \leq 1 \\ J_t^{sell} & \text{otherwise.} \end{cases} \tag{7}$$

It is noticed from (7) that:

1) if $R_t^{DS} = 0$, the smart home prosumers have insufficient energy packets to sell therefore, energy packets are bought from the utility at J_t^{buy};
2) if $R_t^{DS} \geq 1$, the smart home prosumer possess surplus energy packets which can be sold back to the utility grid at J_t^{sell};
3) if $0 < R_t^{DS} < 1$, the energy packets selling price is dynamically regulated between J_t^{sell} and J_t^{buy}.

Meanwhile, considering the energy packet selling cost, P-ESP's charge and utility's charge, an energy packet buying price is defined as

$$H_t^{j,buy} = \begin{cases} H_t^{j,sell} R_t^{DS} + J_t^{buy}(1 - R_t^{DS}) & \text{if } 0 \le R_t^{DS} \le 1 \\ J_t^{sell} & \text{otherwise} \end{cases} \tag{8}$$

where in (8), $0 < R_t^{DS} < 1$ shows that the overall energy packets demand are greater than the total energy packet supply of the smart home prosumers in the energy packet sharing zone, and this energy packet insufficiency is satisfied by procuring energy packets from the utility grid at J_t^{buy}. In-line with the above context, let $K_t^{j,buy}$indicates the cost of energy packets bought by smart home j from the utility grid at time slot t via P-ESP

$$K_t^{j,buy} = H_t^{j,sell}\left(P_t^{M,L} - (E_{t,pv}^j + E_t^{j,s})\right) \quad \text{if } E_t^{M,L} > E_{t,pv}^j + E_t^{j,s} \tag{9}$$

here in (9), $H_t^{j,sell}$ represents the selling cost of energy packets, $P_t^{M,L}$ is the total energy packets demands at time t, and $E_{t,pv}^j, E_t^{j,s}$ are available energy from rooftop PV and energy storage system at time instant j. It is also assumed that a smart home j buys energy packets only if the total energy packets demand can not be satisfied by $E_{t,pv}^j + E_t^{j,s}$. Similarly, (10) formulates the cost of energy packets sold by smart home j to the utility grid at time slot t via P-ESP

$$K_t^{j,sell} = H_t^{j,buy}\left((E_{t,pv}^j + E_t^{j,s}) - P_t^{M,L}\right) \quad \text{if } E_{t,pv}^j + E_t^{j,s} > P_t^{M,L}. \tag{10}$$

Further, the smart home users can sell the surplus energy packets given that $E_{t,pv}^j + E_t^{j,s}$ must be greater than demand of $P_t^{M,L}$. As per [25], eq. (9) and (10)] the average cost of the energy packets transaction ($\overline{K}_t^{tx}$) can be expressed as

$$\overline{K}_{T_0}^{M,tx} = \frac{1}{M}\sum_{t=0}^{T_0-1}\sum_{j=1}^{M}\left(K_t^{j,sell} - K_t^{j,buy}\right). \tag{11}$$

Here, the goal is to maximize the prosumer's energy packet revenue by minimizing the difference between $K_t^{j,sell}$ and $K_t^{j,buy}$. However, the process of energy packets buying and selling is constrained by the following:

$$\sum_{j=1}^{M}\sum_{i=1}^{N}\sum_{t=0}^{T_0-1} x_t^{j,i} = H_{T_0}^{M,L} \tag{12}$$

$$P_{t,\min}^{j,i} \le x_t^{j,i} \le P_{t,\max}^{j,i} \tag{13}$$

$$0 \le H_t^{j,buy} \le H_{t,\max}^{j,buy} \tag{14}$$

$$0 \le H_t^{j,sell} \le H_{t,\max}^{j,sell} \tag{15}$$

$$H_t^{j,i} - x_t^{j,i} \le B_{\max} \tag{16}$$

where (12) implies that ERs can schedule the flexible loads in smart homes at other allowable time slots ($x_t^{j,i}$), while keeping the total energy packets demand constant. Likewise, (13) guarantees that the scheduling of flexible loads ($x_t^{j,i}$) must not exceed smart home's base energy packet demand ($P_{t,\min}^{j,i}$) and the upper bound on supply capacity ($P_{t,\max}^{j,i}$).Constraints (14) and (15) ensure that energy procurement and selling criteria should be controlled and can not exceed given limits i.e., $H_{t,\max}^{j,buy}$ and $H_{t,\max}^{j,sell}$. Finally, (16) constraints on the feed-in energy packets when the utility grid restricts the selling of additionally generated energy packets ($B_{\max}$) due to grid security issues.

C. PV System

As mentioned earlier, roof-top PV panels are installed in the smart homes converting solar energy to electrical energy. Based on the model in [28], let $E_{t,pv}$ be the total amount of harvested energy from the PV panels by M smart homes over the entire horizon (T_0) such that

$$E_{T_0,pv}^{M} = \sum_{j=1}^{M}\sum_{t=0}^{T_0-1} E_{t,pv}^j \tag{17}$$

from (17), $E_{t,pv}$ can be calculated as $E_{t,pv} = \eta_{pv} \times A_{pv} \times I_{ir}(1 - 0.005(K_t((t) - 25))$, the symbols η_{pv}, A_{pv}, and I_{ir} signify conversion efficiency, generator area, and solar irradiance, respectively. While 0.005 is the value use for temperature correction factor (TCF), and K_t respesents outdoor temperature. Let $E_{t,pv}^c$ be the energy consumed from $E_{t,pv}$ in (18) with respective constraint (19) as given as follows:

$$E_{t,pv}^{c,j} = \min\left\{x_t^{N,M}, E_{t,pv}^j\right\} \tag{18}$$

$$0 \le E_{t,pv}^j \le E_{t,pv}^j - E_{t,pv}^{c,j} \tag{19}$$

$$E_{t,pv}^j + E_t^g \in [0, \min\{S_{\max}, E_{t,\max}^{j,s} - E_t^{j,s}\}]. \tag{20}$$

From (18) and (19), it is clear that $E_{t,pv}^j$ is firstly supplied to the scheduled load in j at t ($x_t^{N,M} = \sum_{j=1}^{M}\sum_{i=1}^{N} x_t^{i,j}$), and the remaining part ($E_{t,pv}^r$), if any, is stored in an in-home energy storage system (according to (20). It is worth noting that charging and discharging events of the battery cause a degradation cost in it. Hence, to manage charging or discharging events, PEM-ER can determine whether to store or not the conserved portion of $E_{t,pv}^j$ (i.e., $E_{t,pv}^{r,j}$) in the battery based on joint optimization.

D. Energy Storage System

During the time horizon T_0 the energy storage system can be operated by three possible states: 1) charging; 2) discharging; 3) idle considering the current energy packet demand and supply conditions. That is, during charging state, it can either be charged from the PV panels, the P-ESP, or a combination of both. Likewise, during discharging state, it can be discharged to satisfy the energy packet need of various loads. In an idle state, it is neither charging nor discharging. These state transitions are bounded by the following:

$$k_t^j \in [0, \min\{k_{\max}^j, E_t^{j,s} - E_{\min}^{j,s}\}] \tag{21}$$

$$0 \le E_{t,pv}^j + E_t^g \le S_{\max} \tag{22}$$

$$0 \le k_t^j \le k_{\max}^j \tag{23}$$

$$E_{t,\min}^{j,s} \leq E_t^{j,s} \leq E_{t,\max}^{j,s}. \tag{24}$$

Specifically, (21) and (22) imply that charging and discharging demand at time t can be met by the available energy in the battery. (22) also limits that the total charging amount ($E_{t,pv}^j + E_t^g$) at time slot t does not exceed its upper limit ($S_{\max}$), while (23) restricts the total discharging amount in j at t (k_t^j) by its upper bound ($k_{\max}^j$). Equation (24) imposes per slot minimum and maximum capacity constraints ($E_{t,\min}^{j,s}$ and $E_{t,\max}^{j,s}$) on the current energy state of the battery ($E_t^{j,s}$). The current energy state of the battery system is computed as

$$E_{t+1}^{j,s} = \alpha_t E_t^{j,s} + \eta_t^{(+)} \left(E_{t,pv}^j + E_t^g \right) - \eta_t^{(-)} \left(k_t^j \right) \tag{25}$$

in (25) α_t, $\eta_t^{(+)}$, and $\eta_t^{(-)}$ signify decay rate in the battery, the efficiencies of charging and discharging activities, respectively.

Let $a_t^{(+)} \triangleq \{1, \text{if } E_{t,pv}^j + E_t^g > 0; 0, \text{otherwise}\}$ specify whether an event charging occurred ($a_t^{(+)} = 1$) or not ($a_t^{(+)} = 0$). Likewise, $a_t^{(-)} \triangleq \{1, \text{if } k_t^j > 0; 0, \text{otherwise}\}$ is considered for a discharging event. In this regard, charging and discharging events lead to degradation cost in the battery, indicated by $c_t^{(+)}$ and $c_t^{(-)}$, respectively. Based on a thorough analysis in [29], [30], [31], [32], and [33], the battery degradation costs at t can be formulated as follows:

$$c_t^{j,(+)} = \frac{h_r}{h_t} \left\{ \left(\frac{E_{pv}^{r,j} + E_r^g}{E_{t,pv} + E_t^g} \right)^{w_0} \times \exp^{w_1 \left(\frac{E_{t,pv} + E_t^g}{E_{pv}^{r,j} + E_r^g} - 1 \right)} \right\} \tag{26}$$

$$c_t^{j,(-)} = \frac{h_r}{h_t} \left\{ \left(\frac{k_r}{k_t{}^j} \right)^{w_2} \times \exp^{w_3 \left(\frac{k_t{}^j}{k_r} - 1 \right)} \right\}. \tag{27}$$

In (26) and (27), $c_t^{j,(+)}, c_t^{j,(-)}$ represent battery degradation cost occur due to its charging and discharging activities in a smart home j. It can be noted that the lifetime of the battery storage system depends on fast variation of charging (i.e., $E_{t,pv}^{r,j} + E_t^g$) and discharging (k_t^j) activities, however, if charging and discharging are kept at their rated values then the lifetime of the storage battery is affected by current variations corresponding to their rated values. Therefore, based on (26) and (27), the degradation cost of a the battery in a smart home j at t is given in the following, its average is computed over T_0 as:

$$K_t^{j,s} = a_t^{(+)} c_t^{j,(+)} + a_t^{(-)} c_t^{j,(-)}, \quad a_t^{(+)} + a_t^{(-)} \leq 1 \tag{28}$$

$$\overline{K}_{T_0}^{M,s} = \frac{1}{M} \sum_{j=1}^{M} \sum_{t=0}^{T_0 - 1} K_t^{j,s}. \tag{29}$$

The objective here is to minimize the average battery degradation cost in (29).

From the above discussions, it is clear that minimizing (30) is a joint stochastic optimization problem between the three considered system costs. And solving this problem through traditional mathematical optimization techniques is computationally expensive and required high assessment [16], [17], [18]. Therefore, in the next section, heuristic optimization techniques are adopted to solve the joint stochastic optimization problem of (30).

III. Problem Formulation

Let $\theta_t \triangleq \left[E_t^g, E_{t,pv}^c, E_{t,pv}^r, k_t^j \right]$ be an energy flow vector and control actions for smart homes at time slot t. The aim here is to minimize an average aggregated system cost which consists of the following parts:

1) the energy packet transactions cost (selling and buying) with the P-ESP ($\overline{K}_{T_0}^{M,tx}$);
2) household load scheduling delays cost ($K_d(\overline{d}_{T_0}^{M,N})$);
3) energy storage battery degradation cost ($\overline{K}_{T_0}^{M,s}$).

Our aim is to find an optimal policy $\{\theta_{T_0}, d_{T_0}^{M,N}\}$, while minimizing the average system cost. Thus, the problem can be formulated as

$$\underset{\{\theta_{T_0}, d_{T_0}^{M,N}\}}{\text{minimize:}} \quad K_d \left(\overline{d}_{T_0}^{M,N} \right) + \overline{K}_{T_0}^{M,tx} + \overline{K}_{T_0}^{M,s} \tag{30}$$

where $d_t^{j,i} \triangleq \left[d_t^{1,1}, d_t^{2,2}, \ldots, d_t^{M,N} \right]$, and $K_d \left(\overline{d}_{T_0}^{M,N} \right) \triangleq \left[K_d \left(\overline{d}_{T_0}^{1,1} \right), K_d \left(\overline{d}_{T_0}^{2,2} \right), \ldots, K_d \left(\overline{d}_{T_0}^{M,N} \right) \right]$. The cost function in (30) and the formulated constraints in (6)–(24) are related to energy scheduling, energy procurement, and energy control as discussed in the previous Sections II-A and II-D. Clearly, the optimization problem in (30) is a joint stochastic optimization problem between the three considered system costs. This joint scheduling makes the problem difficult to solve by traditional mathematical optimization techniques [12], [13], [14]. Therefore, in the next section, heuristic optimization techniques are adopted to solve the joint stochastic optimization problem of (30).

IV. Optimization Techniques

Heuristic optimization techniques are generally employed to solve scheduling problems due to their ability to solve high dimensional and complex problems with fast convergence, ease in implementation, and local optima avoidance capabilities [20], [21], [22], [23]. Thus, we employ the following well-known heuristic algorithms: GA, BPSO [34], DE, and HSA [35] methods. These algorithms are briefly discussed in the following.

A. Genetic Algorithm

The GA [35] is employed to solve the joint optimization problem in (30) through the following steps.

1) Population generation: Initialize a set of random population ($\mathrm{P_0}$) such that $\mathrm{X_a} \in \{1 \text{ if } \mathrm{P_0(a)} > 0.5, \text{otherwise } 0\}$. The individuals in $\mathrm{P_0}$ are binary coded $\mathrm{X_{ab}}, \mathrm{b} \in [1, \mathrm{k}]$ where k is a dimensional vector denoting the operation of load as ON and OFF states. The algorithm parameters; $\mathrm{P_0}$, crossover, mutation types (C_{bt}, M_{bt}), and probabilities (P_c, P_m), respectively, where bt is the set of positive integers.

2) System inputs: Obtain the input values of $P_{T_0}^{M,L}, d_t^{j,i}, E_t^g, E_{t,pv}^j, E_t^{j,s}, P_t$ and set upper and lower bounds according to Section II.

3) Evaluation: Calculate $K_d(\overline{d}_{T_0}^{M,N}), \overline{K}_{T_0}^{M,tx}$, and $\overline{K}_{T_0}^{M,s}$ with the given constraints (2), (4), (6)–(10), (13), (16), (18)–(24).

4) Updating P_0: The set of individuals in P_0 are modified and go through crossover and mutation with a probability range between 0 and 1. In each iteration, *stochastic operators* are applied (until *generations* reach a preset number) to achieve optimal solutions and minimize (30).

B. Binary Particle Swarm Optimization

The joint optimization problem in (30) is solved via the BPSO [35] algorithm through the following steps.

1) Population generation: Initialize the swarm (S_0) in a pair ($\overrightarrow{ps_r}, \overrightarrow{v_r}$) using (31). The algorithm parameters are set, including maximum and minimum velocities of the particles, normal distribution between 0 and 1. The position ps_r of the particle r is computed as

$$\overrightarrow{ps_r}(t) = \overrightarrow{ps_r}(t-1) + \overrightarrow{v_r}(t) \tag{31}$$

where $\overrightarrow{ps_r}, \overrightarrow{v_r} \in \mathrm{R}^{\mathrm{n}}$ represent position and velocity of the particles and $\overrightarrow{ps_r}(t-1)$ is the prior position of the particle in S_0.

2) System inputs: Obtain the required input values as mentioned in Section IV-A with upper and lower bounds according to Section II.

3) Evaluation: Calculate $K_d(\overline{d}_{T_0}^{M,N})$, $\overline{K}_{T_0}^{M,tx}$, and $\overline{K}_{T_0}^{M,s}$ with the given constraints (2), (4), (6)–(10), (13), (16), (18)–(24). The particles in this evaluation are named as p_{best}.

4) Updating S_0: For the optimal values of S_0, the search space is refined/altered according to

$$\overrightarrow{v_r}(t) = \overrightarrow{v_r}(t-1) + \alpha_1 \mathrm{rand}_1 \left(p_r - \overrightarrow{ps_r}(t-1)\right) + \cdots$$
$$\alpha_2 \mathrm{rand}_2 \left(p_g - \overrightarrow{ps_r}(t-1)\right) \tag{32}$$

$$\overrightarrow{v_r}(t) = \begin{cases} \overrightarrow{v_r}_{\max} & \text{if } \overrightarrow{v_r} > \overrightarrow{v_r}_{\max} \\ \overrightarrow{v_r}_{\min} & \text{if } \overrightarrow{v_r} < \overrightarrow{v_r}_{\min} \end{cases} \tag{33}$$

where $\alpha_1.\mathrm{rand}_1$ and $\alpha_2.\mathrm{rand}_2$ are random weights for p_r (local) and p_g (global) positions of the particles, respectively. In (33) $\overrightarrow{v_r}_{max}$ and $\overrightarrow{v_r}_{\min}$ signify the maximum and minimum velocities of particle r at random point, respectively. It is to be observed that $\overrightarrow{ps_r}$ is constrained between [0, 1]. The updated particles in S_0 are further tested in the *evaluation* step to achieve best values (until *generations* reach a preset number).

C. Differential Evolution Algorithm

The joint optimization problem in (30) is solved through the DE algorithm [36] involving the steps given below.

1) Population generation: Initial population $\mathrm{P}_1 \in \mathrm{R}^{\mathrm{n}}$ is obtained from (34) with p_e^U, p_e^L being the upper and lower bounds of P_1, respectively, where $\mathrm{rand_i}$ is a uniformly distributed random number between 0 and 1.

$$\mathrm{P}_1 = p_e^L + \mathrm{rand_i}(p_e^U - p_e^L). \tag{34}$$

2) System inputs: Obtain the required input values as mentioned in Section IV-A with upper and lower bounds according to Section II.

3) Evaluation: Calculate $K_d\left(\overline{d}_{T_0}^{M,N}\right)$, $\overline{K}_{T_0}^{M,tx}$, and $\overline{K}_{T_0}^{M,s}$ while respecting the constraints given in (2), (4), (6)–(10), (13), (16), and (18)–(24).

4) Updating P_1: P_1 is updated through mutation process using (35) and new trial vector $\mathrm{T_v}$ is obtained by crossover using (36)

$$M_{de} = v_{r1} + F(v_{r2} - v_{r3}) \tag{35}$$

$$\mathrm{T_v} = \begin{cases} M_{de} & \text{if rand}(j) \leq \mathrm{c}r \\ \mathrm{P}_1 & \text{if rand}(j) > \mathrm{c}r \end{cases} \tag{36}$$

where F in (35) is a constant between [0, 1], v_{r1}, v_{r2}, and v_{r3} are the vectors (randomly) chosen from P_1 and $r1, r2, r3$ are positive integers $\in \{1, 2, 3, 4 \ldots n\}$. Through crossover (cr), new trial vector is generated as per (36). The updated individuals in P_1 are further tested in the *evaluation* step to achieve the best individuals until *generation* reaches a preset number.

D. Harmony Search Algorithm

The joint optimization problem in (30) is solved through the HSA algorithm [35] implemented via the following steps.

1) Population generation: Initialize harmony memory (HM) size and other parameters of the algorithm; such as HM consideration rate (HMc), pitch adjustment ratio (Pa), minimum and maximum bandwidth ($b_{\min}, b_{\max}$)

2) Inputs: Obtain the required input values as mentioned in Section IV-A with upper and lower bounds according to Section II.

3) Evaluation: Calculate $K_d\left(\overline{d}_{T_0}^{M,N}\right)$, $\overline{K}_{T_0}^{M,tx}$, and $\overline{K}_{T_0}^{M,s}$ while respecting the constraints given in (2), (4), (6)–(10), (13), (16), and (18)–(24).

4) Updating HM size: The individuals in HM are updated based on (37). The new harmony is further diversified using Pa as per (38)

$$HM = \begin{cases} HM \in HM_{old} & \text{with } P(HMc) \\ HM \in HM_{new} & \text{with } P(HMc - 1) \end{cases} \tag{37}$$

$$HM = \begin{cases} Yes & \text{with } P(Pa) \\ No & \text{with } P(1 - Pa). \end{cases} \tag{38}$$

In each iteration, HSA operators $P(HMc)$ and $P(Pa)$ are applied to HM to strive for optimal solutions until *generations* reach a preset number.

V. Results and Discussion

In this section, we present simulation results of the designed ER-PEM system model based on the selected four HOMs: GA, BPSO, DE, and HSA. We benchmark the performance of HOMs based on energy scheduling parameters (i.e., energy balance, average transactions, average delay, and average system cost cost) in varying seasons and under different values of HOMs' hyperparameters.

For simulations purpose, we assume $M = 10$ smart homes with the same energy profiles for a finite scheduling horizon of 24 hours (starting from 1:00 A.M. to the next day at 1 A.M.) [37]. Further, PV energy is generated randomly varying over T_0 and I_{ir} with $\overline{E}_{t,pv}^{\max} = 8$ kWh for summer season, $\overline{E}_{t,pv}^{\max} = 5$ kWh for spring season, and $\overline{E}_{t,pv}^{\max} = 3$kWh for winter with η_{pv}=18%. An energy storage system of $\overline{E}_{t,\max}^{s} = 5$kWh with $\alpha_t = 0.8$ and $\eta_t^{(+)} = \eta_t^{(-)} = 0.7$ is considered. Data related to

TABLE II
SELECTED VALUES OF HYPERPARAMETERS

HOMs	Hyper-paramters	Selection I	Selection II	Selection III	Selection IV
GA	C_{bt}	1	2	3	4
	M_{bt}	1	2	3	4
	P_c,P_m	[0.9, 0.1]	[0.8, 0.2]	[0.7,0.5]	[0.5,0.4]
BPSO	$\overrightarrow{v_r}_{\max}, \overrightarrow{v_r}_{\min}$	[4,-4]	[6,-6]	[8,-8]	[10, -10]
	$\alpha_1 = \alpha_2$	1	3	3	5
	$\overrightarrow{v_r}$	2	3	4	8
DE	F	0.7	0.8	0.9	0.5
	P_{ce}	0.9	0.8	0.7	0.5
	$p_e^{L,u}$	[30, 100]	[60, 150]	[70, 200]	[100, 300]
HSA	HMc	0.9	0.8	0.7	0.5
	$Pa_{\min,\max}$	[0.01, 1]	[0.05, 1]	[0.5, 1]	[0.05, 1]
	$b_{\min,\max}$	[0.001, 1]	[0.002, 1]	[0.004, 1]	[0.02, 1]

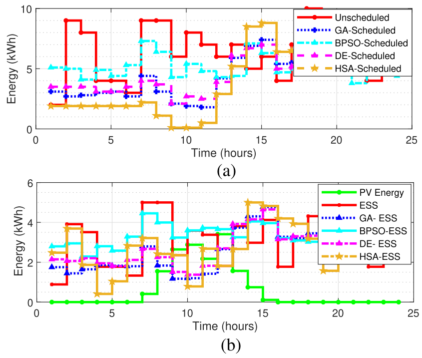


Fig. 3. Unscheduled case versus selected optimization algorithms. (a) Demand and supply balance and (b) energy storage system balance.

solar irradiance and temperature is obtained from the Finnish Meteorological Institute (FMI) [38]. We consider that smart home users can buy or sell their energy packets from or to the utility with $H^{buy}_{t,\min} = 0.6$ cents/kWh, $H^{buy}_{t,\max} = 3.7$ cents/kWh, $H^{sell}_{t,\min} = 0.06$ cents/kWh and $H^{sell}_{t,\min} = 0.57$ cents/kWh [39]. We also consider following sets of hyperparameters:

1) selection of C_{bt}, M_{bt}, P_c, P_m for GA;
2) selection of $\overrightarrow{v_i}_{max}, \overrightarrow{v_i}_{in}, \alpha_1, \alpha_2, \overrightarrow{v_i}$ for BPSO;
3) selection of F, P_{ce}, p_e^L, p_e^u for DE;
4) selection of $HMc, Pa_{\min}, Pa_{\max}, b_{\min}, b_{\max}$ for HSA.

The HOMs are analyzed under varied selection sets of their respective values of hyperparameters as given in Table II. We run our simulation using MATLAB scripts (version R2018b) on a 2.5-GHz PC with 32 GB RAM.

Fig. 3 shows energy balance results for the unscheduled case against the selected HOMs (i.e., GA, BPSO, DE, and HSA). It is clear from Fig. 3 that energy demand of smart homes is met from the on-site renewable resources and external power grid. It can be seen from Fig. 3 that PV energy is insufficient to meet the energy demand of smart homes, however, it is used efficiently by HOMs. Whenever possible, the smart homes procure energy at low prices from the utility grid to meet their energy demand. It can be further noted from Fig. 3 that the selected HOMs schedule the demand of smart homes efficiently while respecting system constraints as discussed in Sections II and III.

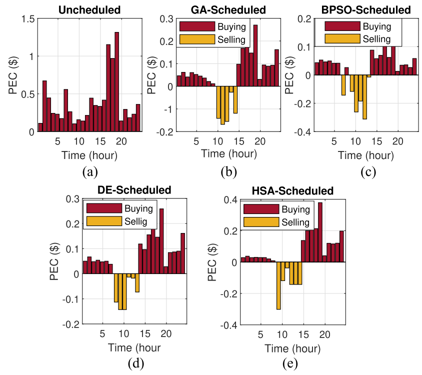


Fig. 4. Average energy transactions between users and P-ESP.

Fig. 4 depicts relative performance of the selected HOMs against the unscheduled case in terms of the PEC involving selling of energy packets to and buying of energy packets from the P-ESP over T_0. In the unscheduled case [see Fig. 4(a)], energy packet transactions are unidirectional only, i.e., E_t's are bought by smart home customers at 2.30$for $E_{t,\max}$. By contrast, the heuristic algorithms [see Fig. 4(b)–(e)] carry bidirectional energy packet transactions among smart home customers and the P-ESP. Fig 4 reflects that the HOMs are efficient to balance the energy demand of smart homes as well as empower the smart home customers to sell surplus energy. Particularly, smart home customers buy energy during 1–5 A.M. When the available PV generated energy exceeds the demand during day time, the surplus energy packets are sold back to the P-ESP.

Quantitatively, the selling costs (in $/slot) for GA, BPSO, DE, and HSA algorithms are 0.61, 1.04, 0.51, and 0.89, respectively. The performance comparison of algorithms shows that the BPSO and HSA utilize the harvested energy from the PV system and energy storage system in a more efficient manner than the GA, and the DE—selling greater amount of energy packets to the P-ESP. This validates that the heuristic optimization algorithms allocate energy resources effectively and facilitate customers to sell back their surplus energy to the utility grid via the P-ESP. Table III illustrates the buying and selling cost of the M smart homes on daily and monthly basis. As mentioned previously, in an unscheduled case, the energy packet transactions are unidirectional and the daily average buying cost is 1.9 $. By contrast, with the inclusion of HOMs, smart home customers are able to sell the surplus energy at an average cost of 0.61, 1,04, 0.51, and 0.89 $ by the GA, BPSO, DE, and HSA, respectively, as shown in Table III. It can be observed from the table that the selling cost of energy packets under various hyperparameters' selection remains constant except for selection IV, where the cost slightly increases by 0.11 ($/slot) for GA, DE, HSA, and 0.6 ($/slot) for BPSO. On the other hand, the procurement cost

TABLE III
AVERAGE ENERGY TRANSACTIONS BETWEEN SMART HOMES AND P-ESP

HOMs	Hyperparamters' selection	P-ESP Energy (buy) ($)	P-ESP Energy (sell) ($)	Daily bill ($)	Monthly bill ($)
Unscheduled	–	1.90	–	1.90	57
GA-Scheduled	I	1.79	0.61	1.18	35.4
	II	1.46	0.61	0.85	25.5
	III	1.55	0.61	0.94	28.2
	IV	1.62	0.72	0.90	27
BPSO-Scheduled	I	1.85	1.04	0.81	24.3
	II	1.53	1.13	0.40	12
	III	1.49	1.13	0.36	10.8
	IV	1.46	1.19	0.27	8.1
DE-Scheduled	I	1.83	0.51	1.32	39.6
	II	1.62	0.51	1.11	33,3
	III	1.65	0.51	1.14	34,2
	IV	1.63	0.61	1.02	30.6
HSA-Scheduled	I	1.99	0.89	1.1	33
	II	1.69	0.89	0.8	24
	III	1.66	0.89	0.77	23.1
	IV	1.64	0.91	0.73	21.9

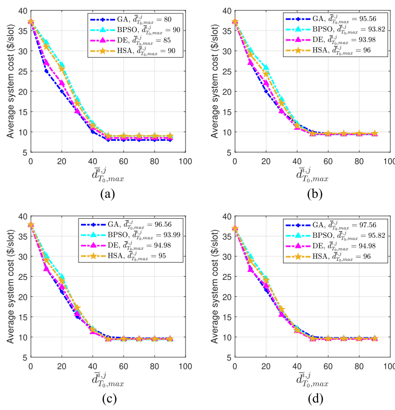


Fig. 5. Performance of HOMs under the hyperparameters' selection I–IV (a)–(d): average system cost vs $\overline{d}^{j,i}_{T_0,\max}$ $\forall\, i, j \in [N, M]$.

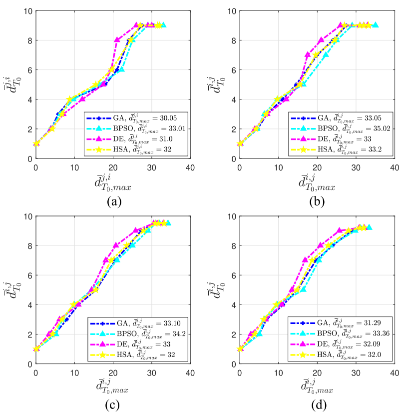


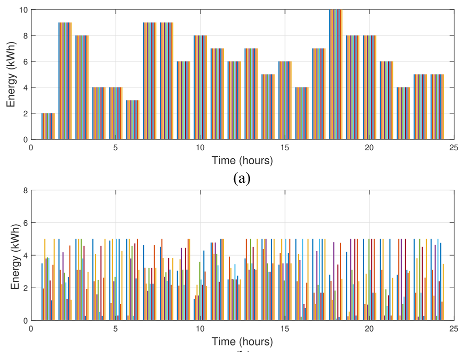
Fig. 6. Delay performance of HOMs under the hyperparameters' selection I–IV (a)–(d): $\overline{d}^{j,i}_{T_0}$ vs $\overline{d}^{j,i}_{T_0,\max}$ $\forall\, i, j \in [N, M]$.

of energy packets varies with the selection of different values of hyperparameters. Essentially, the inclusion of hyperparameters' selection (I–IV) reflects that HOMs has improved the scheduling process (by selling the energy packets and procuring energy packets at low prices) and reduced the overall PEC of smart home customers.

Fig. 5(a)–(d) show the impact of load scheduling delay of the selected algorithms on the average system cost under the hyperparameters' selection I–IV. The average system cost is calculated as energy procurement cost, scheduling delay cost, and battery degradation cost (as mentioned in Section III). The average system cost can be increased/decreased based on the allowable load scheduling delays, which means relaxing the allowable delay can decrease the average cost of the system and vice versa. This relation is depicted in Fig. 5 as strict scheduling delay of the algorithms results in higher average system cost, whereas when scheduling delay is allowed to relax, the cost of the system is reduced. It is important to note that this tradeoff can help the users to operate scheduling delays at their desired level with respect to the average cost of the system. Similarly, the impact of the hyperparameters' selections (II, III, IV) for the average system cost versus $\overline{d}^{j,i}_{T_0,\max}$ is also shown in Fig. 5(b)–(d). It is evident from Fig. 5(a)–(d) that HOMs follow similar behavior, however, the gap between the performance curves of HOMs is decreasing. Essentially, this means that selection of different hyperparameter values improves the randomization process of HOMs and provides effective solutions to the optimization problems. Fig. 6(a)–(d) depict a performance comparison of $\overline{d}^{j,i}_{T_0}$ vs $\overline{d}^{j,i}_{T_0,\max}$ between HOMs (GA, BPSO, DE, and HSA) based on the hyperparamter selection I–IV. It can be observed in Fig. 6 that average experienced delay $\overline{d}^{j,i}_{T_0}$ by load i in a smart home j increases when the $\overline{d}^{j,i}_{T_0,\max}$ (maximum allowable delay requirement) is relaxed.

TABLE IV
DELAY PERFORMANCE OF THE HOMs

Hyper-parameters	Performance of HOMs against $\overline{d}^{j,i}_{T_0}$ vs $\overline{d}^{j,i}_{T_0,max} \forall\, i,j \in [N,M]$
Selection I	BPSO, $\overline{d}^{j,i}_{T_0,max}$=33.10, HSA, $\overline{d}^{j,i}_{T_0,max}$=32, GA,$\overline{d}^{j,i}_{T_0,max}$=30.05, DE $\overline{d}^{j,i}_{T_0,max}$=31,
Selection II	BPSO, $\overline{d}^{j,i}_{T_0,max}$=35.02, GA,$\overline{d}^{j,i}_{T_0,max}$=33.05, HSA, $\overline{d}^{j,i}_{T_0,max}$=33.2, DE, $\overline{d}^{j,i}_{T_0,max}$=33,
Selection III	BPSO, $\overline{d}^{j,i}_{T_0,max}$=34.2, GA,$\overline{d}^{j,i}_{T_0,max}$=33.10, DE $\overline{d}^{j,i}_{T_0,max}$=33, HSA, $\overline{d}^{j,i}_{T_0,max}$=32
Selection IV	BPSO, $\overline{d}^{j,i}_{T_0,max}$=33.36, DE $\overline{d}^{j,i}_{T_0,max}$=32.09, HSA, $\overline{d}^{j,i}_{T_0,max}$=32 GA, $\overline{d}^{j,i}_{T_0,max}$=31.29



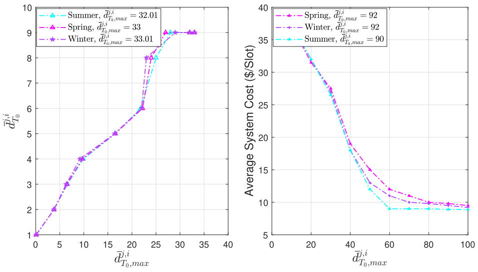
(a)

(b)

Fig. 7. PEM plans for M smart homes. (a) Unscheduled and (b) BPSO-scheduled.

This behavior of $\overline{d}^{j,i}_{T_0}$ against $\overline{d}^{j,i}_{T_0,\max}$ shows sublinear relation for the given algorithms. This means during scheduling process, the operation of the load i can be delayed to obtain flexibility in the average system cost, however, on the other hand, QoS would be compromised. It can also be observed from Fig. 6(a)–(d) that during the scheduling process, BPSO attains $\overline{d}^{j,i}_{T_0,\max}$ and compromises QoS most in comparison to other algorithms which in turn reduces system cost. Note that, in Fig (a)–(c) the HOMs exhibit the same behavior (sublinear), however, the order of the algorithms in terms of $\overline{d}^{j,i}_{T_0,\max}$ has changed due to different set of hyperparameters selection. This reflects that different values of hyperparameters can add flexibility to the scheduling process considering constraints of the scheduling parameters. The order of the algorithms in terms of $\overline{d}^{j,i}_{T_0,\max}$ is presented in the Table IV.

It is worth mentioning that the ER-PEM provides the optimal energy plans for a single home, like HEMS and multiple homes considering the energy-demand requirement as discussed in Section II. Thus, for the sake of simplicity, here, we show the BPSO algorithm to demonstrate the PEM planes for 10 smart homes separately in Fig. 7. Fig. 7(a) and (b) represents the PEM plans for ten smart homes at "t" for an unscheduled case and the BPSO algorithm. It can be observed from Fig. 7(a) that the PEM plans without scheduling are uniform values for smart homes during "t" which consequently generates power peaks in peak hours. In contrast, Fig. 7(b) depicts that the algorithm BPSO tends to provide diverse PEM plans for each smart home in time slot "t" and avoids the peak consumption of energy. Fig. 8(a) and (b) shows the performance of the BPSO algorithm for T_0 during three days: summer–spring–winter in terms of the maximum allowable delay and the average cost of the system. In Fig. 8(a), when the season conditions varied from summer–spring–winter, the value of $\overline{d}^{j,i}_{T_0}$ increases reflecting demanding constraints of energy storage systems due to the increase in imbalance between R_t^{DS}. Next, Fig. 8(b) represents the effect of $\overline{d}^{j,i}_{T_0,\max}$ on the average system cost considering varied season conditions. The tradeoff relation between the average system cost and $\overline{d}^{j,i}_{T_0,\max}$ can be seen, which represents the average system cost can be lowered with the stringent load scheduling delay and vice versa.



(a)

(b)

Fig. 8. Performance of the BPSO in different seasons condition. (a) $\overline{d}^{j,i}_{T_0}$ vs $\overline{d}^{j,i}_{T_0,\max}$. (b) Average system cost versus $\overline{d}^{j,i}_{T_0,\max} \forall\, i,j \in [N,M]$.

VI. CONCLUSION

This article presents an ER-based PEM system for MAs at smart homes in the EI. The goal is to minimize the average aggregated system cost which consists of load scheduling delay cost, energy procurement cost, and battery degradation cost. To achieve the objective, we jointly optimize the energy usage of smart homes, grid-connected PV energy, and energy storage system The ER-PEM solves the joint optimization problem considering the four well-known HOMs: GA, BPSO, DE, and HSA. Through simulations, the selected HOMs are benchmarked in terms of energy scheduling parameters, energy scheduling delays, energy balance, and average system cost parameters. Moreover, the performance of the ER-PEM is also evaluated by considering the impact of the hyperparameters of heuristic techniques and varying weather conditions on ER-PEM system. The results show that the ER-based PEM minimizes the average aggregated system cost and provides effective energy plans for a single smart home and in an energy community of multiple smart homes and varied season conditions. In the future, we aim to investigate the impact of electric vehicles integration on the EI under the assumptions of the proposed model.

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