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An approach towards demand response optimization at the edge in smart energy systems using local clouds

Salman Javed *, Aparajita Tripathy, Jan van Deventer, Hamam Mokayed, Cristina Paniagua, Jerker Delsing

Lulea University of Technology, Sweden

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A B S T R A C T

The fourth and fifth industrial revolutions (Industry 4.0 and Industry 5.0) have driven significant advances in digitalization and integration of advanced technologies, emphasizing the need for sustainable solutions. Smart Energy Systems (SESs) have emerged as crucial tools for addressing climate change, integrating smart grids and smart homes/buildings to improve energy infrastructure. To achieve a robust and sustainable SES, stakeholders must collaborate efficiently through an energy management framework based on the Internet of Things (IoT). Demand Response (DR) is key to balancing energy demands and costs. This research proposes an edge-based automation cloud solution, utilizing Eclipse Arrowhead local clouds, which are based on Service-Oriented Architecture that promotes the integration of stakeholders. This novel solution guarantees secure, low-latency communication among various smart home and industrial IoT technologies. The study also introduces a theoretical framework that employs AI at the edge to create environment profiles for smart buildings, optimizing DR and ensuring human comfort. By focusing on room-level optimization, the research aims to improve the overall efficiency of SESs and foster sustainable energy practices.

1. Introduction

We are currently experiencing an era characterized by widespread digitalization. This extensive digitalization and integration of advanced technologies has led to the emergence of the fourth industrial revolution, which signifies a profound change in the way industries operate. The aim is to create a smart industry and a flexible environment where virtual and physical technologies can interact [1]. This latest transformation marked the beginning of Industry 4.0 (I4.0) in Germany. I4.0 aims to reduce new product time-to-market, improve customer responsiveness, enable custom mass production without increasing production costs, create a more flexible and friendly working environment, and promote the efficient use of natural resources and energy [2]. The progress made in I4.0 has paved the way for the advent of the fifth industrial revolution, known as Industry 5.0 (I5.0), based on three core values: Resilience, Sustainability, and Human Centricity [3]. Furthermore, unlike I4.0, I5.0 strongly emphasizes addressing social fairness and sustainability concerns. It seeks to balance technological advancements and human-centric values, ensuring that the benefits of digitalization and AI technologies are distributed equitably across society [3] .

The dynamic landscape of I4.0 and I5.0 has ushered in numerous innovative applications, among which Smart Energy Systems (SESs) are crucial to climate change mitigation. An SES, by its very definition, represents an intelligent, harmonized amalgamation of smart electricity, thermal, and gas grids, interfaced with cutting-edge storage technologies [4]. This holistic integration creates synergies across different energy systems, creating an ideal energy solution that transcends sector-specific assumptions and improves the energy infrastructure [5]. In the contemporary discourse of Sustainable Development Goals, the growing prominence of 'Green Issues' has been markedly noticeable [6]. The onset of the Fourth Industrial Revolution has highlighted the need of green technology, setting the groundwork for local, sustainable projects that contribute towards buffering the environment against adverse climatic shifts. Noteworthy in this context, the key study of Morelli et al. [7] shows the positive correlation between green activities, smart grids, and IoT-enabled consumer devices like smart meters. Through an aptly constructed secure integration infrastructure, these elements coalesce to construct a robust, sustainable SES. In addition, all stakeholders in SESs, that is, producers, distributors, and consumers, must be able to collaborate continuously and dynamically and respond

* Corresponding author.
E-mail address: salman.javed@ltu.se (S. Javed).

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to changing conditions and energy demands of society. An optimal IoT-based energy management framework can permit a radical exchange of information among stakeholders to reach the energy balance at the minimum cost (i.e., an efficient smart-grid system). This integration can be ensured through efficient management of energy using the concept of Demand Response (DR). DR can be defined as consumers' actions that change their energy consumption (demand) in response to price signals, incentives, or directions from the grid operators [8]. When applied to the paradigm of SES, DR gives customers the opportunity to significantly influence how the SES operates by lowering or adjusting their energy use during peak hours [9–11].

Recent research in DR automation employs technologies such as Service-Oriented Architecture (SOA), Internet of Things (IoT), and global cloud-based technologies [12]. Although SOA-based global cloud solutions are highly scalable, they lack security and privacy and pose high latency issues [13,14]. To address these challenges, an alternative approach known as the "local cloud" has gained prominence [15]. The local cloud refers to a collection of interconnected services and systems that operate within a confined environment (at the Edge), typically within a specific organization, stakeholder, or location [16]. Furthermore, current state-of-the-art approaches lack any mechanism for DR optimization at the edge using local clouds that are based on secure, private, and dynamic cooperation among all stakeholders and sectors of an SES [17]. This research aims to develop a DR solution for SESs that prioritizes total data privacy, security, and low latency. To address this objective, the study seeks to answer the following research questions: 1) How can smart buildings, energy production plants/grids, and energy distribution networks cooperate in optimizing the DR? 2) How to incorporate environmental factors in a room (smallest and discrete closed space or unit of smart home or building) to further optimize the DR?

The primary contribution of this research is to propose an approach to DR optimization in SESs using edge-based automation clouds. We implement SOA-based Eclipse Arrowhead local clouds (LCs) to enable secure integration among all stakeholders involved in SESs. Our solution ensures reliable, safe, and low-latency communication among vendor-independent smart home and industrial IoT technologies. We also propose a theoretical framework that uses AI at the edge and creates environment profiling of each room of smart buildings to further optimize the DR process and ensure human comfort. In this way, we can avoid expensive remote energy sources and heat pumps designed to handle the DR of the whole home or building instead of each room separately.

The remaining sections are as follows: Section 2 provides a review of the literature with specifics on the SESs, DR, and the local cloud-based Arrowhead framework. Section 3 describes the related work and knowledge gaps in the state-of-the-art. Section 4 explains the proposed solution design, including the proposed architecture. Section 5 explains two-stage automation for DR optimization and provides the experimental setup with results. Next, Section 6 discusses the outcomes of this research. Section 7 concludes this research work with future direction. Lastly, Section 8 provides disclosure of ethical values.

2. Background

2.1. Smart energy systems (SESs)

The concept of SESs represents a paradigm shift in the scientific field away from single-sector thinking and toward coherent energy systems that integrate all energy sectors, distribution networks, and infrastructures. The smart energy system comprises three grid infrastructures: 1) Smart Electricity Grids to link flexible electricity needs, such as heat pumps and electric cars, to inflexible renewable supplies, including wind and solar power. 2) Smart Thermal Grids (District Heating and Cooling) to link the power and heating industries. This allows the use of thermal storage to increase the flexibility of the energy system and to recycle heat losses. 3) Smart Gas Grids to link the electrical, heating, and transportation industries. This permits the use of gas storage to increase flexibility. If the gas is processed into liquid fuel, liquid fuel storage facilities can also be used [9]. In the current era of digitalization through Industry 4.0 and 5.0, SESs can be integrated using smart home and industrial Internet of Things (IoT) technologies [18]. The notion is that when each subsector is coupled with the other sectors through IoT technologies, the most efficient and cost-effective solutions can be developed.

2.2. Demand Side Management and response in SESs

Demand Side Management (DSM) pertains to the proactive management and regulation of energy use at the consumer level with the aim of enhancing energy efficiency and mitigating peak demand [19]. The fundamental objective of DSM is to focus on long-term energy management and encourage energy-efficient practices, technologies, and behavioral changes among consumers and businesses. DR is a specific component of DSM that focuses on the short-term, temporary reduction or shift in energy usage by consumers in response to signals from the grid operator, energy provider, or demand response programs. It is more concerned with managing energy demand during critical peak periods or in response to sudden grid stability issues. The primary goal of DR is to manage and balance energy demand and supply in real-time or during specific events by engaging consumers to alter their energy consumption patterns promptly.

DR programs are basically divided into two categories: incentive-based DR and price-based DR [20]. We have used the priced-based DR techniques in our solution, as explained in Section 5.1. The application areas for DR are diverse and are tailored to suit various types of consumers, such as; residential, commercial, and industrial [21]. In the residential sector, consumers can adjust their HVAC systems and participate in utility-sponsored DR programs. The commercial sector can optimize lighting and HVAC in office buildings and retail stores, while industrial facilities can reduce non-essential production and implement process optimization. Overall, DR plays a vital role in balancing energy supply and demand, enhancing grid stability, and promoting energy efficiency across diverse application areas.

2.3. Arrowhead framework local clouds

The European Arrowhead project started the Eclipse Arrowhead framework, which facilitates the automation and digitalization of the Internet of Things through the use of open-source integration solutions [22]. It is based on SOA, as illustrated in Fig. 3. Key design principles include service composability and abstraction, dynamicity, autonomy, loose coupling, late binding, and standardization of service contracts [15]. Its appeal in the present case is that a local cloud can represent each smart energy system and consumer (smart home, smart building, smart grid, etc.). The local cloud promotes the manageability of the systems, its cybersecurity, total data privacy, scalability, and low latency within the cloud. The framework allows for automation at the edge, based on the notion of self-contained, automated, and autonomous LC. An LC at the edge contains three mandatory core systems: Service Registry (SR), Authorization, and Orchestrator, as well as many supporting systems: Data Manager, Event Handler, Gateway, Gatekeeper, etc. [23]. These core systems offer governance and connectivity amongst services, constituting the base of LC automation. In addition, application systems are defined by users based on their needs. These application systems may carry out activities by registering their particular services with the core systems. The framework is Industry 4.0/5.0 standardized and is fully interoperable with industrial IoT protocols such as RESTfull, OPC-UA, ROS, ModBus, CoAP, MQTT, and smart home IoT protocols such as Z-Way [16,18,24,25].

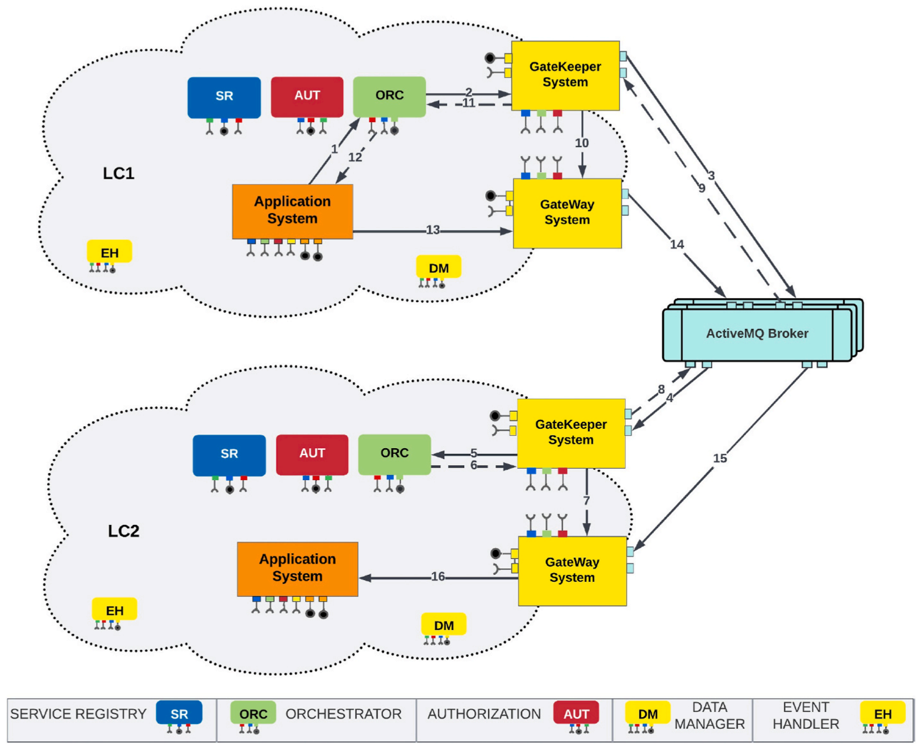

Fig. 1. Overview of the fully-fledged inter-cloud orchestration process.

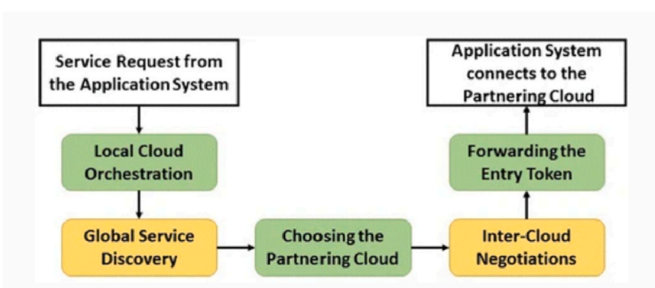

Fig. 2. Inter-Cloud consumer–provider relationship referred from [27].

2.3.1. Basic service exchange flow within a local cloud

The process of basic service exchange begins with the provider system registering all its available ser-vices into the service registry system of the LC. Subsequently, the consumer system initiates a request to the orchestrator, seeking the desired service. The orchestrator plays a pivotal role by verifying the availability of the requested service in the SR system. Additionally, it queries the Authorization system to ascertain whether the consumer possesses the necessary authorization for the service exchange. Upon successful verification, the orchestrator provides the consumer with the service endpoints. These endpoints serve as the communication links that enable the consumer to send service requests to the provider system. The consumer can now directly interact with the provider system and access the requested services through this orchestrated approach.

2.3.2. Inter-cloud service discovery and exchange

The Arrowhead Framework facilitates inter-cloud service exchange between stakeholders residing in different LCs through the utilization of the Gatekeeper, Gateway, and Relay (ActiveMQ broker) systems [26]. The Gatekeeper offers two services; the Global Service Discovery (GSD) and Inter-Cloud Negotiation (ICN) process, which aims to locate adequate service offerings in neighboring (accessible) LCs [27]. The basic inter-cloud communication process is depicted in Fig. 2. A detailed explanation of the inter-cloud process is also available on the Arrowhead GitHub repository [1].

Fig. 1 is presented here in order to offer a step-by-step description of the procedure. It represents the inter-cloud communication that takes place between two LCs.

- The inter-cloud process starts with the Orchestrator from LC1 requesting the Gatekeeper from LC1 on behalf of the service consumer by consuming the GSD service.

- The Gatekeeper from LC1 collects the preferred or neighbor LC and the Relay information.
- Then the Gatekeeper from LC1 queries the Gatekeeper from LC2 via the Relay to verify if they could facilitate this request or not and sends the response to the Orchestrator from LC1.
- The Orchestrator from LC1 evaluates the GSD response, chooses a partnering cloud and invokes the ICNInit service from its own Gatekeeper.
- Then the Gatekeeper from LC1 consumes the LC2 Gatekeeper's ICN Proposal service via the Relay.
- The Gatekeeper from LC2 validates the Authorization Control and requests Orchestration from the Orchestrator of LC2.
- The Orchestrator from LC2 then sends a response to the Gatekeeper from LC2, which in turn sends a response to the Gatekeeper from LC1, which ultimately sends a response to the Orchestrator from LC1.
- During the ICN process, both the Gatekeepers invoke the "ConnectToProvider" and "ConnectToCon-sumer" services from their respective Gateways. This leads to creating a secured datapath between the consumer and provider systems via the Relay system.

3. Related work and knowledge gap

Automated DR is an important objective for the next generation of SES in the fourth industrial revolution era. Much research has focused on the DR of each individual sector of SESs rather than the DR in SESs as a whole. Mathiesen et al. emphasize the need for a comprehensive approach to 100% renewable energy and transport solutions by integrating smart electrical, thermal, and gas infrastructures [28]. The authors suggest that an SES design can ensure sustainable 100% renewable energy systems. Furthermore, IndustryPLAN and its guiding principles provide a vision to combine smart heating and electricity grids to create economically viable and fuel-efficient renewable energy scenarios [29]. The solution proposed in this work provides a local cloud-based ICT framework to implement and enable the vision of EnergyPLAN [28] and IndustryPLAN [29].

Recent approaches that use DR in IoT-enabled SESs are shown in Table 1. For a comparison study and knowledge gap analysis, in the table, we also list a set of paradigms that should be addressed by any IoT solution to build a fully automated intelligent DR system for SES [21]. Although all of the studies cited in Table 1 have provided successful solutions, they have constrained the scope or provided limited services. Yaghmaee et al. argue that achieving higher DR performance incurs a higher communication cost [14]. Therefore, the DR approaches presented in the table that use centralized global-cloud-based solutions may not be efficient, secure, and cost-effective. All provide flexibility and dynamic operation, but none of them provide the distributed data and control mechanisms of local clouds while ensuring important IoT properties such as system authentication, service authorization, and data privacy. The majority of the solutions available are proprietary and lack open-source accessibility. Furthermore, they have very limited or no integration between smart homes and industrial IoT technologies. Most of the solutions also lack focus on the I5.0 core values.

4. Proposed solution design

To address the challenges listed in Section 1 and the knowledge gap in Section 3, we propose a two-stage automation solution using local cloud-based automation and AI at edge-based environment profiling. Our solution is built on a value-driven, decentralized, and automated approach to DR optimization using edge AI-based environment profiling. Our proposed approach adheres to the core values of I5.0: a) resilience,b) sustainability, and c) human-centricity. We suggest that every stakeholder involved in the energy supply chain life cycle, including SES subsectors, distribution networks, and consumers, has its own secure local cloud.

Table 1

DR solutions built for the IoT-enabled SES. Each row is a parameter under investigation [21]. We reffer DIST:DISTRIBUTED, CENT:CENTRALIZED, H-APP:HOME APPLIANCES I-APP:INDUSTRIAL APPLIANCES.

Paradigms		Selected References in Literature following Demand Response in Smart Energy Systems													
		Proposed Solution	2021 [30]	2023 [31]	2023 [32]	2022 [33]	2022 [34]	2023 [35]	2023 [36]	2023 [37]	2021 [12]	2023 [38]	2020 [39]	2021 [40]	2022 [41]
Cloud Framework		✓	×	✓	✓	✓	×	✓	×	✓	✓	×	×	✓	✓
SES Scalability		✓	×	✓	✓	✓	×	✓	✓	✓	✓	✓	×	×	✓
Open Source		✓	×	×	×	×	×	×	×	✓	✓	×	×	×	×
Data Distribution & Control Mechanism		Dist	Dist	Cent	Dist	Cent	Cent	Cent	Dist	Dist	Cent	Dist	Cent	Cent	Cent
Security Focus	System Authen-tication	✓	×	✓	×	✓	×	×	×	×	✓	×	×	×	×
	Service Author-ization	✓	×	×	×	✓	×	×	×	×	✓	×	×	×	×
	Data Privacy	✓	×	✓	✓	✓	×	×	×	✓	✓	×	×	×	×
Dynamic Operation		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Technology Integration		Zwave, Modbus, OPC UA /OPC, ROS	–	ZigBee	–	OPC	–	–	–	–	–	–	–	–	–
Flexibility		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Stakeholders Interoperability		✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	×	×	✓
Communication Protocols		HTTPS, CoAP, MQTT, Z-Wave, ZigBee, OPC UA	–	HTTP, ZigBee, WI-FI	–	OPC	–	HTTP, MQTT	–	MQTT	HTTP, MQTT	–	–	–	–
DR Application Use-Cases		HVAC	HVAC, H-App	HVAC, H-App	HVAC, H-App	I-App	HVAC, H-App	HVAC	H-App	HVAC	HVAC, H-App	HVAC, H-App	HVAC	HVAC	HVAC
Real system implementation		✓	×	✓	×	✓	×	✓	×	✓	✓	×	×	×	✓
Simulation-based implementation		×	✓	×	✓	×	✓	×	✓	×	×	✓	✓	✓	×
Focus on Forward Compatibility to Industry 5.0		✓	×	✓	×	×	×	×	×	×	×	×	×	×	×
Proposed/ Implemented AI/ML Solution		✓	×	×	✓	✓	✓	×	×	✓	×	✓	✓	✓	×
Real-time		✓	✓	✓	✓	✓	×	✓	×	✓	✓	✓	✓	×	×

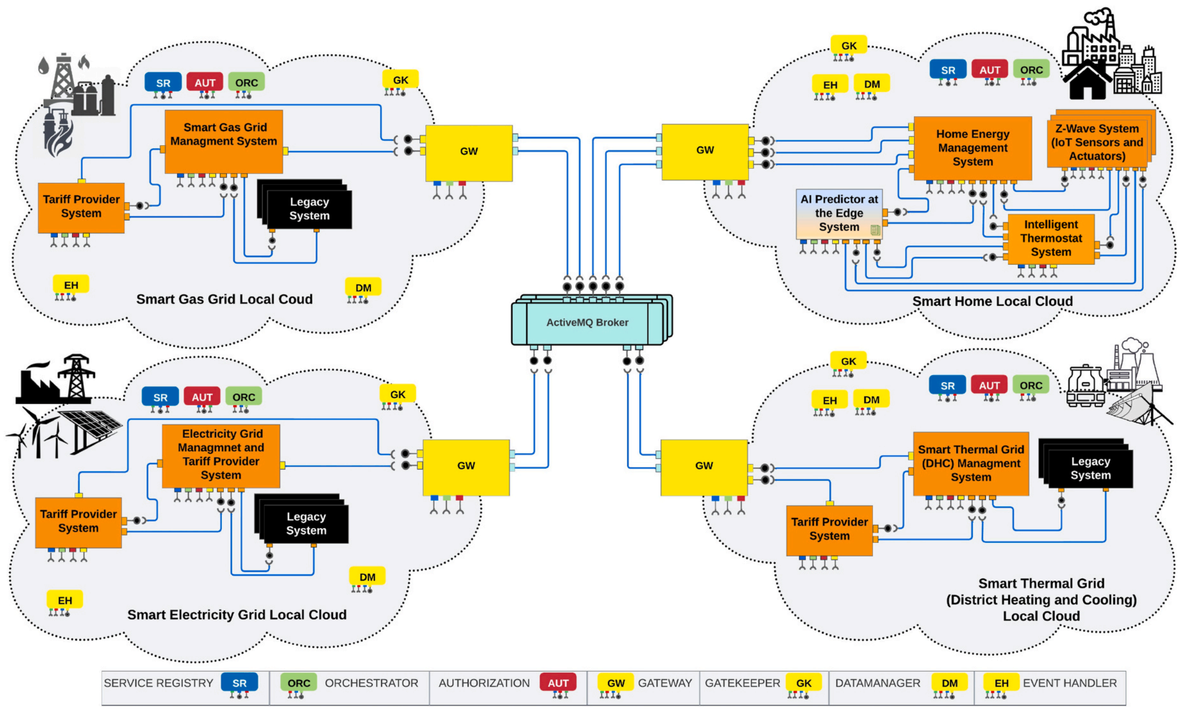

Fig. 3. The systems using Eclipse Arrowhead Local Cloud and Application Systems for the demonstration experiment.

We have selected the local cloud-based Eclipse Arrowhead framework as it is compatible with the industrial and smart home IoT domains [18]. Although the framework integrates various industrial and smart home IoT protocols and technologies, any legacy systems can communicate with the framework through the REST/MQTT APIs. Hence, the framework ensures seamless deployment and integration with any existing legacy SES sectors. The distributed local cloud-based architecture of the framework ensures total data privacy, as all data is stored in the local cloud at the edge. The use of the Arrowhead framework to realize our solution makes the ecosystem resilient by design, as the framework already provides service-level composability and authorization, dynamic orchestration, and access control, which are required for a resilient system operation.

4.1. *Proposed architecture*

The proposed solution consists of a fully integrated and cooperative Smart Thermal Grid Local Cloud, Smart Electricity Grid Local Cloud, Smart Gas Grid Local Cloud, and Smart Home and Building Local Cloud, as shown in Fig. 3. For simplicity, we have shown only four local clouds, whereas every stakeholder involved in the DR has its own local cloud with all the mandatory and supporting core systems. The proposed architecture uses Arrowhead inter-cloud communication between various sectors and subsectors of an SES and Smart Homes and Buildings local clouds. Every local cloud of an SES sector has a Tariff Provider application system that offers a service to supply the hourly price of energy produced by that sector.

4.1.1. *Smart Thermal Grid Local Cloud*

The purpose of this local cloud is to provide district heating/cooling tariffs to smart homes/buildings energy management systems as shown in Fig. 3.

4.1.2. *Smart Electricity Grid local cloud*

This local cloud integrates the electricity grid with the rest of the stakeholders of an SES. It provides energy tariffs to smart home/building energy management systems as shown in Fig. 3.

4.1.3. *Smart Gas Grid Local Cloud*

The objective of this local cloud is to integrate the gas grid with all stakeholders in an SES. We propose integrating Arrowhead-compliant gas grid management and tariffs application systems to ensure real-time cooperation within an SES, which can assist in efficient energy conversion from heat/electric to gas and visa versa.

4.1.4. *Smart home local cloud*

The purpose of this local cloud is to integrate a smart home or a building with all the stakeholders of an SES. The Arrowhead framework already supports the integration of building IoT devices, such as Z-Wave thermostat valves and energy plugs [18]. This ensures efficient management of energy systems, which can lead to a significant reduction in energy wastage. Additionally, it promotes sustainability by supporting environmental preservation and pursuing zero net emissions. The SmartHome cloud provides engineering redundancy and has several application systems: a Home Energy Management System (HEMS) that keeps the current prices from all the energy sources; an Intelligent Thermostat System (ITS) that sets the thermostat setpoint of the hydronic and auxiliary electric heating and cooling devices; a Z-Wave System to integrate the IoT enabled and Z-Way protocol-based actuators such as thermostat valves, energy plugs, etc. and sensors such as temperature, humidity, PIR, dewpoint, light, sound, CO2, etc.; and an AI Predictor at the Edge System that predicts setpoints based on room-based environment profiles.

The desired setpoint of each room is derived based on several inputs from the consumer end, including the upper and lower thresholds for acceptable indoor temperatures (Tmax and Tmin) as well as the range of maximum and minimum energy prices (Pmax and Pmin). The consumer selects a desired indoor temperature of Tmax provided that the associated price does not exceed or equal to Pmin. The consumer's minimum tolerable temperature is Tmin, and that is only if the energy price reaches or exceeds Pmax. According to Van et al. [42], when the price falls between the range of Pmin and Pmax, it is recommended to determine the interior temperature by interpolation of these two points. Ensuring customer comfort is of paramount importance, establishing a correlation between energy pricing and indoor comfort.

5. Two-stage automation of space heating DR optimization

In this section, we present a two-stage approach to automated DR optimization that uses the local cloud-based Arrowhead framework. We have implemented Stage 1 for local cloud-based automation and optimization of DR, and the results are discussed in Section 5.1.1. We employ the Arrowhead framework for intra- and inter-cloud communication within a smart home/building and among all the stakeholders of an SES, respectively. Therefore, all stakeholders, including energy producers, distributors, and consumers, collaborate to optimize DR, as shown in Fig. 3. In addition, this paper introduces a theoretical concept to further optimize the DR based on environment profiling using AI at the edge in Stage 2. The current implementation of Stage 1 builds the foundation for the implementation of Stage 2. However, Stage 2 implementation and testing of different AI models, such as (Decision tree, Support Vector Machine a.k.a. SVM, TinyML, Linear Regression, etc.) is out of the scope of this paper and part of future work.

Every IoT-enabled appliance in a smart home/building, such as smart hydronic radiators, smart electric heaters, smart washing machines, smart cooking stoves, smart HVAC, smart air conditioning devices, smart lights, smart charging stations for electric vehicles, etc., participates in energy DR optimization in their respective use case scenarios. However, as a proof of concept, we only discuss the use case of a space heating scenario using a smart hydronic radiator and a smart electric heater for optimizing the DR. The same approach of DR optimization can be applied to any use case scenario that involves an IoT-enabled appliance/device mentioned above and is powered by electric, gas, or thermal energy.

5.1. Stage 1: local cloud-based automation of DR

In a space heating scenario, Stage 1 involves secure inter-cloud cooperation between the smart home local cloud and local clouds of all sectors/subsectors of an SES. Every smart home local cloud has a HEMS that gets the day-ahead prices of all available energy sources through inter-cloud communication, as shown in Fig. 8. The ITS obtains the current energy prices from HEMS and is responsible for setting the thermostat setpoints for each room of the smart home/building. We bring human comfort and energy budget into the loop by incorporating human/consumer input to select the minimum and maximum thresholds for room temperature and energy prices. Therefore, the proposed DR automation approach is human-centric. The ITS calculates the current setpoint based on human-provided thresholds and current energy prices. Then, it sends the calculated setpoint to the appropriate thermostat valve or electric heater via the Z-Wave System. In addition, the ITS and HEMS store all the data in the Arrowhead supporting core system, DataManager. Using the SOA-based Arrowhead framework, we provide service discovery and dynamic orchestration at run time, which ensures resilience, total data privacy, scalability, and security [15,43].

Furthermore, whenever there is a peak in heat demand caused by an external event that suddenly lowers the room temperature below the desired setpoint, as shown in Figs. 8 and 5, the ITS automatically selects an auxiliary smart electric heater to increase the room temperature. The ITS also ensures that the least expensive energy source increases room temperature if multiple renewable energy sources are available. In our use case scenario, where a smart hydronic radiator is the primary source of space heating in a room, ITS will use the auxiliary electric heater until the room temperature reaches the desired setpoint. The proposed approach optimizes DR by significantly reducing peak demand without jeopardizing consumer comfort and burdening energy producers and distribution networks in an SES.

5.1.1. Experimental setup

To demonstrate our DR optimization approach explained in Section 5.1, we performed an experiment for a scenario of space heating within a SmartHome in Luleå, Sweden. We used both district heating and electric heating energy sources simultaneously in a room of a smart home/building, as shown in Fig. 8. We selected Z-Wave as a smart home/building IoT technology for our use case scenario. The selection is based on its apparent dominance in smart home IoT technologies [18].

The hardware used for the experimental setup is shown in Fig. 4. The Smart Home Local Cloud hardware includes: 1) a Raspberry Pi 4: a nano-computer running the Eclipse Arrowhead Framework; 2) a RaZberry: a Z-Wave master controller add-on card for Raspberry Pi 4 that is running Smart Home Local Cloud; 3) a Fibaro Binary Plug: a Z-Wave compatible device to control the ON and OFF switching of the electric heater; 4) a Fibaro TempSensor: to monitor the room temperature; 5) an Electric Heater: an element heater of 2000 W; 6) a Eurotronic Thermostat Valve: a Z-Wave compatible valve to control the setpoint of the hydronic radiator; and 7) a Hydronic Radiator: a hydronic radiator controlled by the Eurotronic thermostat valve. The high level of interoperability among various vendor-independent IoT devices is ensured by the Arrowhead framework.

Another Raspberry PI-4 was used to run the Apache ActiveMQ broker

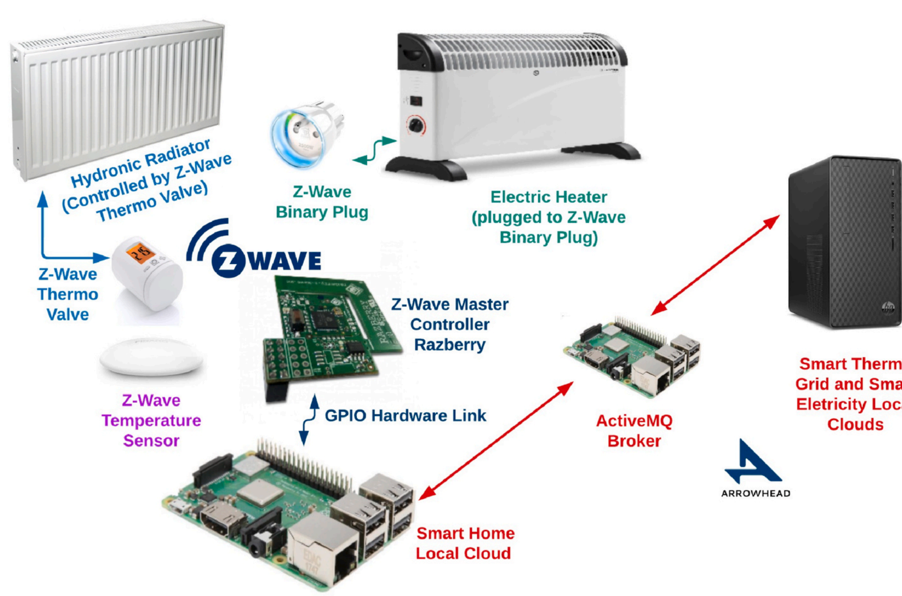

Fig. 4. The Hardware Setup for local cloud-based DR optimization experiment.

system to securely relay all the inter-cloud communication. We used an HP Desktop computer to emulate the Smart Thermal Grid Local Cloud and the Smart Electricity Grid Local Cloud. All local clouds used the Arrowhead framework with mandatory core systems, supporting systems, and our additional application systems, as explained in Section 5.1. The Local Cloud of Smart Electricity Grid uses the Enso-E API to provide the day-ahead prices of electricity [44]. The Smart Thermal Grid used Helen's price data to provide current prices for district heating [45]. Although we carried out experiments in Luleå, Sweden, due to the limitation of resources, we were unable to obtain current prices for the Luleå district heating. Therefore, we used the reference district heating price data from Sweden for the sake of experiments.

5.1.2. Results

To validate our proposed DR optimization approach, we designed an experiment for a space heating scenario in a smart home in Lulea, Sweden. We ran the experiments for seven days as proof of concept. The consumer set the upper and lower thresholds for the energy price at 180 and 70 euros per MWh, respectively. In addition, the consumer sets the limit for the setpoint between 19 and 25° Celsius. Hence, we kept humans in the loop of DR optimization by allowing consumers to set their own comfort level and energy budget. We used Z-Wave sensors for monitoring the indoor temperature, setpoint, energy prices, valve position, and radiator inlet pipe temperature curves. Although the valve position and the radiator inlet pipe temperature are not used for the setpoint calculation, they provide important information on the working performance and monitoring of the hydronic radiator condition.

The plot suggests two main observations. First, for the first day, we used district heating as the sole energy source for space heating, using a hydronic radiator as shown in Fig. 5. We see that when there.

Is a drop in the indoor temperature of the room, and energy prices are lower, the setpoint of the thermostat valve goes to the upper threshold of 25° Celsius. However, we used district heating and electricity as energy sources for the rest of the six days, using a hydronic radiator as the primary source and an electric heater as an auxiliary source of space heating, as shown in Fig. 8. Second, we observed two events during these six days when a window was open in the room that caused a sudden drop in indoor temperature and a peak in energy demand. However, the set point of the thermostat valve of the hydronic radiator remained optimal and was significantly below 25° Celsius. Therefore, we show that using a combination of energy sources can avoid peak demand by using the Arrowhead framework local cloud architecture in a fully secure and dynamic way.

In addition, we can use sensor data for the cloud-based collaborative learning (CCL) based condition monitoring of hydronic radiators and other IoT devices/appliances in a smart home [46]. Furthermore, smart homes/buildings that build local clouds, which are authorized to communicate securely between clouds, can collaborate and learn from each other about condition monitoring, similar to the proposed mechanism for wind turbines in Javed et al. [46]. Hence ensuring resilience and fault tolerance through predictive maintenance and engineering redundancy.

5.2. Stage 2: DR optimization using AI at the edge

In Stage 2, we propose using AI in edge-based environment profiling to optimize DR in a room of a smart home/building. The optimal set point is determined and affected by the current state of the environment. For example, the ideal temperature setting may differ when a human is present or not. The proposed AI predictor.

Will have a great impact on the determination of the set point, taking into account various factors that affect temperature changes, as shown in Fig. 6. It consists of two important stages: factor identification and setpoint determination, as shown in Fig. 7. The first stage involves identifying the source of temperature changes, such as human presence, unexpected external events (e.g., opening a window or cooking), or system failures. AI, in this stage, uses IoT sensors and a machine learning classifier to detect events based on collecting multiple inputs from the environment. These inputs, such as light, PIR, sound, and CO2 emissions, determine the presence of humans. In addition, humidity and indoor/outdoor temperatures are used to detect external events.

After detecting the cause of the temperature change through factor identification, the subsequent step of setpoint prediction is never activated until the temperature change time limit has been surpassed. If the

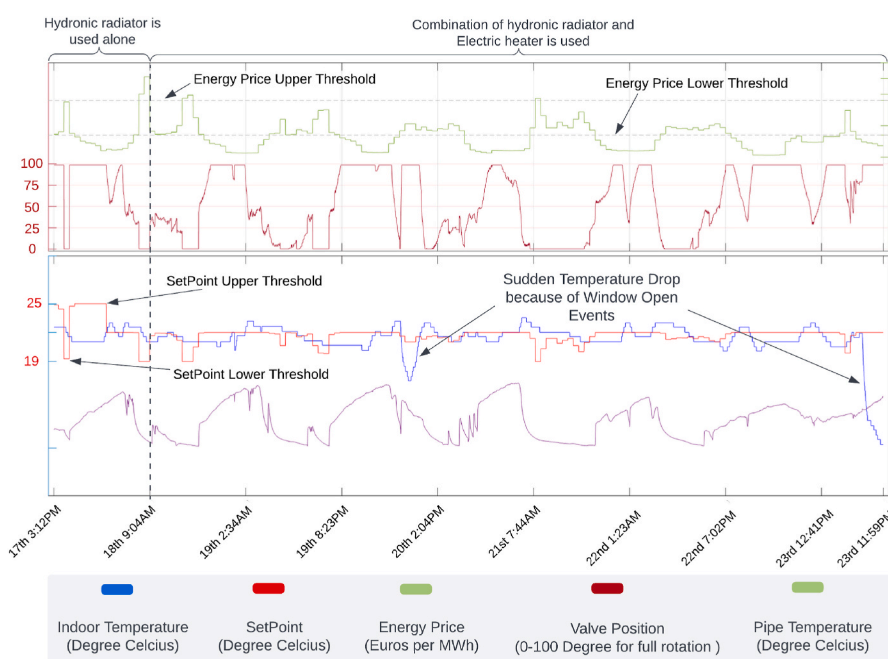

Fig. 5. The results of the local cloud-based DR optimization experiments for a space heating scenario in a smart home in Lulea, Sweden. We ran the experiments for seven days. The horizontal axis represents the timestamps, and multiple vertical axes show the indoor temperature, setpoint, energy prices, valve position, and radiator inlet pipe temperature curves.

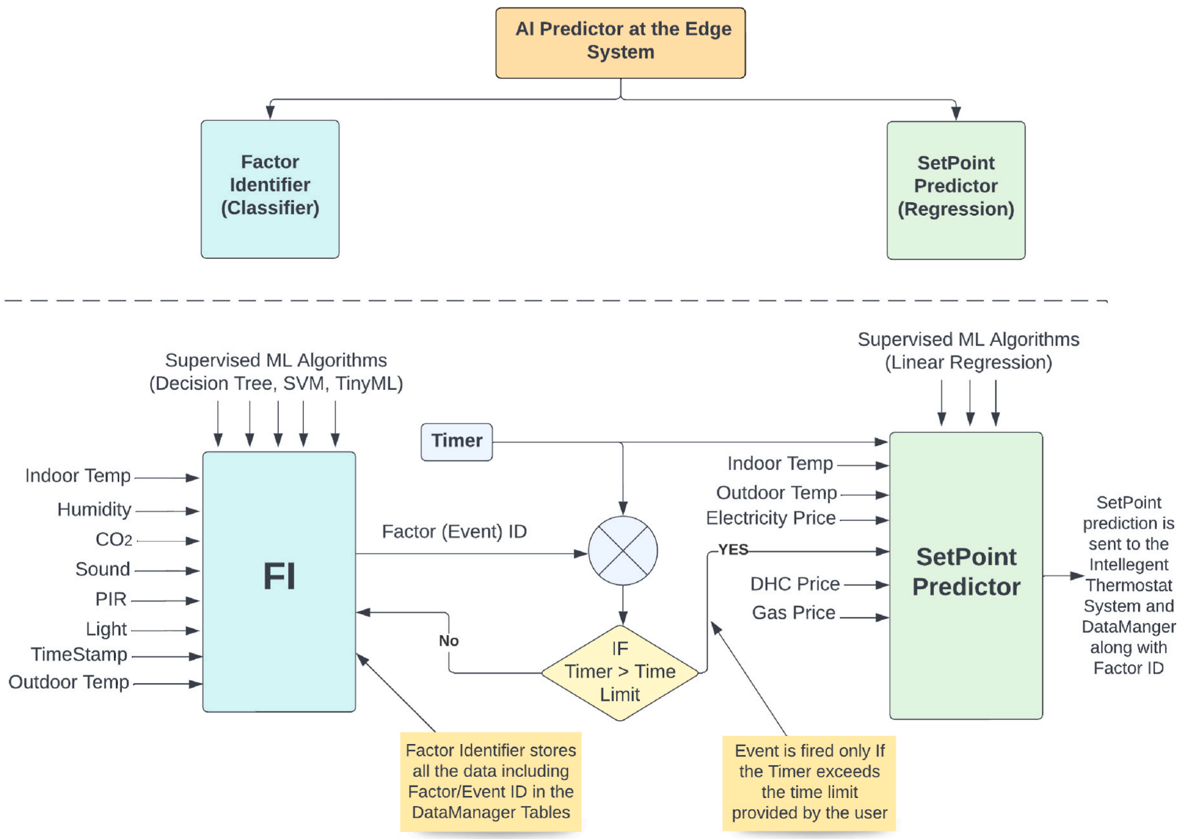

Fig. 6. The AI Predictor at the edge systems.

time constraint is met, the factor/event ID, the time stamp, energy prices, and current temperature readings are inputted into a regression model to calculate the optimal set point, as shown in Figs. 6 and 7. To implement the AI Predictor system at the edge, we propose to utilize a thread-pooling mechanism to enable parallel execution of optimizations to efficiently run our AI Predictor at the edge [47] in the Smart Home Local Cloud.

6. Discussion

In this paper, we provide a local-cloud-based DR solution that significantly reduces energy consumption while preserving end-user comfort. To further optimize the DR solution, we also proposed a value-driven approach based on I5.0 core values. It provides local and remote condition monitoring of devices and systems with environmental profiling using AI at the edge. AI on the edge provides various benefits, but it also introduces several obstacles. Successfully tackling these challenges involves utilizing a combination of frameworks, hardware advancements, and the suggested AI models. The Arrowhead framework, in particular, can prove instrumental in addressing issues like the heterogeneity of edge devices, interoperability, standardization, data quality, data privacy, and secure data management and storage. In order to enhance efficiency in handling intricate tasks, Mokayed et al. [47] have proposed deploying a multi-threading and concurrency architecture for their services. By adopting these techniques, lower-powered systems can effectively support these processes. The suggested architecture includes a flexible and robust processing pipeline, utilizing the thread pool design pattern, which ensures adaptability and resilience in the system's operations. Having a comprehensive comprehension of the distinctions between AI applications and the environment where the solution will be deployed is crucial. AI models can be used to serve different applications like document analysis, security and tracking, health, industry, and many others [48–50]. In this study, the primary focus is not on the general use of AI; instead, it revolves around determining whether the proposed machine learning models can effectively address challenges associated with constrained computational resources, power limitations, latency, real-time processing, and the ability to adapt to dynamic conditions. Ensuring the suitability of AI models for classifying the factor and establishing the appropriate threshold involves considering factors such as model size, inference speed, memory usage, and the complexity of the task. Various supervised learning models can be suggested to accomplish these objectives.

SVM is a popular choice for classification tasks and performs well on edge devices, especially when the dataset is not overly large. Decision trees and random forests are simple and interpretable models that are suitable for edge devices with limited processing capabilities. These models are less resource-intensive compared to complex neural networks. Additionally, there are specialized models like MobileNet, SqueezeNet, and TinyML, designed specifically for resource-constrained environments. These models are optimized to provide efficient inference on edge devices while requiring reduced memory and computational resources. For certain applications, lightweight and interpretable models like Naive Bayes are commonly used, particularly for text classification and other simple classification tasks. linear regression can be a practical choice for edge devices when the task involves simple regression analysis, and efficiency and interpretability are essential considerations. We designed the step-by-step process flow of the AI Predictor used for environmental profiling in a space heating scenario using AI at the edge. Therefore, this collaboration among all stakeholders helps to keep the energy demand low, which is essential for a sustainable society. Our DR optimization approach adheres to the core values of I5.0.

- Resilience: Resilience refers to keeping the system alive. By incorporating early prediction using proposed environment profiling, we

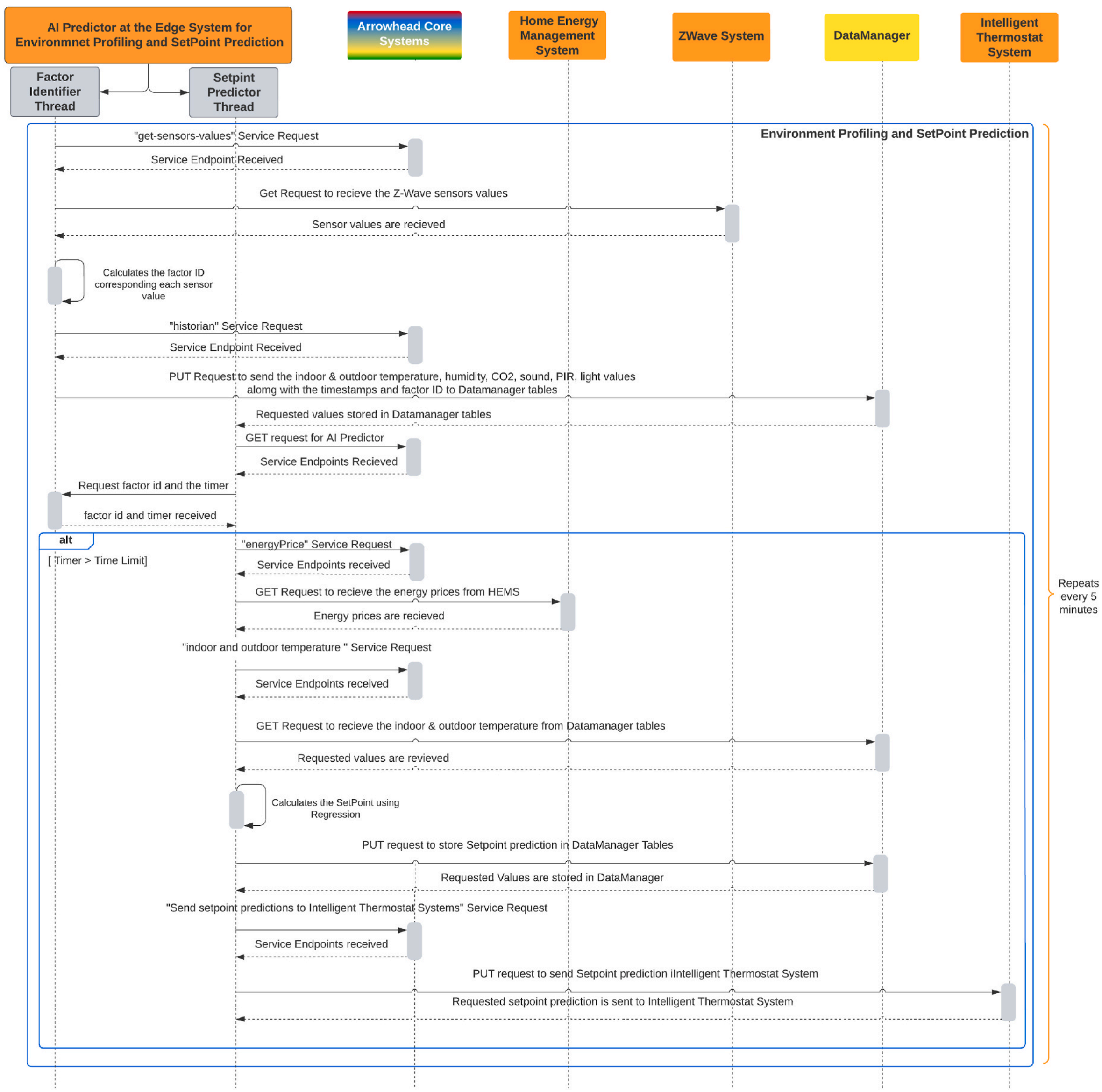

Fig. 7. Sequence diagram of environment profiling and setpoint prediction.

can monitor and predict whether any IoT device/appliance will fail, which can be replaced beforehand, ensuring the continuous operation of the system.

- Sustainability: Sustainability is consistent with the principle of energy efficiency and DR optimization. Promote efficient energy resource management to reduce energy waste and carbon footprint.
- Human Centricity: I5.0 visualized industrial automation by keeping humans in the manufacturing loop. We applied this to SES and evolved this principal value by including consumers and end users in the energy supply chain life cycle. Our proposed DR optimization is designed on the principle of digitalization for the betterment of humans. DR optimization ensures maximum human comfort throughout the supply chain of energy production, distribution, and consumption.

7. Conclusion and future work

As proposed in this research, enabling distributed, secure, and fully automated DR solutions combined with AI at the edge can take DR in SES on the road to meeting net-zero targets. We proposed a local cloud-based solution built on the open-source Eclipse Arrowhead framework that reduces time, manual effort, and human dependencies while ensuring cybersecurity, interoperability, scalability, dynamism, and flexibility. For the scope of this paper, we implemented and presented results from Stage 1 of DR optimization and provided a theoretical concept of using edge AI-based environmental profiling in Stage 2. This innovative two-stage DR optimization combination has the potential to be adapted in any SES.

In future work, we will implement and test different AI approaches, such as Decision Tree, SVM, TinyML, Linear Regression, etc., for environment profiling and setpoint prediction in a space-heating scenario use case. In addition, we will test the thread-pooling concept proposed by Mokayed et al. using services within the Arrowhead local cloud [47]. Next, we plan to implement shared learning and collaboration among the smart home local clouds so that the home energy management system of different homes/buildings can learn from each other using the Arrowhead framework secure inter-cloud communication.

Ethical concerns

Humans are part of SESs, but we carefully curate the proposed solution so that it does not conflict with privacy concerns about data.

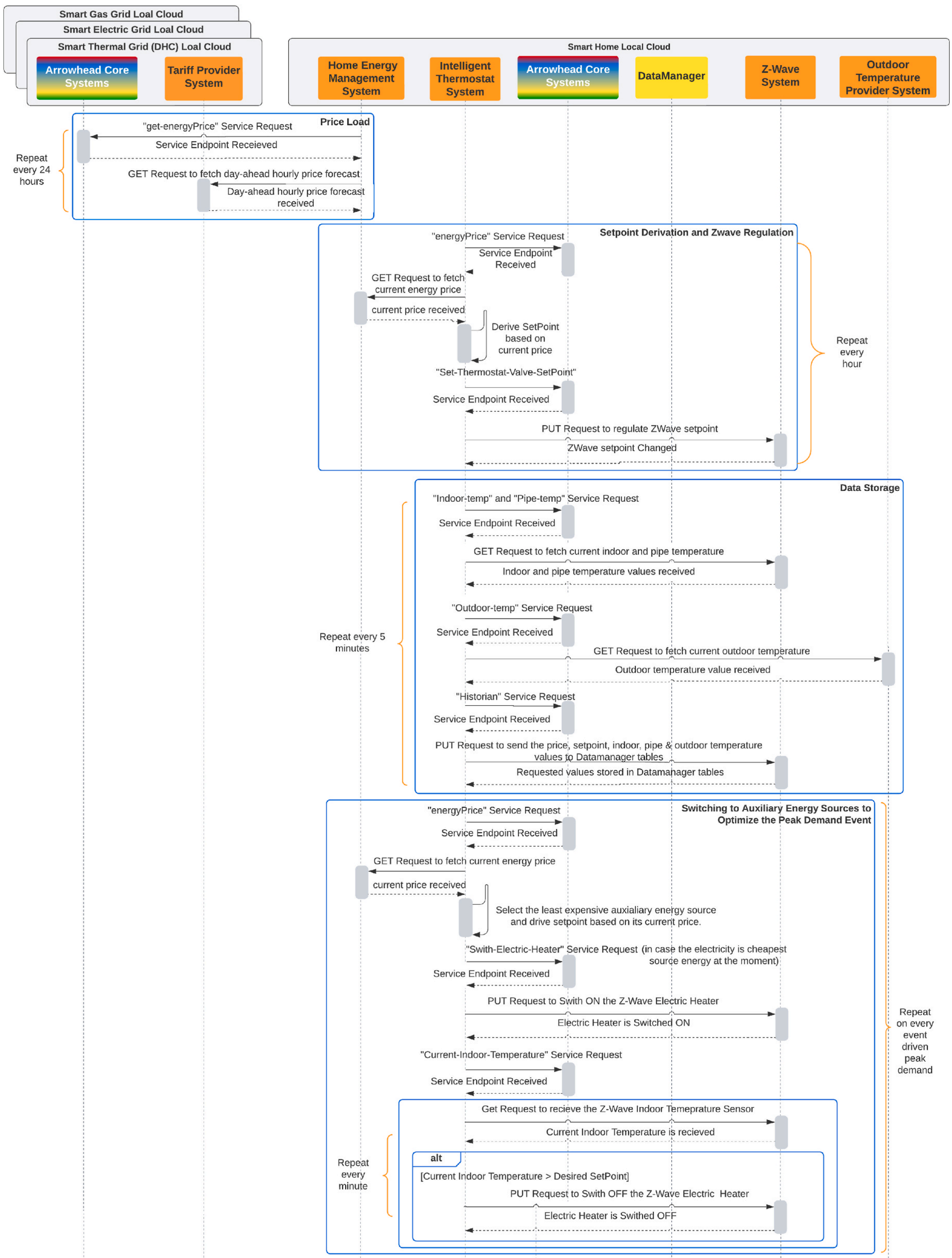

Fig. 8. Arrowhead Systems Interaction using both Intra- and Inter-Cloud communication for space heating scenario.

Moreover, each automation process and machine learning algorithm is designed so that it can be used mainly for the betterment of society and humans.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.segy.2023.100123.

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