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Integrated Smart-Home Architecture for Supporting Monitoring and Scheduling Strategies in Residential Clusters

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Abstract: The monitoring of power consumption and the forecasting of load profiles for residential appliances are essential aspects of the control of energy savings/exchanges at multiple hierarchical levels: house, house cluster, neighborhood, and city. External environmental factors (weather conditions) and inhabitants' behavior influence power consumption, and their usage as part of forecasting activity may lead to added value in the estimation of daily-load profiles. This paper proposes a distributed sensing infrastructure for supporting the following tasks: the monitoring of appliances' power consumption, the monitoring of environmental parameters, the generation of records for a database that can be used for both identifying load models and testing load-scheduling algorithms, and the real-time acquisition of consumption data. The hardware/software codesign of an integrated architecture that can combine the typical distributed sensing and control networks present in modern buildings (targeting user comfort) with energy-monitoring and management systems is presented. Methods for generating simplified piecewise linear (PWL) representations of the load profiles based on these records are introduced and their benefits compared with classic averaged representations are demonstrated for the case of peak-shaving strategies. The proposed approach is validated through implementing and testing a smart-meter node with wireless communication and other wired/wireless embedded modules, enabling the tight integration of the energy-monitoring system into smart-home/building-automation systems. The ability of this node to process power measurements with a programable granularity level (seconds/minutes/hours) at the edge level and stream the processed measurement results at the selected granularity to the cloud is identified as a valuable feature for a large range of applications (model identification, power saving, prediction).

Keywords: building-energy monitoring; smart-meter node; distributed sensing; cloud database; load profile modeling

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1. Introduction

Home automation systems have evolved from simple implementations to complex configurations lying at the confluence of three concepts: building-management systems, smart homes, and ambient-assisted living. The essential problems that arise when designing a home-automation system are as follows: not all devices "speak" the same language; the failure of a device must not compromise the operation of the system; mobility and aesthetic requirements demand a choice between wired and wireless communications; security issues (access to the elements of home-automation networks by unauthorized or malicious persons) are not completely solved by the current standards; and the optimal interface between the home automation system and users (inhabitants of the house) can benefit from the new technologies, but their price/efficiency ratio must be carefully evaluated.

In recent years, a new dimension has been added to the aspects listed above: the management of energy transfer, implied by both neighborhood-level (Cluster) and city-level (Smart City) integration [1]. This dimension involves the intra-cluster (between houses within the same neighborhoods) and inter-cluster (with the operators of municipal utility networks) management and transfer of energy. The situation is becoming even more complex, since many countries have introduced mechanisms for the dynamic adjustment of energy costs, based on the demand response (DR) paradigm.

In each of the main application fields associated with smart home systems (energy-consumption optimization, user comfort, assisting elderly users), the authors of Ref. [2] identify some common architectural levels: a hardware platform for data acquisition (environmental or wearable sensors), a set of applications to gather measurement data, and a repository to store these data. These are the constituents upon which the constructing and training of models are done and the control algorithms are implemented.

Harmonizing energy saving with residential comfort is a challenging issue in all seasons and is intricately connected to the peaks encountered in the power-consumption profiles of modern houses. A basic example is given in Ref. [3]: large appliances, such as stoves, clothes dryers, and dishwashers expel heat, requiring more space-cooling to meet the zone setpoint in the summer; the simultaneous use of appliances and space cooling can cause spikes in a house's peak electricity consumption.

As indicated in Ref. [4], houses represent a substantial fraction of the summer peak electrical load (primarily due to rising air-conditioning (AC) loads), and, therefore, measures to reduce peak demand at the household level may be valuable in stabilizing the grid and lowering peak costs.

An interesting aspect of implementing energy optimization is related to the swapping of consumption from one energy domain to the other: simulations by the author of Ref. [3] suggested that reductions in annual electrical energy use are accompanied by increased annual natural gas use. On the other hand, the opposite transition, from gas to electricity, is obviously indicated by the growing usage of electrically actuated heat pumps in the residential sector. Research into the heating market presented in Ref. [5] indicates that a growing share of this market is represented by heat pumps (about 3% in 2018) and that, in 2019, at international level, from the perspective of application, 83% of the market share was accounted for by the residential sector.

Many articles in the literature present the development of energy-management systems for smart homes as a global priority for achieving a sustainable and reliable energy-supply system in smart micro-grids.

In order to understand how the extended sensing capabilities can support optimal energy management for residential buildings, the foundations of the underlying processes must be explored:

- When and how must energy be stored in residential buildings?
- When and how must energy be transferred from one building to another building?
- When and how must energy be transferred from one building to the grid?

The literature exploring these topics has so far proposed different approaches to answering these questions based on a series of optimization criteria. When exploring the above-mentioned strategies, the following basic considerations arise:

- The dynamic scheduling strategies for residential loads must consider multiple objectives, each of which reflecting the optimal behavior of an actor present in the context: energy-cost reduction and comfort maximization from the perspective of inhabitants, reductions in load demand during the peak period from the perspective of energy providers, and peak-shaving behavior from the perspective of distribution-grid management.

- The vast majority of the optimization algorithms rely on methods for forecasting the residential power load. Such methods rely on a modeling structure that must be identified and validated with large measurement datasets.
- When an objective load curve for one day ahead is defined, the scheduling algorithm uses the load-forecasting model (considering multiple parameters such as electricity price, load demand, and weather forecast). The scheduling algorithm must run in real time to update the forecasted schedule, considering variations such as user intervention.

It is easily seen from these considerations that *the availability of precise and detailed consumption data is essential at each main stage*, including the identification of the load models, the simulation of the scheduling algorithm, the real-time running of the algorithm and, finally, the computation of the figures of merit defined for assessing the success of the proposed strategy.

This paper proposes *an integrative approach for adding functionalities such as energy monitoring and scheduling strategies for smart-home network infrastructure*. The monitoring and control processes should be examined in different essential stages, from the following perspectives:

- The review of saving strategies and algorithms in the complex environment of the residential sector;
- Data sources for constructing and training models;
- Data sources for running control algorithms;
- The implementation of wireless-sensor networks as data sources;
- The development of a smart meter node with wireless communication and easy integration into smart home network;
- Exploiting the sampling and processing facilities of actual smart meters through a more accurate, yet convenient, representation of load curves and demonstrating the advantage of the proposed representation in load-scheduling algorithms;
- A prototype system for validating *integrated* residential sensing infrastructure (reducing the costs of harmonizing the infrastructures associated with energy saving and residential comfort).

Following this approach, the next two sections will address the following topics:

- The study of residential loads and their aggregated impact at the relevant levels of granularity (single buildings, clusters, sectors, and cities);
- The review of the modeling and planning strategies for *identifying the relevant variables to be monitored* (i.e., those affecting model identification, planning-algorithm simulation, and the evaluation of energy-management-system performance) and *the appropriate sampling rates* for these relevant variables;
- The review of the architectures that are appropriate for energy monitoring, considering the four fundamental aspects: data acquisition, data collection, data recording and data visualization, and their implications for both hardware and software levels.

2. Modeling and Optimization Methods for Energy Systems in Residential Buildings

2.1. Smart Homes and the Urban Energy System

To provide sustainability and security, the urban energy system is undergoing an accelerated transition from a centralized to a highly distributed architecture. One of the reasons for this is a significant increase in the integration of distributed renewable-energy sources (RES). This increase is mainly due to the successful adoption of adaptive solutions for buildings, such as building-integrated photovoltaic (BIPV) [6] or hybrid photovoltaic/thermal (BIPV/T) [7], solar thermal facades (STF) [8], and the components for heat pumps [9] and related energy storage [10] or thermal storage systems [11].

In the context of the European Union (EU), building renovation provides a good opportunity to meet the objectives of the EU's policy on near-zero-energy buildings (NZEB) [12] and integrated RES for buildings [13].

Current EU policy promotes the reduction in the energy needs of building by 80%, achievable by 2050 through specific building renovation [14].

The related technical challenges lead to the development of innovative approaches, addressing buildings and energy systems at different levels: single buildings, clusters, sectors, and cities.

Energy planning at the cluster level facilitates the provision of local energy supply through decentralized energy production and the enhancement of sector energy systems, by combining factors such as energy-efficient building retrofitting and the integration of local renewable energy [15]. Similar to the concept of micro-communities in society, neighboring buildings tend to form clusters through an open cyber-physical system to take advantage of the economic opportunities offered by distributed RES systems [16].

In this context, the problem of optimal energy management for residential buildings acquires new dimensions, leading to some new challenges that must be addressed:

- The integration of the sensing infrastructure associated with smart homes with the necessary power-monitoring architecture;
- The development of new algorithms for harmonizing energy saving with residential comfort;
- The design of the communication infrastructure for energy hubs and the algorithms able to support optimization at upper hierarchical levels (clusters, sectors, and cities);
- The upgrade of smart-home control equipment (hardware and software) in order to support the energy exchange between neighboring homes and balance the local production of renewable energy with energy demand.

2.2. Modeling and Control of Energy Saving/Exchange at Home Level and Cluster Level

The cluster level of buildings is an intermediate level between single buildings and the sector or city level. When modeling a building cluster, a diameter between 0.1 and about 1 km is recommended [1].

The main benefits of introducing energy-management systems at the cluster level and of energy hubs include reduced energy usage, carbon emissions, and costs. Furthermore, important secondary benefits include air quality in buildings, thermal comfort, and a reduced risk of exposure to future energy price crises. This approach promotes economic efficiency and operational feasibility to optimize the procurement of distributed renewable energy in the context of energy demand and supply equivalence.

The research presented in Ref. [17] led to the development of algorithms through which energy exchange takes place between neighboring homes to balance the local production of renewable energy (electricity-photovoltaic panels and thermal energy-solar thermal panels) with energy demand. At the group level (neighborhood, cluster, micro-grid) two key issues related to energy distribution and exchange have to be considered: 1. Which homes need to transfer energy? 2. What are the times when these exchanges must take place?

Currently, a significant research effort is dedicated to residential-power-load forecasting (RPLF) methods [18]. These have an important role in solving a major challenge posed by the management of micro-grids and energy hubs: optimal energy management for residential buildings.

According to Ref. [19], two classes of methods are available for estimating residential energy consumption. Bottom-up modeling techniques estimate the load demand of individual buildings using statistical (i.e., regression, conditional demand analysis, neural networks) or engineering models (i.e., population distribution, archetypes, samples). The estimated models are then combined to obtain the energy usage for a larger region. On the other hand, top-down modeling techniques consider the energy consumption of a larger region based on econometric and technological data and assign an energy consumption to the studied building.

The bottom-up modeling technique, focused on the formulation of a consumption model for each household appliance, is facilitated by a smart infrastructure deployed in the building, which is able to monitor and communicate the information related to the consumption of each appliance to the data center, contributing to the accuracy and efficiency of building-load forecasting [20].

To extract the load-behavior model from historical data, the usage of an algorithm able to detect historical days with consumption characteristics similar to those of the forecasted day increases the prediction accuracy (Figure 1) [20]. The similarity algorithm compares both external environmental factors, such as weather conditions (air temperature and relative humidity, wind speed), weekday type (weekday/workday), events (e.g., holiday), and internal household factors, such as family structure and residents' behavior.

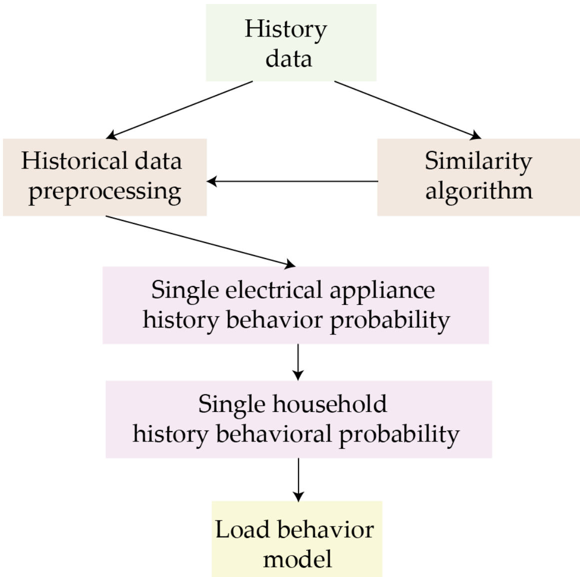

Figure 1. Framework for forecasting the energy consumption of a household appliance (after Ref. [20]).

The short-term forecasting of energy consumption for homes is an essential tool in optimizing energy management and has been addressed in the literature by methods such as [21]: auto-regressive models, regression based models, exponential smoothing, artificial neural networks, fuzzy logic, and expert systems. If buildings are equipped with smart home systems, it is possible to automatically collect the operating intervals of the main electricity consumers and of the main thermal energy consumers for intervals of several weeks with a very good temporal resolution. This allows the statistical exploration of a data set consisting of consumption values and the values of other sensors in the home (temperatures, air humidity, presence detectors, etc.), as well as the training of neural networks that can accurately estimate the consumption 24 h ahead.

It is expected that the optimal and dynamic schedule of residential loads considering multiple objectives (i.e., energy costs, comfort optimization, reductions in load demand during peak periods) will be enabled through the deployment of smart meters, smart sensors, and home energy-management systems (HEMSs). HEMS models, which are designed to manage available resources considering an appropriate balance between accuracy and computational complexity, and their interaction are expected to improve the results not only at the level of single homes, but also at the level of communities. The operation of a HEMS platform comprises the following phases: input data collection, optimal scheduling, and control of connected devices [22].

2.3. Estimating the Load Profiles in Residential Buildings

The main sources of energy consumption in homes comprise appliances (televisions, washing machines, clothes dryers, refrigerators, electric ovens, dishwashers, etc.), heating systems, air conditioning, lighting systems, and electric vehicles. In Refs. [23,24], three types of residential load are identified and classified according to their ability to reduce the peak load demand:

1. Must-run/baseline loads, consisting of devices whose operation does not allow delays (e.g., lighting, television, networking devices, cooking devices);
2. Shiftable/burst loads, consisting of devices that operate for a fixed duration and can be started/stopped within a specific deadline (e.g., dishwashers, washing machines, clothes dryers, electric vehicles);
3. Steady/regular loads, consisting of devices running steadily for a long period according to their internal controller (e.g., refrigerators, water heaters, heating systems, air conditioning).

Figure 2 presents typical residential consumers, while in Figure 3, a typical connection of single-phase loads on power lines is presented.

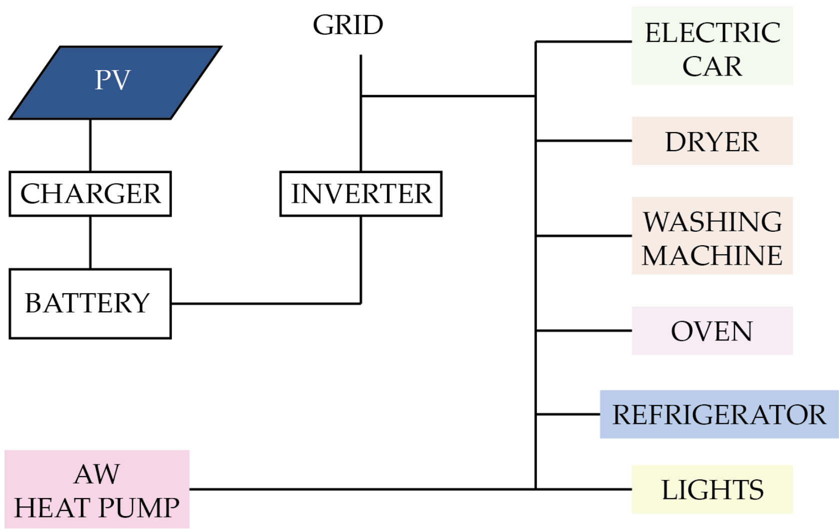

Figure 2. Typical loads in residential buildings with PV system.

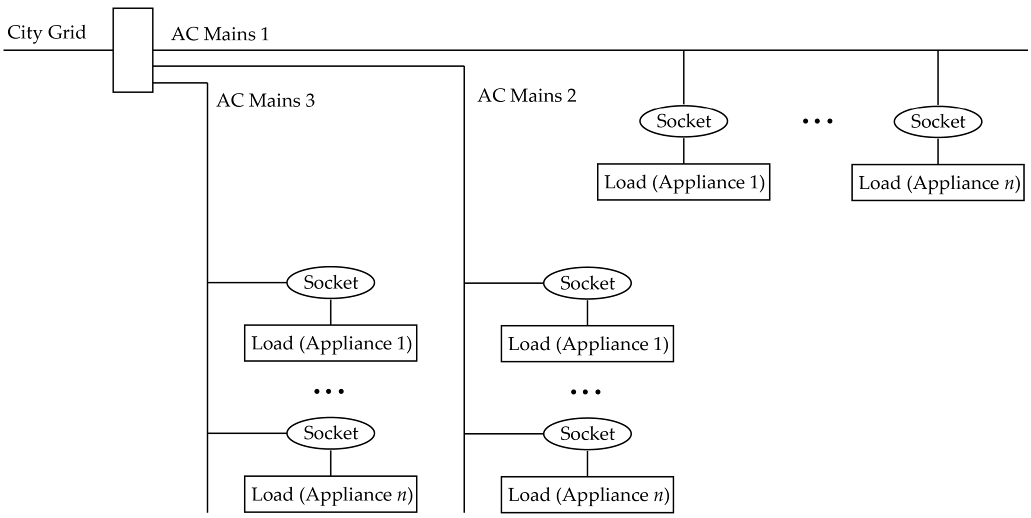

Figure 3. Typical topology for residential loads.

Due to the multitude of residential appliances, the authors of Ref. [22] identify the following aspects to be considered when selecting an appropriate modeling strategy:

- Operating principle (i.e., cyclic/non cyclic, with variable power/ON OFF control), which determines the variable type (i.e., binary/integer/continuous), load profile, and operating constraints;

- Flexibility (i.e., time, temperature, dependence on residents' behavior), which influences the formulation of constraints and objective functions.

The authors of Refs. [23,25] use finite state machines for the modeling of regular and burst loads controlled through ON/OFF commands. The authors of Ref. [26] focus on centralized scheduling for large-scale flexible loads (i.e., loads possessing the ability to perform power-consumption adjustment during a certain time interval, while the total energy consumed is fixed). The loads are clustered considering their parameters (rated power, start/end time of the schedulable period, necessary work intervals) into several categories, an equivalent model is established for each category, and an aggregated model obtained by summing all the equivalent models is used for system scheduling. Models for both continuous loads (controlled through the continuous adjustment of power) and ON/OFF loads (controlled through ON/OFF commands) are provided.

2.4. Planning Strategies

Load-scheduling algorithms aim to shift the operation of programmable consumers to off-peak hours so that the peak load demand is reduced, taking into account users' comfort. Various architectures and algorithms for flattening the peak-load demand are encountered in the literature.

The authors of Ref. [27] propose a scheduler that implies two stages: first, a load-forecasting model is applied for defining an objective load curve for one day ahead based on input parameters such as electricity price, load demand, and weather forecast, followed by an online scheduling algorithm running in real time that updates the forecasted schedule by taking into account variations, such as user intervention. The multi-objective problem targeted by the day-ahead-load-scheduling technique is defined in terms of the minimization of the distance between the objective load pattern and the scheduled load profile, the reduction in electricity cost, the maximization of user comfort through the minimization of the waiting time, and the minimization of the peak-to-average ratio (PAR). Two nature-inspired optimization techniques are proposed: multi-objective binary bird swarm optimization (MBBSO) and multi-objective binary hybrid bird swarm optimization and cuckoo search (MBHBCO). The simulation results are compared with multi-objective binary particle swarm optimization (MBPSO) and multi-objective cuckoo search (MOCSO) algorithms. The real-time rescheduling problem is formulated as a single objective problem, i.e., the maximization of user comfort, and is initiated by user-generated run-time interruptions of the appliances. The simulation scenario involves 15 appliances in a smart home grouped as schedulable (interruptible and non-interruptible) and non-schedulable loads, for which the corresponding power ratings and daily usage are known. Experiments were performed using three pricing tariffs: time of use (ToU), real-time pricing (RTP), and day-and-critical-peak pricing (CPP).

The authors of Ref. [28] use a harmonic model defined as a function of three components—base load (i.e., economic activities and human-behavior patterns), an hourly load, and a Fourier series (for capturing load periodicity)—for the forecasting of daily-load curves on a monthly peak day, assuming a constant relation between the load and the weather variables. The model parameters are estimated using historical data in order to minimize the forecasting errors. The daily-load curves of various customers of the Provincial Electricity Authority of Thailand (residential, commercial and industrial) were forecasted separately, considering four tariff schedules: general residential and small, medium, and large general service.

The authors of Ref. [29] experimented with the symbiotic organisms search (SOS) and cuckoo search (CS) algorithms for the day-ahead forecasting of load scheduling based on consumer preferences (i.e., the time intervals commonly used for shiftable appliances) obtained after a public survey on 51 residential users and concluded that the SOS algorithm provides better results in terms of convergence and requires fewer parameters (i.e., no specific parameters are required other than maximum evaluation number and population size).

Approaches integrating machine-learning techniques have been proposed in Refs. [30,31]. In Ref. [30] a load-scheduling scheme integrating a support vector machine (SVM) model for short-term demand forecasting is introduced and applied experimentally on load-schedulable electrical devices (LSEDs). LSEDs are devices with repeated ON/OFF cycles, whose ON intervals may be divided into smaller intervals distributed over a cycle, as long as their objectives are fulfilled. Interleaving the ON intervals of every LSED may lead to overall peak flattening. Limited preemption has been used in order not to shorten the lifetime of the device (i.e., once a device is turned ON, preemption may occur only after a certain time interval has passed). The authors of Ref. [31] propose a method based on a long-short-term memory (LSTM) neural network model for forecasting the load demand curve of a smart micro grid using historic data consisting of daily temperature, humidity, day of the week, and hourly load power. The predicted curve and the real-time status parameters are used within a control strategy for managing the operation of a thermal-storage electric boiler in order to store excess energy, provide heat energy, and regulate the peak load and frequency modulation of the power grid.

2.5. Identification of Users' Behavior Patterns

The identification of repetitive patterns in residents' activities in smart homes based on sequences of data recorded using smart sensor systems may assist the load-demand forecasting model.

The authors of Ref. [32] present the results obtained from collecting data that were relevant to activity recognition using passive infrared sensors, force sensing resistors, reed switches, mini-photocell light sensors, temperature and humidity sensors, and smart plugs.

The authors of Ref. [33] propose a residual recurrent neural network structure for predicting resident activity in smart homes. The experiments, performed on a dataset from a Massachusetts Institute of Technology (MIT) laboratory consisting in records provided by various sensors (reed switches, pressure, light, temperature, gas sensors), installed in an apartment with one resident for 14 days, indicated that residual LSTM/GRU models provide better results than classical LSTM and GRU (Gated Recurrent Units) models.

A survey on multi-user activity recognition is presented in [34]. Ambiental sensors, such as motion detectors, contact switches, inertial and break-beam sensors, and pressure mats, are described as being frequently employed for human activity detection.

3. Sensing Architectures for Energy Monitoring

As pointed out in the previous sections, the modeling and algorithm-development activities that are relevant to energy optimization are *heavily reliant on large measurement datasets for both identification and validation*. The number and range of the sensors that are required tend to transform the residential environment into a highly instrumented one. In fact, all the relevant variables for the daily consumption curves (usage patterns, weather parameters, individual appliance profiles) need to be acquired, collected, and archived. The sources for all the datasets are the appropriate sensing systems.

The usage of sensor networks for load-demand monitoring facilitates the construction of precise models (load profiles), the association of user behavior patterns with the identified load profiles, and real-time scheduling and optimization.

In [4], it is specified that the studied homes were highly instrumentalized: the individual appliance energy use, interior temperature and humidity at multiple locations, and exterior climate data were all recorded at five-minute intervals.

The authors of Ref. [35] investigate the possibility of improving energy-consumption forecasting by including various sensors (light intensity, CO_2, air quality, temperature, and humidity) in addition to electricity-consumption monitoring devices. Experiments performed in an office building indicate that light intensity and CO_2 present the highest correlation with electricity consumption.

The authors of Ref. [36] indicate that there is a strong interdependency between energy consumption and weather. Records collected into an unoccupied TxAIRE Research home (i.e., the day number, outdoor temperature, solar radiation, and energy consumption of the home and of the heat pump) are used to identify the parameters of two NN models with $n_i = 3$ inputs, $n_o = 1$ output, and $n_h = 2n_i + 1$ neurons in the hidden layer, $E_T = f(t, T, SR)$, $E_H = f(t, T, SR)$, where E_T is the total electrical energy consumption of the home, E_H is the energy consumption of the heat pump, t is the day number, T is the dry-bulb temperature, and SR is the solar radiation. The intention is to capture the changes in monthly energy consumption due to weather.

The authors of Ref. [37] present a system for energy monitoring in residential homes using sensor networks (Figure 4). For energy-consumption monitoring, a series of wireless smart-power strip nodes interfaced by a sink node are used. A gateway module implementing a data-stream management system (DSMS) for real-time data processing is connected through the RS-232 interface to the sink node. A DB server (PostgreSQL) is used to store the data, which can be visualized as trend charts through a web server (Apache running PHP). Each monitoring node has the ability to measure and send the energy consumption of the connected appliance within one second. The DSMS facilitates the aggregation and saving of the data into DB tables with various time granularities (month, day, hour, minute).

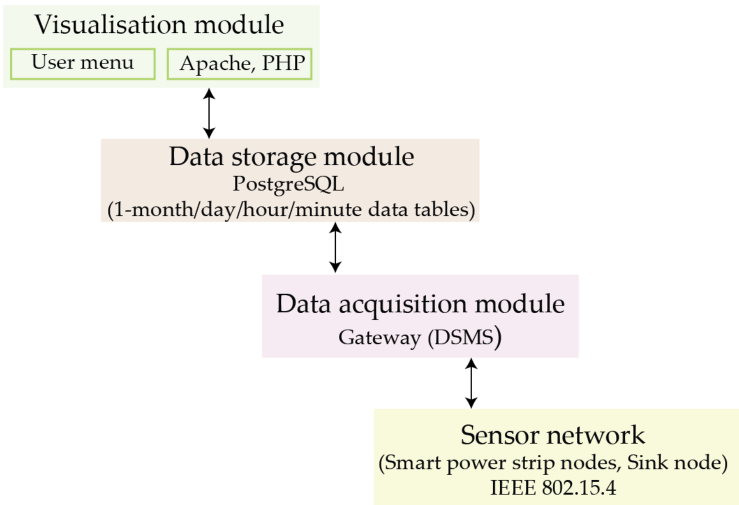

Figure 4. A four-layer arhitecture for energy monitoring (after Ref. [37]).

The authors of Ref. [38] focus on analyzing passive house (PH) requirements from the perspective of human comfort. A schematic view of the proposed passive house system manager is indicated in Figure 5. The Environmental comfort block is responsible for estimating an indicator of the comfort level based on the thermal, visual, indoor air, acoustic, and spatial comfort inferred from the monitored parameters (including air temperature and relative humidity, air velocity, mean radiant temperature, illuminance/shading level, CO_2 level, and sound level). The predicted mean vote (PMV) value is considered as an indicator of the thermal sensation of a body. The PH manager block, based on the information received from the Environmental comfort block and considering the occupant's preferences and energy usage, is responsible for sending commands to the Actuator control block in order to perform various adjustments. In the experiments, a WSN consisting in SunSPOT sensor nodes is used to measure the air temperature, compute the PMV value, and transmit the data to a central PC via a SunSPOT base station.

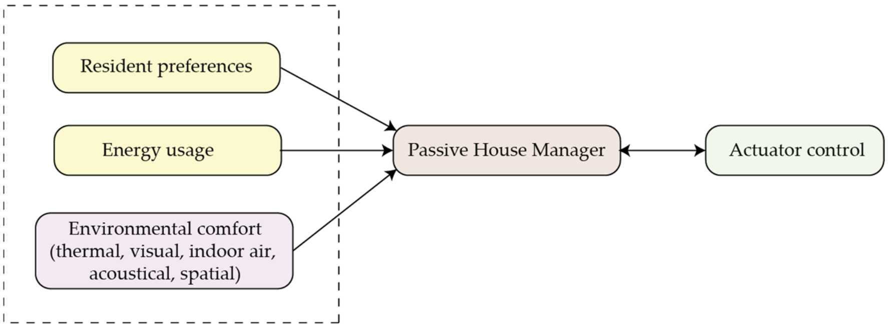

Figure 5. Schematic view of a passive house system manager (after Ref. [38]).

A review of the data types used in the literature for experiments on load-demand scheduling is presented in Table 1.

Table 1. Data types for load-demand scheduling.

Reference	Data Type	Sampling Period
[35]	Power consumption, light intensity, CO_2	5 min
[37]	Power consumption (W)	1 sec
[36]	Energy consumption (Wh) of the heat pump and of the home, outdoor dry-bulb temperature (C), solar radiation (Wh/m^2)	1 day
[27,29]	Power rate (kWh) of appliances	Daily usage (hours)
[28]	Energy consumption for each customer (kWh)	15 min
[30]	Power consumption (W) of appliances	1 sec
[31]	Temperature, humidity, day of week Load power	Daily 1/2 h

Table 2 presents a series of recent developments described in the literature, analyzed from the perspective of several key features: hardware architecture, software technologies, smart-home capabilities, energy-monitoring capabilities, the maturity of hardware and hardware/software scalability, and the availability of local display for immediate user information/interaction.

Table 2. Smart-home systems, energy-monitoring devices, and energy-monitoring platforms.

Ref.	Architecture	Technologies	Smart Home Capabilities	Energy Monitoring Capabilities	Maturity and Scalability	Local Display
[39]	'Cloud-first' implementation	Open-source, publish/subscribe, MongoDB	End-to-end IoT technologies	Energy footprints of appliances (not accurate due to nonlinear nature of time-energy footprint)	Raspberry-Pi-3-based ON/OFF detection for appliances; load test of servers with Apache JMeter	N/A [1]
[40]	Arduino + ESP8266 Wi-Fi Module	Web server	N/A	Current and voltage sensors interfaced to Arduino Leonardo	Arduino-based prototype; Wi-Fi connection demonstrated between meter and web application. Upper level (gateway, cloud DB) not present	Character LCD
[41]	Intel Edison board-based station	MQTT, AWS IoT, DynamoDB	N/A	Allegro ACS712 current sensor interfaced to Intel Edison board	Prototype tested individually	N/A

Table 2. *Cont.*

Ref.	Architecture	Technologies	Smart Home Capabilities	Energy Monitoring Capabilities	Maturity and Scalability	Local Display
[37]	Wireless sensor network, data-acquisition module (gateway), data-storage module, visualization module	PostgreSQL, Apache, PHP, data-stream management system	N/A	Wireless smart-power strip nodes interfaced by a sink node	Prototype	N/A
[42]	Data-acquisition module (microcontroller for HVAC unit management), middleware module, client-application module	MQTT server, storage server, analytics engine server, Webserver	RFID reader, temperature and humidity sensors	Current sensor for measuring AC unit current, solid-state relay for switching devices ON/OFF	Hardware prototype, scalability simulated using Webserver stress tool	N/A
[43]	Wireless sensor network, gateway, cloud servers	Virtual End Node server for handling Virtual Top Node events, Bluetooth 4.0 (BLE)	BLE nodes for monitoring of temperature, humidity, air pressure, CO_2, and air pressure differences	Controllable smart devices, monitoring of data from distributed resources (solar PV, wind mill, ESS, and electric vehicle charging posts)	Pilot project implemented at VTT's research apartment	N/A
[44]	HEMS-IoT architecture integrating 7 layers (presentation, IoT services, security, management, communication, data, and device layer)	ZigBee, IoT (REST) services, big-data technologies, and machine learning	Smart-home monitoring (motion and room location, lighting, temperature, water flow, gas, sound sensors) for ensuring comfort and safety	Smart-home monitoring (energy control sensors) for reducing energy consumption	Case study conducted on 10 homes (with two types of design and characteristics) in a residential complex for identifying energy-consumption patterns	N/A
Current work	Layered architecture integrating wired/wireless sensor nodes, gateway-managed networks, cloud processing	BLE, MongoDB, Cloud DB server, iOS, XCode, Qt	Sensor nodes for environmental variables (temperature, humidity, CO_2, light intensity), controller nodes/smart actuator nodes for regulation of room environment	Measurement of: active power and energy, reactive power and energy, apparent power and energy from RMS data, apparent power vectorial calculation, zero-crossing, line period, phase-delay between voltage and current, sag and swell events.	Prototype devices with high technology readiness level (beta prototypes) are validated and installed in residential and office buildings. Energy-monitoring nodes fully integrated into the smart-home/BMS networks. Scalability of the network based on wireless hubs and wired gateways (up to 60 controller and sensor nodes managed by a gateway). Technologies with proven scalability used at cloud level.	LCD graphic display: local editing of the control/ monitoring parameters; current measured values; plot of the last 12/24 h

[1] N/A–feature not available.

Most of the papers cited in the table describe devices for energy monitoring that are not integrated with the smart-home/smart-building automation infrastructure. A cloud-based setup for data storage, visualization, and analysis appears to be the most appropriate method for handling measurement data and offers an important contribution to the scalability of the platforms. Analyzing the maturity and the level of integration between smart homes and energy-monitoring networks, the authors of Refs. [43,44] identified approaches close to the integration paradigm promoted in the current paper. However, the precision of the energy monitoring and the integration with smart homes/buildings presented in the current work are not reached in the other implementations reported in Table 2.

4. Integration of Energy Monitoring with Smart Building Network Infrastructure

4.1. The Proposed Sensing and Control Architecture

The architecture of the system designed for supporting scheduling-based energy saving in residential clusters through monitoring the power consumption of typical consumers, the provision of auxiliary sensor data for supporting the scheduling algorithms, the extraction of load profiles for several appliances, the storage of monitored data and of load-profile approximations into a cloud database server, the support for the exchange of data with the inference engine, strategy planner block, and cluster-management unit, is presented in Figure 6.

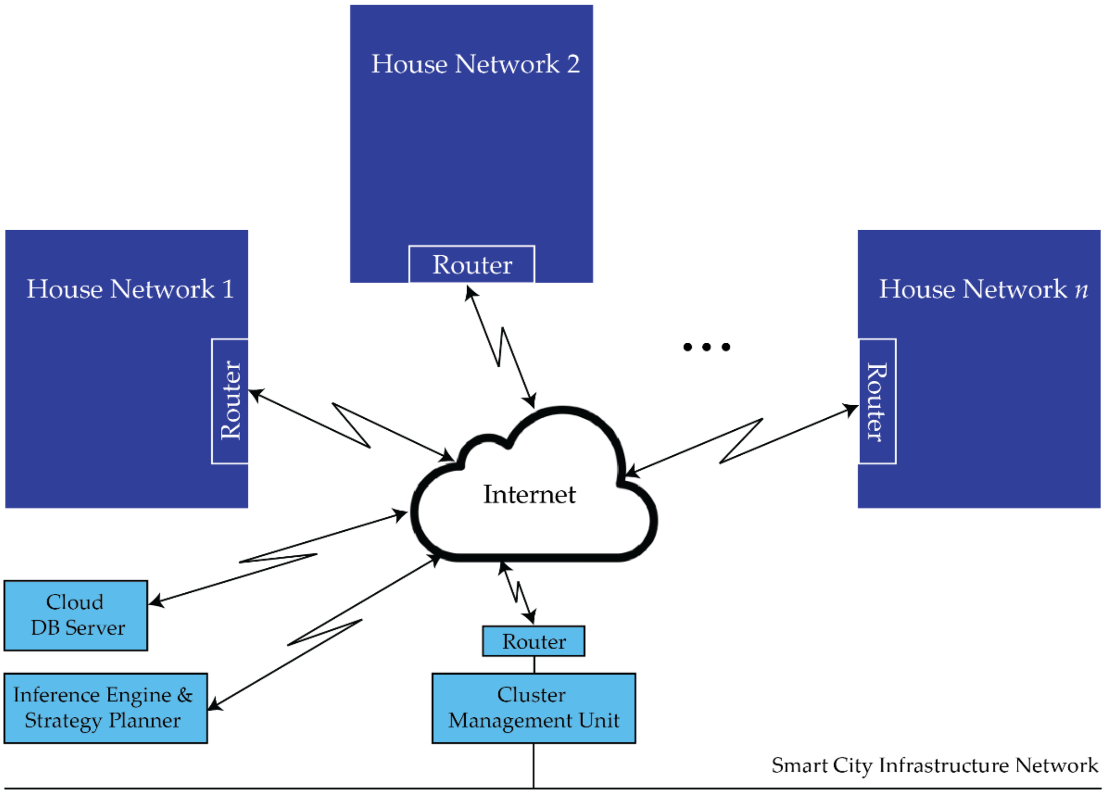

Figure 6. System architecture.

With reference to Figure 3, a monitoring infrastructure must be deployed in the building, such that the monitoring of the power is performed for each active socket. The measured power levels must be communicated and logged at the level of each home, not only for supporting the bottom-up identification strategy, but also for providing the necessary feedback to the scheduling algorithm. A monitoring infrastructure that organizes the required power meters into networks of smart wireless nodes, managed by wireless hubs, is indicated in Figure 7.

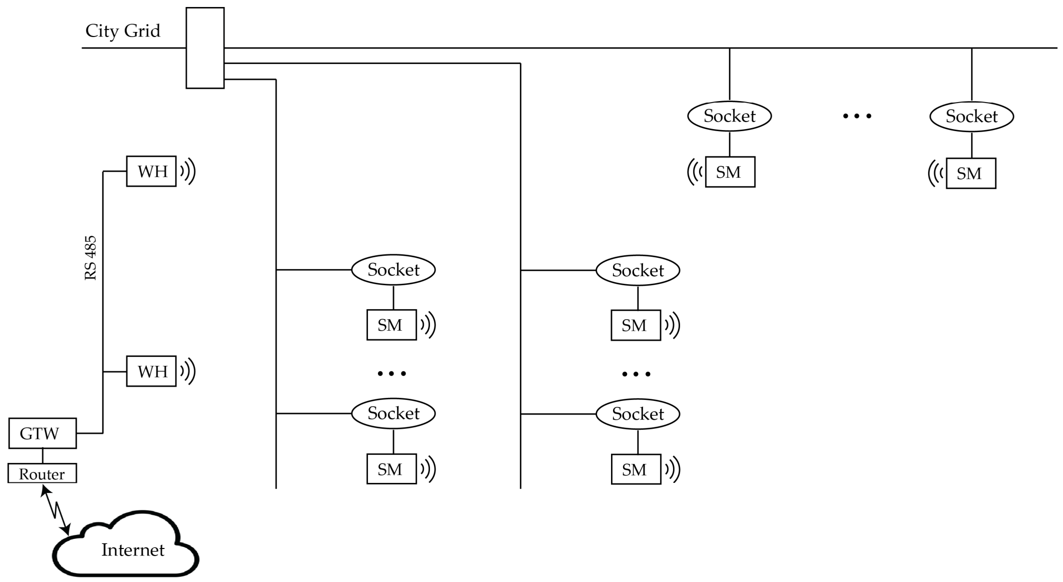

Figure 7. Wireless-sensor network for monitoring residential loads (SM—smart meter, WH—wireless hub, GTW—gateway).

The hubs are connected on a RS-485 bus, interfaced by a gateway module. Bluetooth low-energy (BLE) protocol is used in the wireless network, the hub allowing up to eight concurrent peripheral connections. The role of the wireless hub is to act as a virtual sensor node in the network, ensuring the communication of the values measured by the wireless sensor nodes into the wired bus on request. Various wired sensors may be connected on the RS-485 bus. The sensor's measurements are collected by the gateway modules and sent periodically through TCP/IP sockets to the application running on the cloud database server.

This architecture was already validated as a distributed monitoring and control solution for building management systems (Figure 8 [45]), paving the road for an integrated smart home architecture (Figure 9) that encompasses all the implied areas (energy management, HVAC control, access control, entertainment, non-intrusive user detection, etc.).

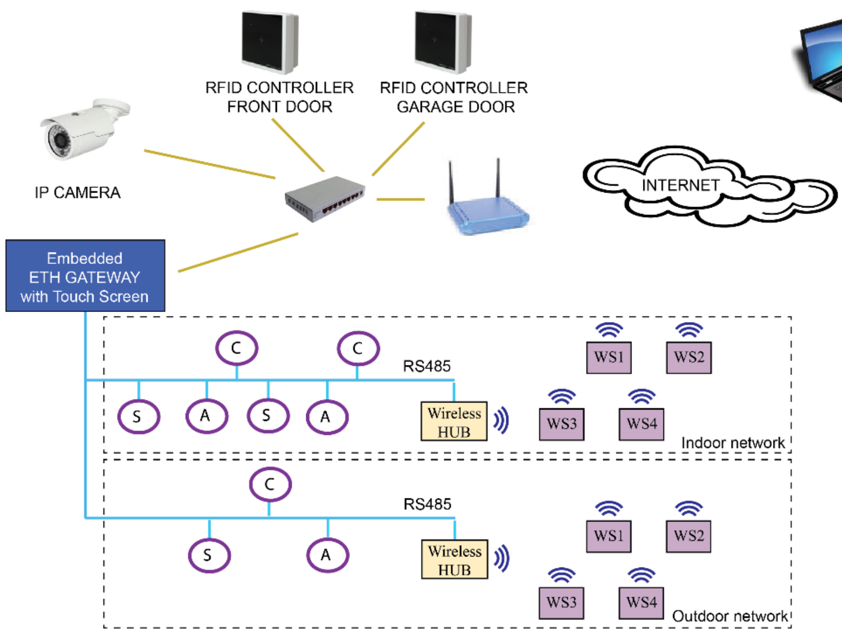

Figure 8. Structure of a typical Physis system (S—sensor, C—controller, A—actuator, WS—wireless sensor) (after Ref. [45]).

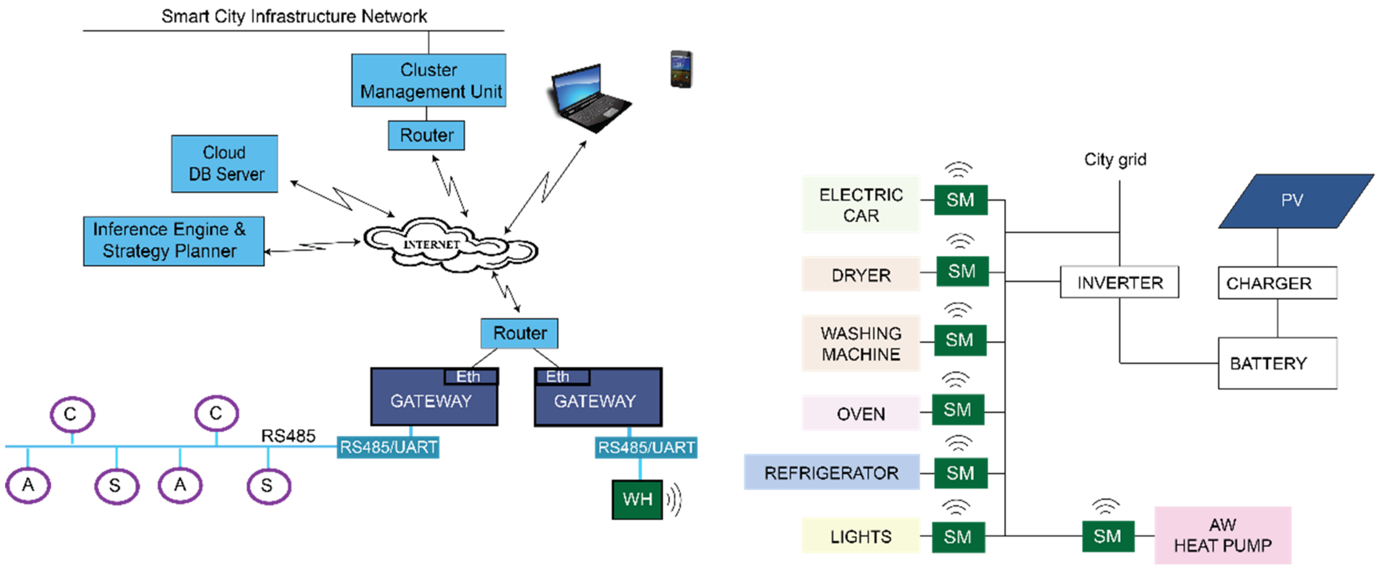

Figure 9. Integrated smart-home architecture.

The growing demand on data-storage platforms favors the use of cloud computing and virtualization technologies [46]. An interesting approach to aggregating, visualizing, and analyzing live data streams in the cloud for cooling and ventilation measurements was introduced in Ref. [47]. The elements are structured in a similar manner: a first level contains sensor nodes, a second level contains IoT gateways, and a third level is the IoT cloud.

When selecting a temporal database for large data sets, the scaling of the database is an important issue [48]. The literature reports both relational databases and non-relational databases for the storage of the time series produced by the environmental sensors and smart meters deployed in residential buildings.

The authors of Ref. [2] indicate that the high availability and on-demand scalability of an open-source relational database management system (RDMS) might be the preferred solution for dealing with a heterogeneous collection of sensor systems based on different types of sensor network and facilitates the implementation of processing and reasoning software modules independent of the origins of the data.

From an internal architecture perspective, non-relational databases are the preferred choice, due to their horizontal scaling and schema flexibility characteristics, which facilitates the first 3 Vs of big data [49]: volume, velocity, and variety. MongoDB, a NoSQL, document-oriented database, is indicated in Ref. [46] as being appropriate for handling timestamped data. Timestamped data may be stored in RDBMS by adding a new row in a table for each data point. In MongoDB, this procedure is equivalent to saving a new document for each event (document-per-event approach). Alternative approaches that take advantage of the document-embedding capability of MongoDB, such as document-per-minute or document-per-hour, are indicated in Ref. [49] as being more optimized in the context of storage/retrieval. Updates at the field level imply a simple update operation instead of writing a new document in a new location.

To model the measurements in a way that facilitates the saving of records for each sensor with a granularity of one second, documents are created per day and per measurand. The document storing measurements for a specific day contains subdocuments per minute, organized in an array of subdocuments per second. The document structures defined for a sensor or data source and for measurements are presented below.

```
DataSources {
    _id: ObjectId,
    schemaVersion: int,
    dataSourceIdx: int,
    gtwSerialNumber: str,
    type: str,
    name: str,
    userAlias: str,
    address: int,
    gain: double,
    offset: double,
    maxValue: double,
    minValue: double,
    measuringUnit: str,
    resolution: str,
    precision: str
}
Measurements {
    _id: ObjectId,
    schemaVersion: int,
    timestamp: date,
    dataSourceIdx: int,
    gtwSerialNumber: str,
    records: [
    { minute: int,
    dataentries: [
    { second: int, value: double }
]
}
]
}
```

4.2. Development of the Smart-Meter Node with Wireless Communication

Considering previously developed sensing modules (Figure 10) ([45,50–53]), and the versatile modular architecture that was demonstrated in a broad range of applications (greenhouse climate control, smart-home on-demand ventilation, air-quality monitoring, etc.), the first approach considered was to reuse the hardware functionality of the host module, based on a 32-bit microcontroller, as much as possible, and to interface it to the energy metering board. The block diagram of the host module and of the interfacing board are presented in Figures 11 and 12. A picture of the interfacing board is presented in Figure 13.

While, from the hardware point of view, this approach accelerated the development of the prototype smart meter, from the software point of view, the reusability of the existing module (tailored for the protocol, procedures, and usage scenarios of the Physis platform), guarantees an easy integration with existing residential comfort infrastructures. This creates the framework for achieving the alignment of the smart metering solution with the existing BMS and smart-home systems, toward the integrated smart-home architecture indicated in Figure 9.

The STMicroelectronics STPM32 energy metering evaluation board [54] was used to monitor the active/reactive power of the appliances. The characteristics of the board include: 0.2%-accuracy single-phase meter, V_{nom}(RMS) = 140–300 V, I_{nom}/I_{max}(RMS) = 5/100 A, f_{lin} = 50/60 Hz $\pm$ 10%, USB and RS232/UART isolated connectors, SPI interface, two programmable LEDs, 3.3-volt power supply.

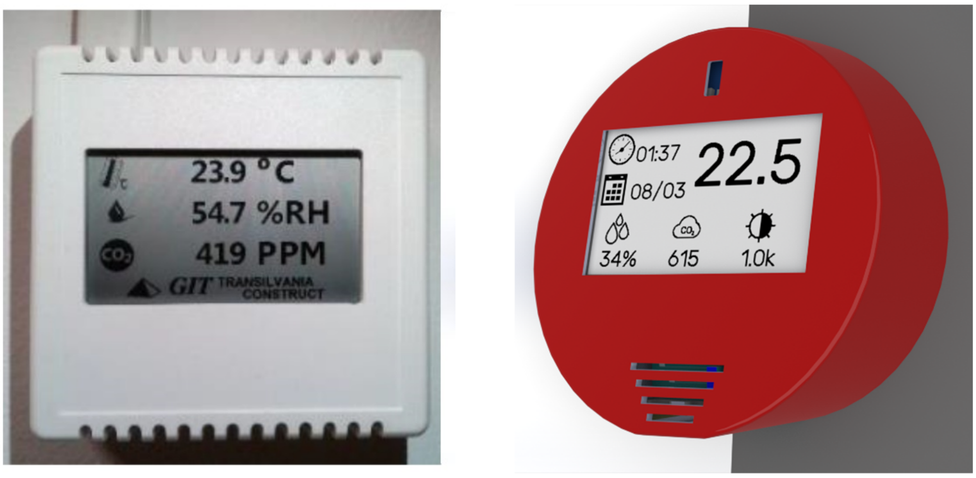

Figure 10. Sensors for air temperature, humidity, and CO_2 content (Ref. [50]).

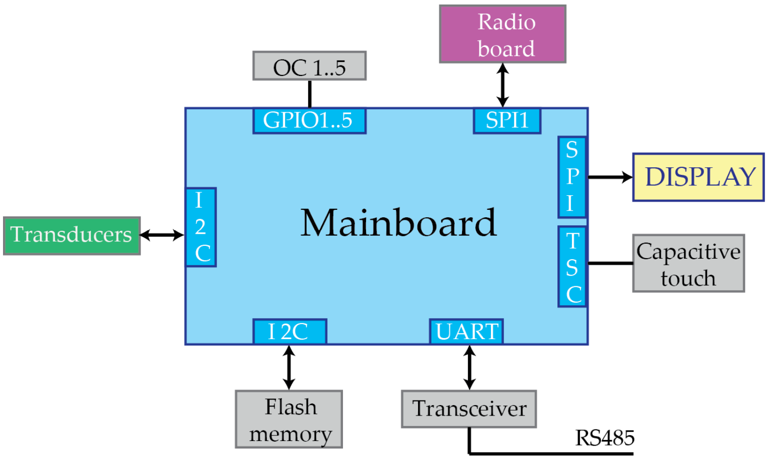

Figure 11. Host module block diagram (OC—optocoupler, GPIO—general-purpose input/output, TSC—touch-sensing controller).

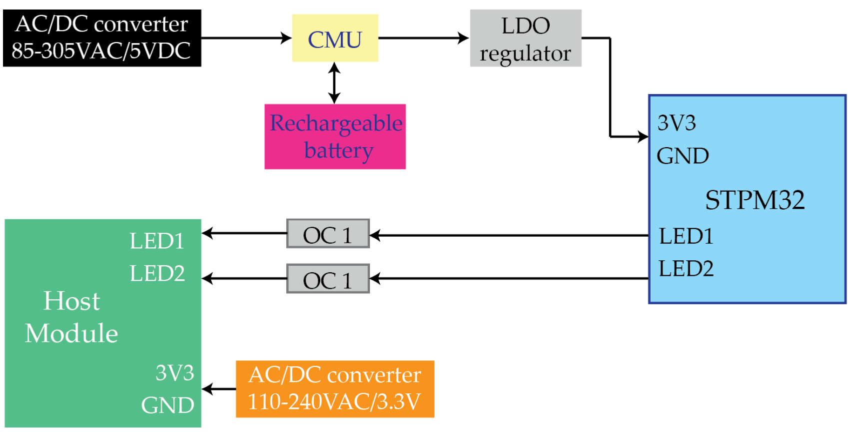

Figure 12. Interfacing board block diagram (CMU—charging management unit, OC—optocoupler, LDO regulator—low-dropout regulator).

Figure 13. Interfacing board prototype.

The on-board frequency output signals of the STPM32 were used to estimate the power consumption; their frequency was proportional to the power (characterized by the proportionality constant, the number of pulses per kW). Since the board does not save the configurable parameter values in the nonvolatile memory, a rechargeable battery was included in the setup, to continuously maintain the power supply of the board.

The host board is responsible for reading the frequency, for computing the average power consumption in each second, and for communicating the values to the wireless hub connected in the home sensor network.

The implementation on the microcontroller follows the algorithm presented in the following pseudocode:

```
EXT_INT_IRQHandler:
stop timer1
if (i ≥ 0) then
 Δt[i] ← get_counter(timer1)
endif
i ← i + 1
reset timer1 value
start timer1

main_thread:
start auto reload timer2 (1 s overflow)
i ← −1
loop
   if (timer2 overflow)
     clear timer2 overflow flag
     compute average value of Δt counters stored during the last second
     estimate average power consumption
     i ← −1
   endif
endloop
```

The external interrupt is driven by the output of the optocoupler connected to the LED1 signal of the STPM32 board and is configured to trigger an event on the rising edge. One timer (timer 1) counts the number of cycles between two successive events. A general-purpose timer (denoted here as timer 2) is used to signal a one-second-elapsed event.

The timing diagram of Figure 14 shows the events handled by the microcontroller.

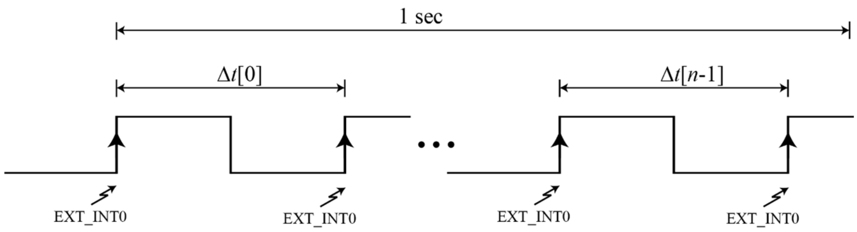

Figure 14. Events handled by the microcontroller for power-consumption estimation.

A picture showing the developed smart-meter module is presented in Figure 15. The measurement board is mounted in the box with the plug on the back and the socket on the front face. The minimum, maximum, and current average are displayed next to the graphical representation of the load profile when the trace mode is activated (the sampling time is one second).

Figure 15. Smart-meter module.

4.3. Experiments and Results

The following figures (Figures 16–19) present records of the consumption (medium power at an interval of 1 s). For the experiments, the energy consumers presented in Table 3 were considered.

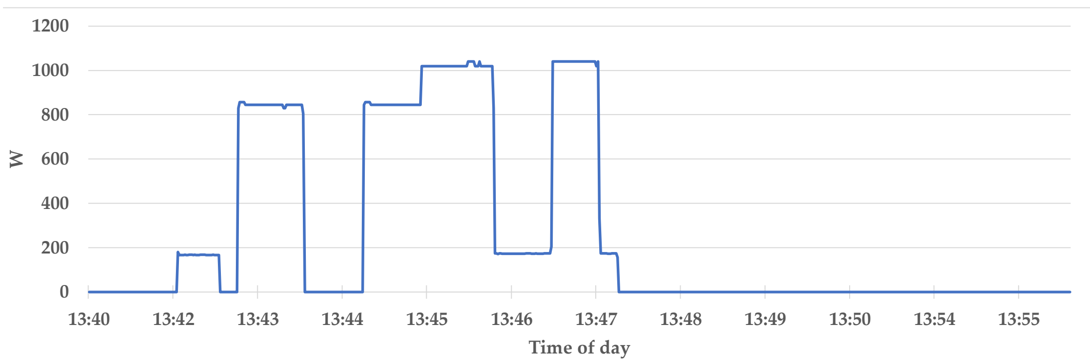

Figure 16. Combined profile of the lamp and of the electric heater.

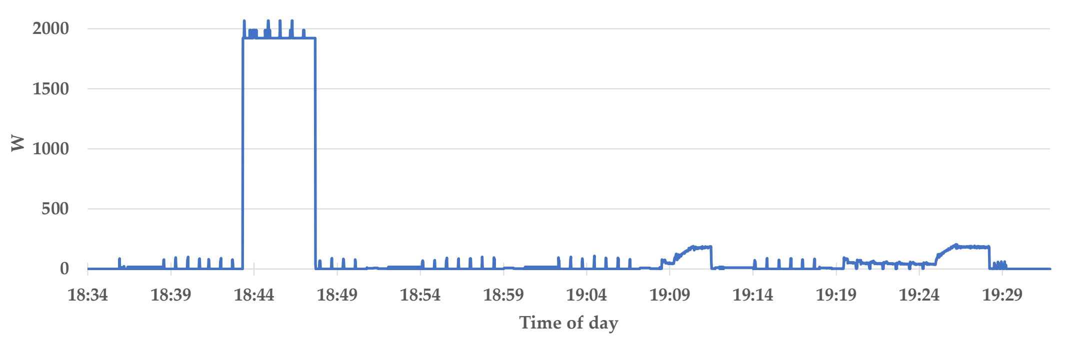

Figure 17. Load profile of the washing machine for a wool cycle (54 min).

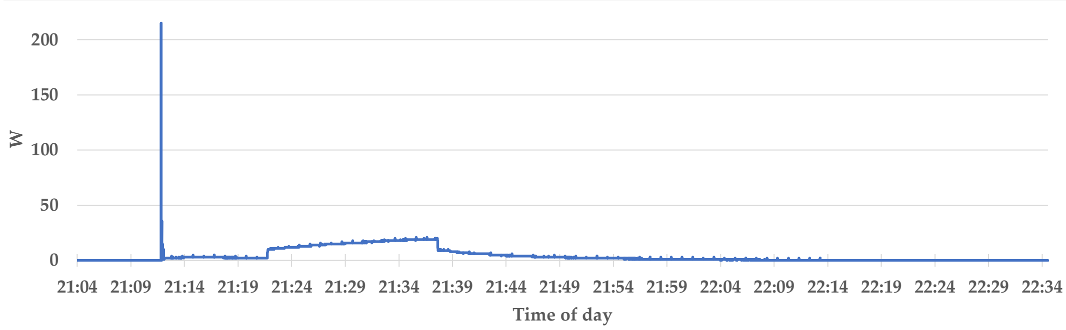

Figure 18. Load profile of the refrigerator.

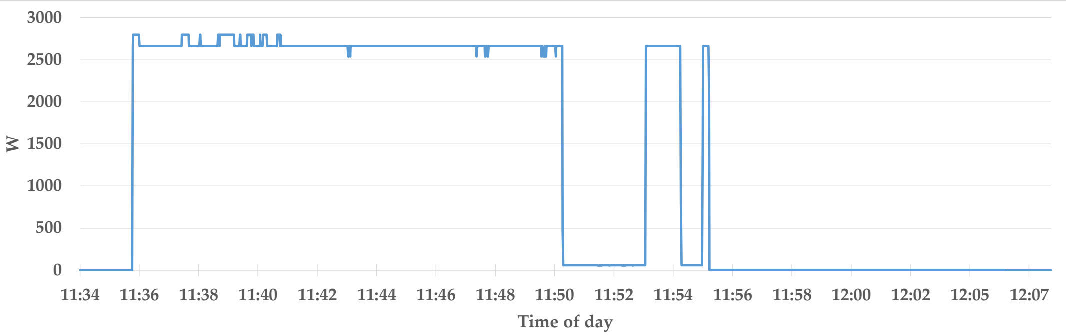

Figure 19. Load profile of the electric oven.

Table 3. Appliances used for experiments.

Device	Model	Consumption
Washing machine	ARCTIC APL71222BDW3	173 kWh/year
Refrigerator	Bosch KGE39AI40/13	156 kWh/year
Electric oven	Electrolux EOF5C70X	0.81 kWh/cycle, max. 2790 W
Electric heater	Electrolux ER 2009	Max. 2000 W
Lamp with light bulb	Osram	200 W

4.3.1. Linear Approximation of Load Profiles

Local approximation through linear models is widely used in simulation environments, such as SPICE. Piecewise linear representations have distinct advantages for numerical methods used in simulation and optimization. Problems such as the mixed-integer linear program (MILP) are simplified by the use of linear models. The authors of Ref. [55] consider an optimization-based approach to the intentional islanding of power networks and show that the inclusion of a piecewise linear model (PWL) for the AC power flow facilitates the determination of AC-feasible islands.

Bearing in mind its ease of representation and suitability for fast optimization algorithms, the PWL representation was considered for the load profiles of the residential appliances. To obtain a piecewise linear approximation of the load profiles corresponding to specific appliances, the following steps were performed:

- Apply a Gaussian filter, for smoothing the data;
- Apply a first-order derivative of a Gaussian filter on the smoothed data, in order to emphasize the steep changes in the signal;
- Extract the extrema points;
- Using the extrema as breakpoints, find a linear approximation for each interval.

The procedure applied on the power measurements performed on the refrigerator, oven, and washing machine resulted in the approximations presented in Figures 20–23.

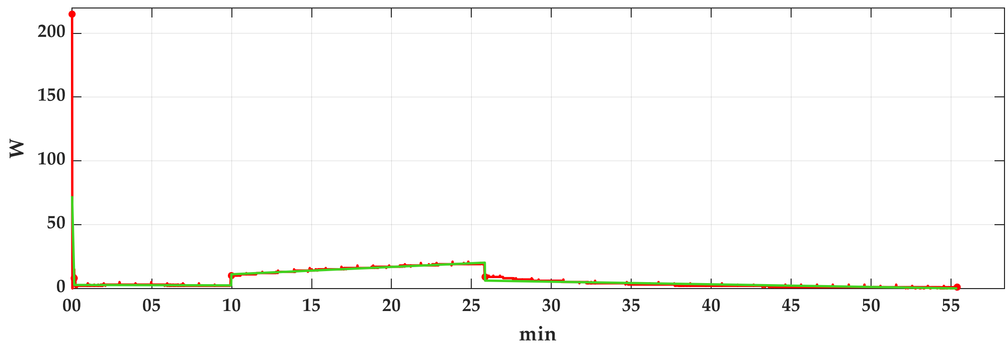

Figure 20. PWL approximation of the refrigerator's load profile—RMS value 3.16 (measured data—red vs. approximated profile—green).

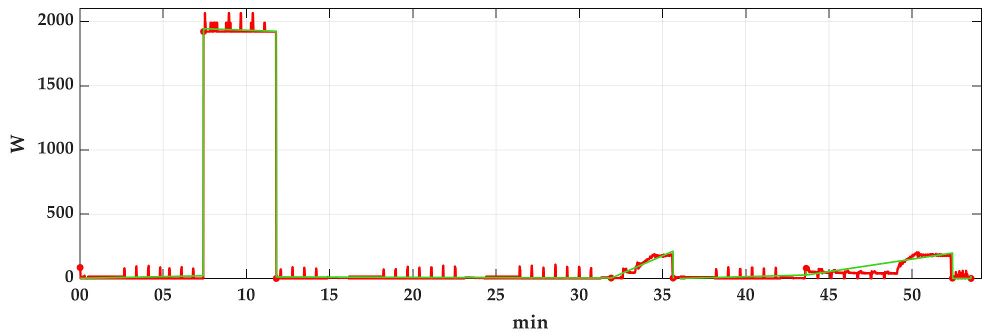

Figure 21. PWL approximation of the washing machine's load profile—RMS value 27.04 (measured data—red vs. approximated profile—green).

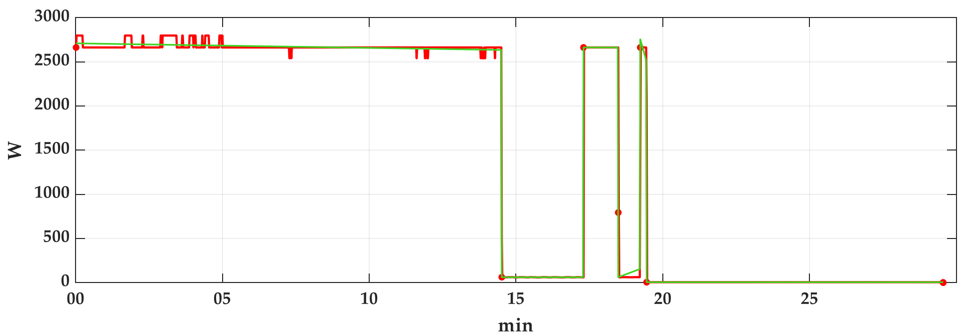

Figure 22. PWL approximation of the oven load profile—RMS value 110.9 (measured data—red vs. approximated profile—green).

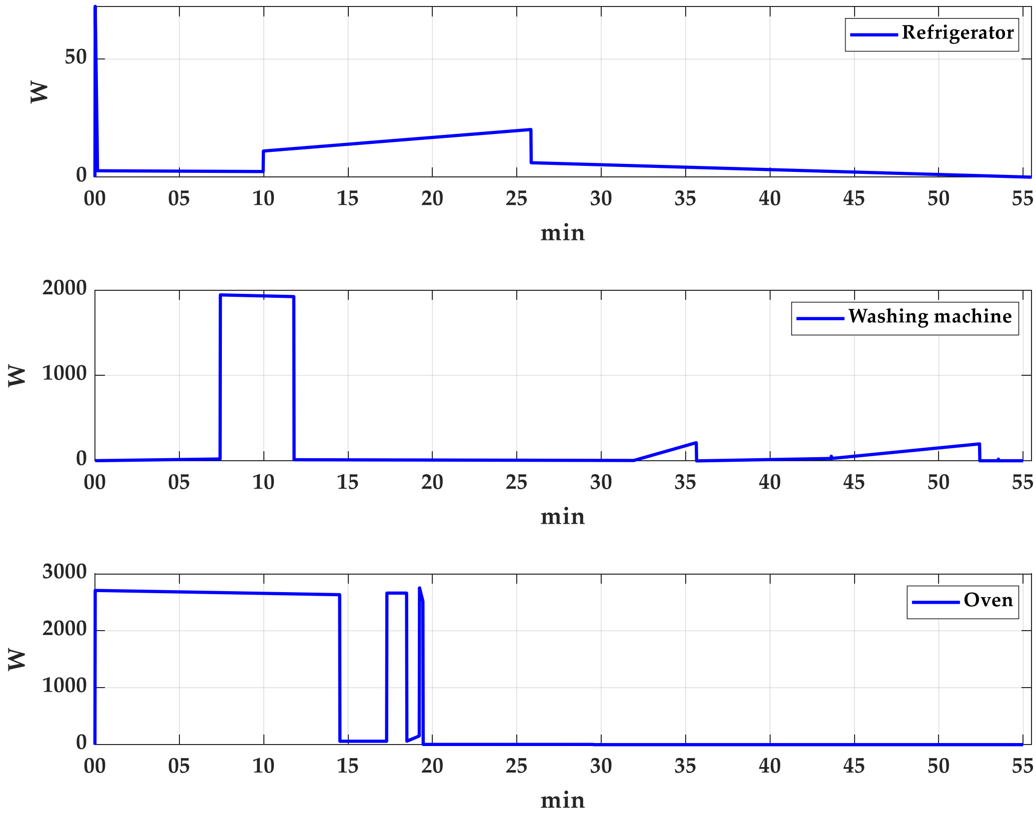

Figure 23. PWL approximations of the load profiles.

The simple algebra involved in defining the summation operation is:

$$P = \sum_{i=1}^{n} P_i(t - t_i)$$

where $P_i(t - t_i)$ is the PWL representation of the appliance i load profile (shifted with the time t_i). It allows the generation of artificial daily profiles based on real appliance load profiles. This fact demonstrates the versatility of the PWL representation in generating a sufficiently broad spectrum of daily profiles to simulate the optimization algorithms. The rescheduling of the loads is, in fact, in this representation, just equivalent with the time shifting of the appliance profiles. As an example, an artificial daily-load profile, generated by considering that the oven starts at 12:30 and at 18:30 and the washing machine starts at 16:00, is presented in Figure 24.

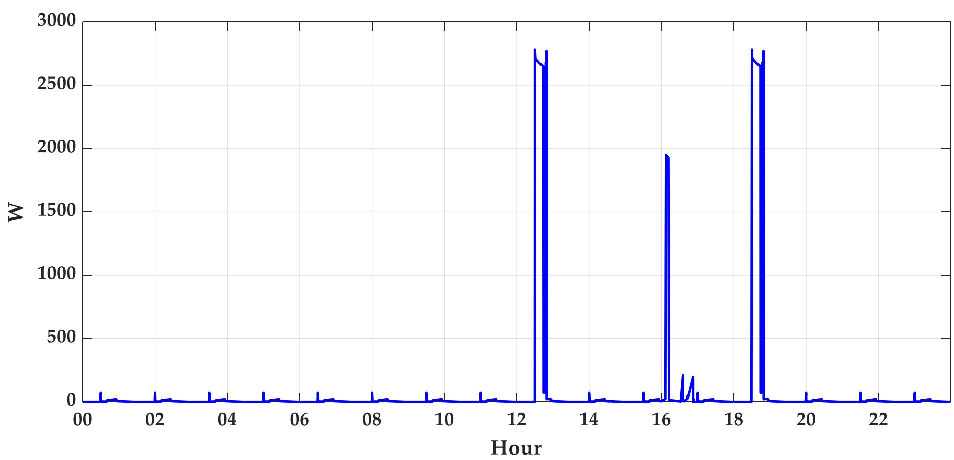

Figure 24. Artificial daily-load profile.

4.3.2. Advantages of PWL Representations for Load Scheduling

From a function-approximation perspective, a PWL representation offers a better representation for the load profiles than a classic staircase approximation (for an hourly-averaged approximation, see Ref. [56]). The more accurate representation and the higher sampling rate should be examined from the perspective of evaluating their potential for improved energy saving in typical real-time scheduling scenarios.

A common approach to load scheduling is load shifting ([27,56,57]). A least slack time (LST)-based approach is introduced in Ref. [57] for the real-time scheduling of smart home appliances. The scheduling scheme aims to minimize energy costs while handling user requests within the earliest possible time frame. These types of strategies, based on preemptions, are appropriate for appliances that can be stopped for a certain amount of time and restarted afterward. The shifting algorithms introduced in Ref. [56] are used for flattening the daily-load profile by iteratively shifting the operation of programmable appliances from peak hours to off-peak hours. These optimization algorithms use a time granularity of 1 h.

Table 4 enumerates several recent approaches reported in the literature. They are based on several optimization strategies, and their efficiency is generally demonstrated on hourly-averaged power-measurement series.

Table 4. Load scheduling algorithms for appliances.

Ref.	Algorithm	Types of Devices	Time Granularity
[57]	Least Slack Time (LST)	Devices with different duty cycles	N/A [1]
[58]	Full/limited preemption Earliest Deadline First (EDF)	Interruptible devices	N/A
[56]	Gradual- and lump-shifting algorithms	Programmable interruptible/non-interruptible devices	1 h
[59]	Cuckoo Search (CS), Mixed-Integer Linear Programming (MILP)	Shiftable and non-shiftable devices	1 h
[60]	Particle Swarm Optimization (PSO), Grasshopper Optimization Algorithm (GOA)	Controllable devices	1 h
[61]	Genetic Algorithm (GA)	Controllable devices	1 h
[62]	Whale Optimization Algorithm	Controllable devices	1 h
[63]	Hybrid Gray Wolf Differential Evolution (HGWDE)	Shiftable, non-shiftable, and controllable devices	15, 30, and 60 min
[64]	Enhanced Binary Gray Wolf Optimization (EBGWO), Binary Particle Swarm Optimization (BPSO) and Binary Gray Wolf Optimization (BGWO)	Controllable/uncontrollable shiftable/non-shiftable devices	N/A
[65]	PSO, vortex search (VS), differential evolution (DE), Hybrid-Adaptive DE (HyDE), HyDE with decay function (HyDE-DF)	Shiftable and real-time devices	15 min
[66]	WFS2ACSO (hybrid technique incorporating Wingsuit Flying Search Algorithm (WFSA) and Artificial Cell Swarm Optimization (ACSO))	Controllable devices	N/A
[67]	Moth-Flame Optimization (MFO) algorithm, Genetic Algorithm (GA), TG-MFO (Time-Constrained Genetic-Moth-Flame Optimization)	Fixed and elastic devices	30 min

[1] N/A–information not available.

The test problem is formulated as follows: for a given shift step, s_{hstep}, starting from the representation of the load profile of each appliance i, $LP_i\ (t) = 0$ and $t \notin (s_i, S_i)$, where (s_i, S_i) is the start/stop pair for $LP_i\ (t)$, find the values s_{hi} corresponding to the shifted start/stop points $(s_i, S_i)_{\text{shifted}} = (s_i, S_i) + s_{hi} \cdot s_{hstep}$ that minimize the peak-to-average power ratio (PAPR), $\frac{|x_{peak}|^2}{x_{RMS}{}^2}$, of the aggregated profile.

A first experiment considers a simple configuration: a cluster with three homes. At the level of each home, the shiftable loads are a washing machine and a dryer, whose profiles are indicated in Figure 25. The activity intervals accepted by the users for each home (AI_i) are illustrated in Figure 26.

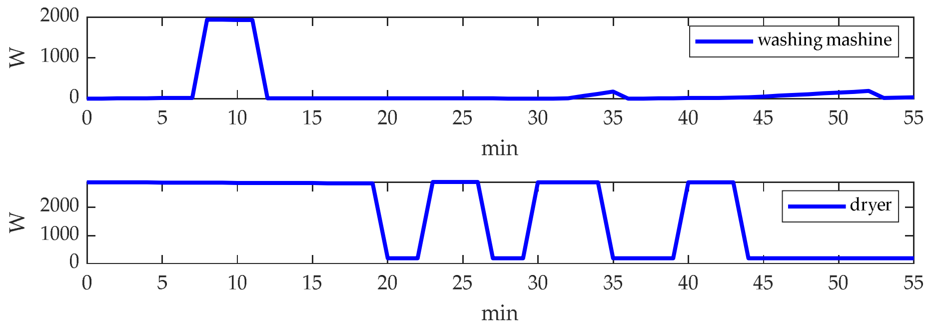

Figure 25. Load profiles used in experiment (sampling time 1 min).

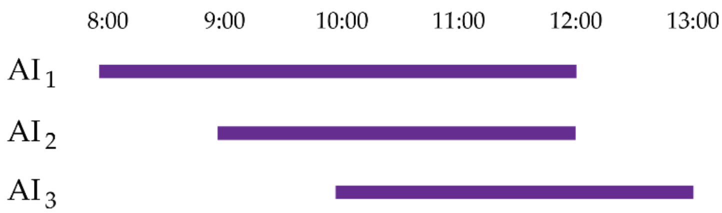

Figure 26. Activity intervals used in experiment.

The shifting step used in the simulation was 15 min. The following restriction related to the order of running was imposed: the dryer should start after the washing machine finishes its program. The shifting configuration produced was (1 6 1 7 2 6) (Figure 27).

This type of day-ahead planning strategy can be easily disturbed by a random perturbation (the user manually switches on another appliance). To simulate the load-rescheduling algorithm behavior in the presence of perturbations, a must-run load (an oven, in our example) was introduced at the level of home 3. Its profile is presented in Figure 28.

The initial optimal profile was no longer valid: the appliances that were already activated would remain unshifted, but those that were not yet activated at the time when the perturbing load is switched on must be rescheduled. The simulation led to a shifting configuration (1 6 1 8 3 8 0) (Figure 29). It can be observed that the not-yet active loads (with reference to the switching-on of the oven) were pushed to the right along the time axis (when compared with Figure 27) to accommodate the insertion of the oven profile, and the peak consumption was reduced accordingly.

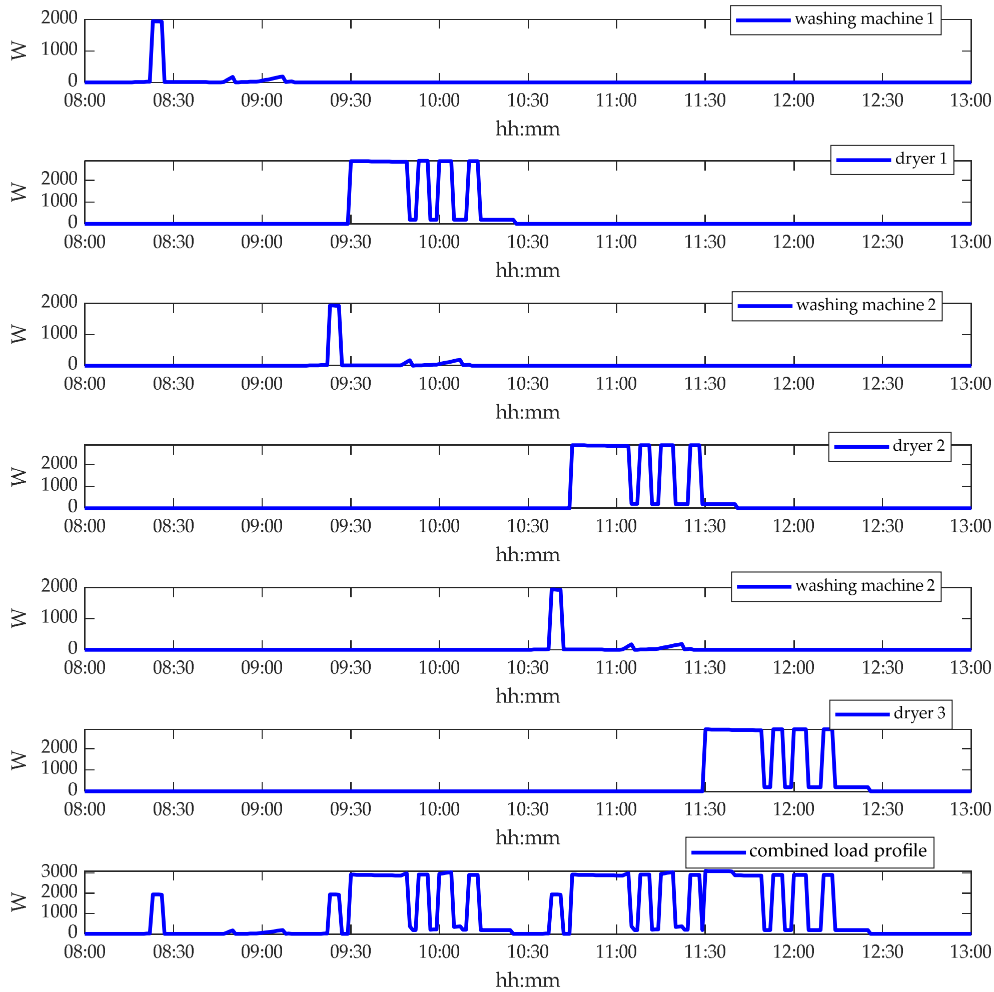

Figure 27. Simulation results.

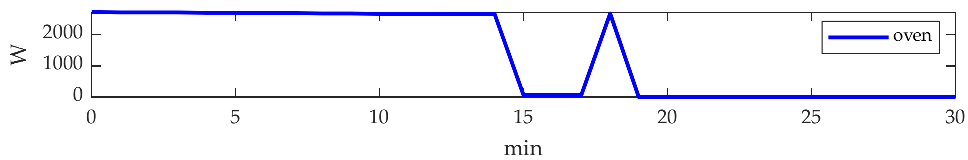

Figure 28. Profile of the non-shiftable load used in simulation (sampling time 1 min).

The presence of the smart-meter nodes (Figure 9) *enables this reactive behavior*: the detection of the switch-on event occurs at the level of the wireless sensor, and it is further propagated on the route wireless-hub-gateway-inference engine and strategy planner. This last block is responsible for the running of the rescheduling, such that the response time of the system is strictly related to the computational complexity of the rescheduling algorithm and the computational power of the hardware on which it runs. The granularity of the configuration space is essential. A two-stage approach strategy can help to obtain better response times: a first-stage exploration with a larger shifting step can be followed by a refining stage with a smaller shifting step.

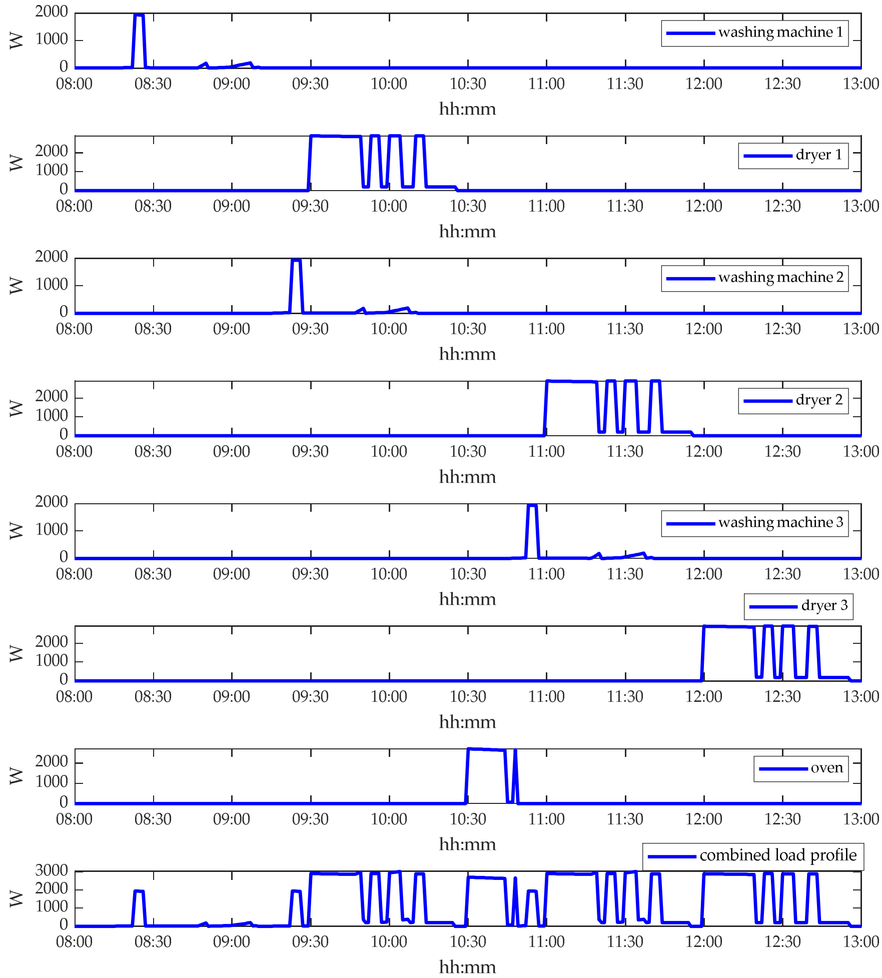

Figure 29. Simulation results in the presence of a perturbation.

A second experiment was performed to assess the advantage of using PWL representations for load scheduling instead of staircase approximations, this time in a complex home cluster/neighborhood setup (165—washing machines, 120—dryers, 180—dish washers). The cuckoo search (CS) algorithm [68] was applied on a combined profile of three types of shiftable appliance, totaling 465 appliances (Figure 30). The activity interval considered was from 8 AM to 3 PM.

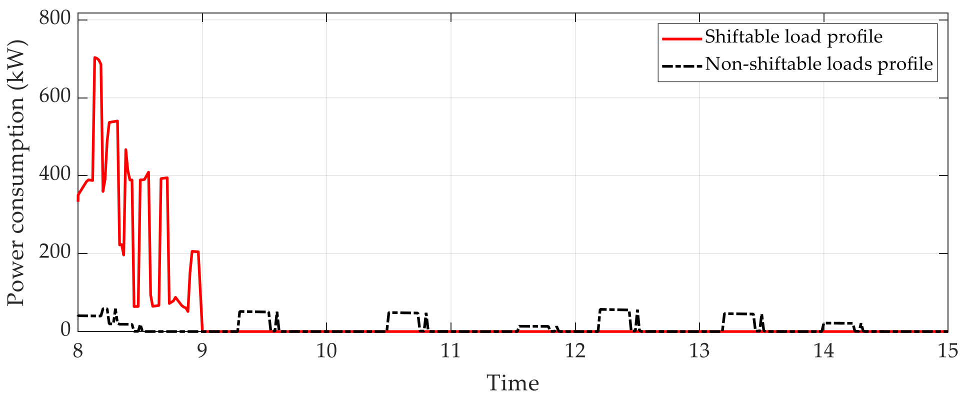

Figure 30. Load profile considered for scheduling.

Two simulations were performed: one using PWL representations, and one using hourly approximations (Figure 31).

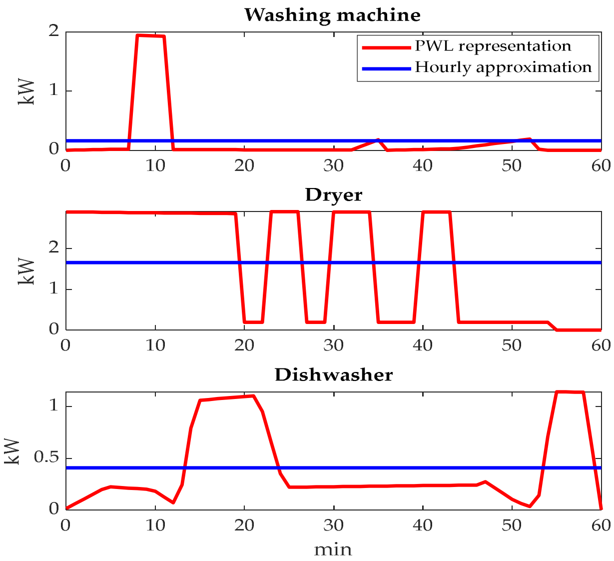

Figure 31. Load-profile representations considered for simulation.

For the first simulation, a shift step of 10 min was used, while for the second, the shift step was set to one hour. Running the CS algorithm with a population size of 25 candidate solutions for 2500 generations for the two representations considered (PWL/staircase) resulted in two shifting configurations (two sets of s_{hi} values i = 1.465).

A shifting configuration specifies for each load profile the number of times it should be shifted by s_{hstep} such that the aggregated profile is the "best" according to the measure of flatness considered. Figure 32 presents the PWL representations of the aggregated load profiles for the two shifting configurations obtained (the one obtained using PWL representations for the load profiles and the one obtained using staircase approximations for the load profiles). The superior peak-shaving performance demonstrated by the PWL representations is obvious.

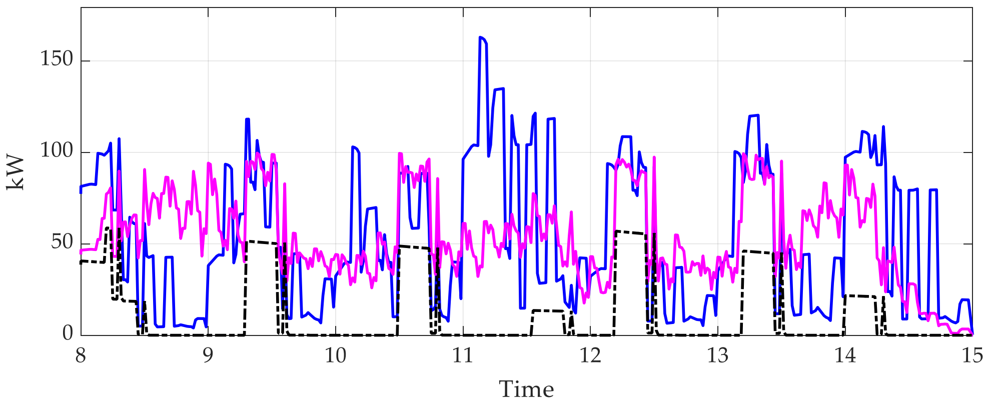

Figure 32. PWL representations of the optimal load profiles (magenta—aggregated profile based on the shifting configuration resulted from the PWL approximation, blue—aggregated profile based on the shifting configuration resulted from the staircase approximation, black—non-shiftable loads).

4.3.3. Software Applications for Recording and Visualization

In the initial process of installing and configuring the monitoring networks, as well as later in the maintenance, the testing and debugging activities are strongly supported by visualization tools. The software applications that were developed for running on the embedded sensing modules were implemented in a way that supported dual data-collection behavior: gateway-based data collection and the direct connection of a mobile application to the sensing modules via the BLE interface. On one hand, the mobile app not only collects current readings, but also downloads the logged values for visualization. A screenshot from the developed iPhone/iPad app is shown in Figure 33.

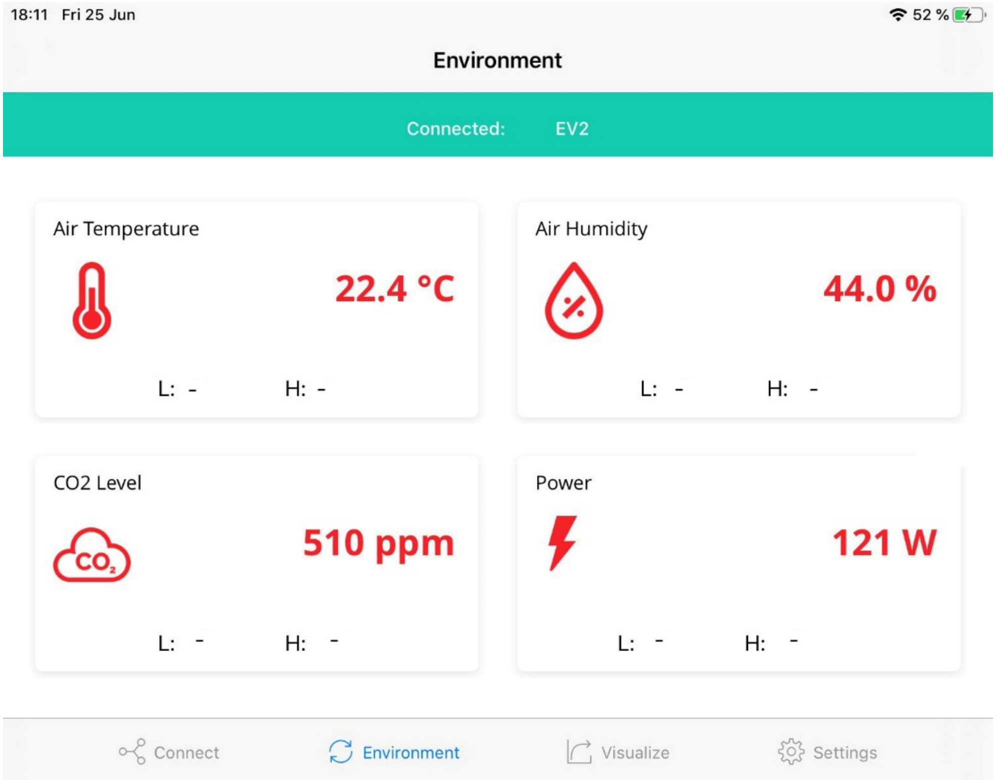

Figure 33. The iPhone/iPad application.

On the other hand, the automated process of data collection and archiving is supported by the software modules inherited from the smart-home distributed system: wireless hubs are integrated with gateways that periodically send the logged data toward the cloud databases using the scalable software architecture described in the next section.

Visualization screens generated from the records of the environmental variables acquired using the integrated monitoring system are presented in Figures 34–38.

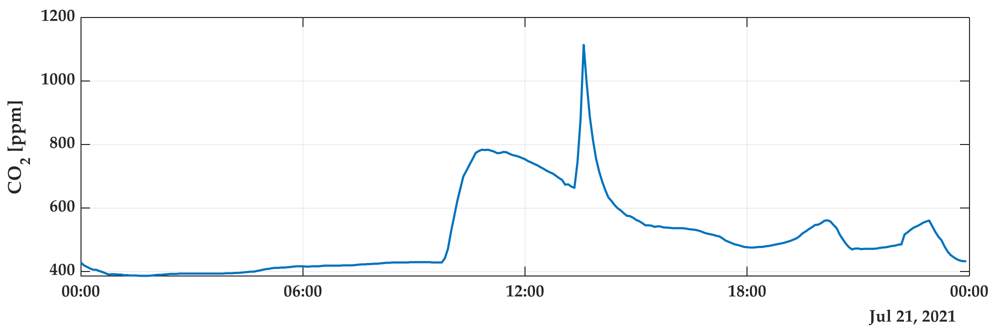

Figure 34. Records of CO_2 levels.

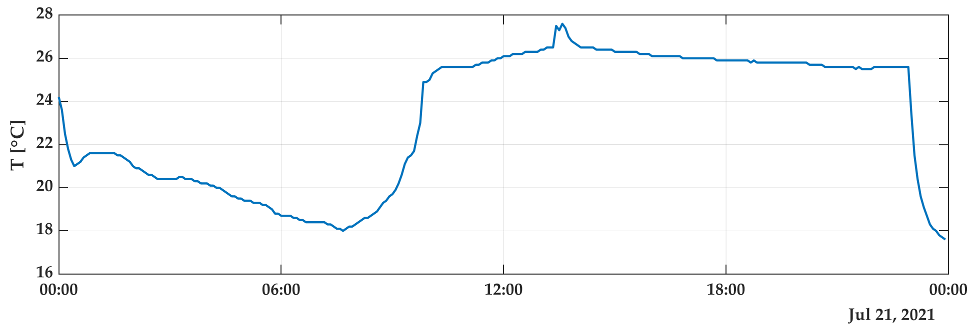

Figure 35. Records of air temperature.

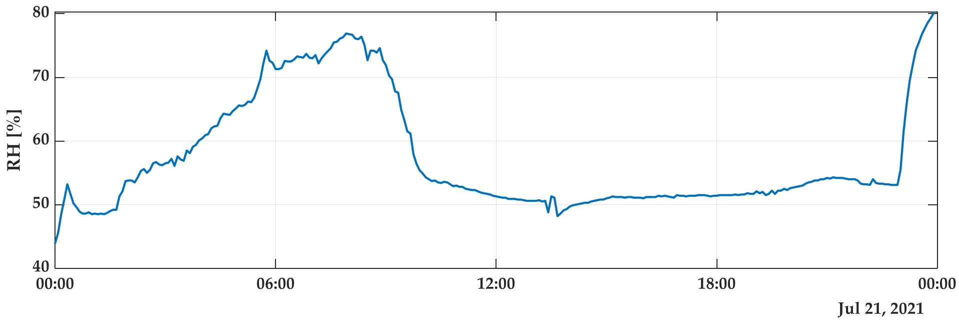

Figure 36. Records of relative air humidity.

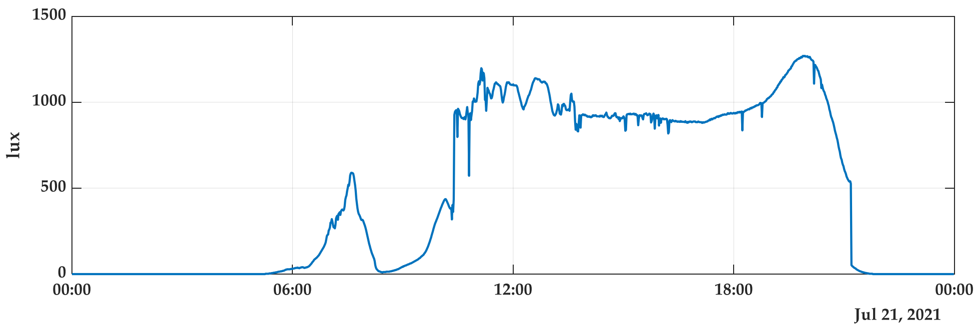

Figure 37. Records of light intensity.

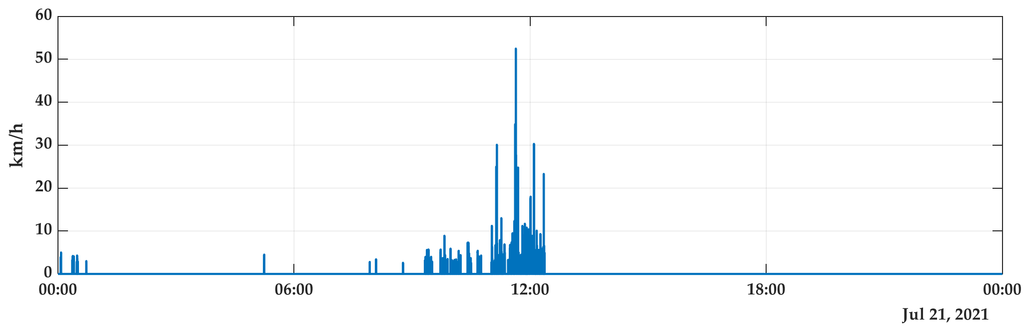

Figure 38. Records of wind speed.

5. Discussion

5.1. Privacy

An important aspect related to smart metering is residents' privacy. The provision of accurate, granular data related to energy consumption to utility providers may be a threat to residents' privacy, facilitating the identification of specific appliances' power signatures and inferences about residents' private lives. Based on the smart-meter data, malicious attackers may find information related to residents, such as their presence at home, disabilities/illnesses, eating habits, sleep cycles, time spent in front of TV, age, gender, or ethnicity [69].

The usage of load-shifting techniques and of alternative representations of the load profiles instead of the whole data set are among the privacy-preserving techniques considered. The proposed PWL representation can successfully support such approaches.

5.2. Scalability

To address the matter of scalability, both building-level and city-level integration must be considered.

In the current setup of the home network, the hub is equipped with a BLE interface for communicating with the wireless network and an RS-485 interface for integration on the wired side into the home network. The home network is interfaced by a gateway module that provides a wired ethernet interface. For a larger office building or an industrial building, an increase in the number of monitored loads may need a larger bandwidth than is achievable through the BLE and RS-485 interfaces of the wireless hub (when higher rates, of a few measurements/second, are considered).

To improve the communication architecture to support the real-time transfer of the measured data from each smart meter directly to the upper hierarchical levels (cloud database server, inference engine, and strategy planner), the usage of wired and wireless Ethernet is considered. There are two alternative solutions: either the RS-485 port of the hub is replaced with an Ethernet port (wired or wireless), or the BLE interface of the sensing modules is directly replaced by a wireless Ethernet module. The transition from BLE to Wi-Fi is facilitated by the modular design of the host module (see Figure 11), the only part affected being the radio board. The usage of a low-power Wi-Fi module, such as the Silicon Labs WGM160P Wi-Fi Module [70] (a module suitable for cloud-connected IoT applications, integrating a chip antenna, 802.11 b/g/n radio, certifications, Wi-Fi and IP stacks, HTTP server, and a microcontroller that can host user applications or be used with an external host controller in network-co-processor (NCP) mode), allows easy transition from BLE to Wi-Fi and direct integration with the current motherboard through the SPI interfaces.

For the city-level integration, the software architecture is mainly concerned with issues generated when a large number of buildings are connected. The proposed approach is indicated in Figure 39.

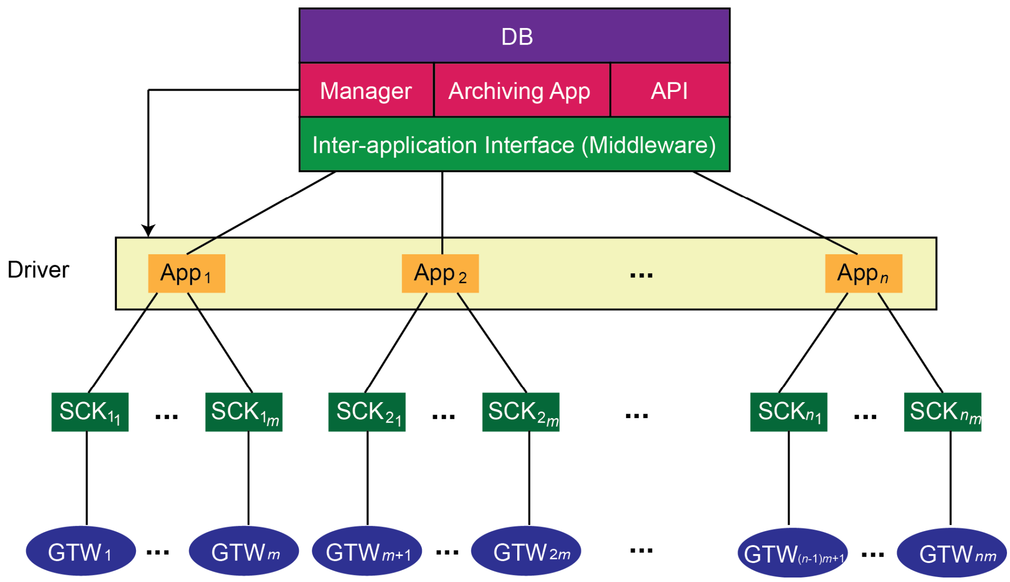

Figure 39. Scalable software architecture.

The gateway modules periodically connect through TCP-IP sockets to the Apps in the Driver layer to send the latest measurements and to receive user commands (the setting points and the switch-ON/OFF commands issued through the graphic interface by the inhabitants). The gateway-issued messages used for transmitting the measurements contain the following information: the timestamp, gateways' serial number, message type, priority, number of measurements included in the message, and pairs <dataSourceIdx, value>. The App must be seen as a message broker: its main functionality is to listen for incoming connections, create a queue of lists (one list contains messages from one gateway), and pass it to the upper hierarchical level. Each App handles 1 to m gateways. If the number of requests per second is greater than the threshold, another App is launched. The Apps are configured by the Manager.

Industrial environments typically use three-phase power supply. One solution for metering systems that can be adopted in these environments is the ST's three-phase meter [71], integrating a STPM34 board for sensing the current and voltage in the primary and secondary phase and a STPM33 board for sensing the current and voltage in the third phase. A microcontroller facilitates the aggregation of the information provided by the two metering devices, computing total energy and power. Direct communication with each individual metering device is also possible.

While for residential homes, the most important measurement is the active power, for industrial environments, the measurements of interest are power quality, reactive power, and harmonics. STPM3x measures voltages and currents on up to two lines and computes the following quantities [72]:

- Active power and energy wideband 0 Hz (4 Hz)–3.6 kHz (the effects of harmonics within this range are included);
- Fundamental active power and energy 45–65 Hz (the current and voltage waveforms are filtered for removing all the harmonics except the first);
- Reactive power and energy;
- Apparent power and energy from RMS data;
- Apparent power vectorial calculation based on the scalar product of active and reactive power;
- Signal parameters, such as the zero-crossing, line period, phase-delay between voltage and current, sag and swell events, tamper and RMS values of the current and voltage on each phase are computed on T = 200 ms every 128 µs.

Each computed power value is stored in a 32-bit register and accumulated (with sign) in the corresponding 32-bit energy register at a rate of 7.8125 kHz.

Another solution appropriate for three-phase smart-meter nodes is indicated in [73]. It combines a hardware front-end realized with sigma-delta modulators with a dedicated digital filter for sigma–delta modulator (DFSDM) blocks available in STM32F413. The setup depicted in Figure 40 uses only three pairs of two-wire communication lines, which need to be optically isolated. When compared with the direct extension toward the three-phase measurement of the single-phase setup implemented in the prototype smart meter (i.e., replicating the measurement chip three times, Figure 41), the galvanic isolation block significantly increases the cost. The high rates and higher number of lines in the case of SPI affect this, as indicated in Tables 5 and 6.

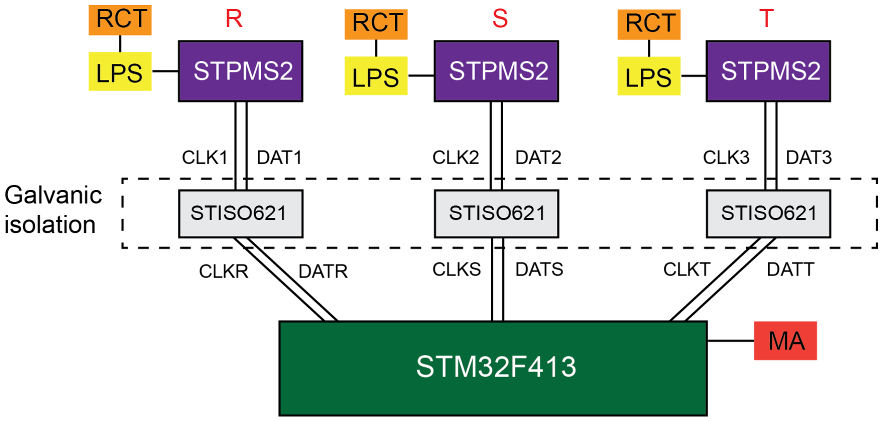

Figure 40. Three-phase meter block diagram with sigma–delta modulators (RCT—rectifier, LPS—linear power supply, MA—mains adapter).

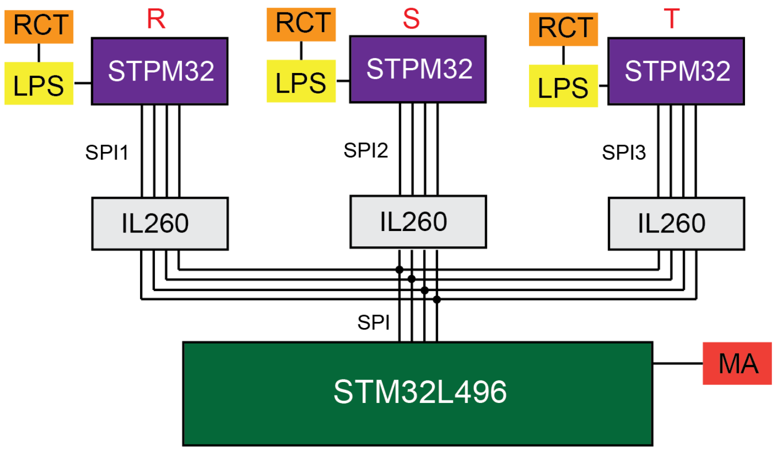

Figure 41. Extension of the implemented single-phase setup for measurements in three-phase systems.

Table 5. Main components in the setup of Figure 40.

Component	Producer	Unit Price	Quantity	Total
STPMS2	STMicroelectronics	1.10	3.00	3.30
STISO621W	STMicroelectronics	1.30	3.00	3.90
STM32F413RHT6TR	STMicroelectronics	6.79	1.00	6.79
	Total			13.99

Table 6. Main components in the setup of Figure 41.

Component	Producer	Unit Price	Quantity	Total
STPM32	STMicroelectronics	1.39	3.00	4.17
IL260	NVE Corporation	5.71	3.00	17.12
STM32L496RGT3	STMicroelectronics	7.40	1.00	7.40
	Total			28.69

6. Conclusions

The paper introduced the hardware/software codesign of an integrated smart-home architecture that is able to combine typical distributed sensing and control networks (targeting user comfort in smart homes) with energy-monitoring and management systems, implemented as smart nodes organized in sensor networks.

Communication architectures and data-management systems appropriate for real-time aggregating time series were reviewed and analyzed from the perspective of consumption-data measurement and logging. A scalable data-transfer architecture that can cope with time series generated by a large number of home-energy-management systems was introduced, together with associated database applications for supporting the optimization and modeling of load profiles at cluster level, sector level, and city level.

A smart-meter node that shares the processing and communication architecture with the smart sensors previously implemented for user-comfort management (smart home infrastructure) was developed to support the automated process of power-measurement collection and archiving. The ability of this node to process power measurements with a programable granularity level (seconds/minutes/hours) at the local (edge) level and stream the processed measurement results at the selected granularity to the cloud was identified as a valuable feature for a large range of applications (model identification, power saving, prediction). The impact of the real-time transfer of the measured data from each smart meter directly to the upper hierarchical levels (cloud database server, inference engine, and strategy planner) was analyzed in relation to the scaling-up of the number of monitored buildings. Solutions for extending the proposed setup for buildings in industrial environments (three phase systems) were proposed.

It should be emphasized that the node introduced here is implemented at a mature level of technology readiness and provides the essential functionalities of a smart meter [74]: regular and precise metering, two-way communication, appliance control, and support for demand-side management procedures.

The recorded profiles generated by the smart meter nodes and by the sensors involved on HVAC control are easily visualized with the developed suite of software applications. Piecewise linear approximations of the load profiles corresponding to specific appliances were introduced and implemented in the DB application. Their ease of representation and suitability for generating the daily profiles needed in the simulation of the optimization algorithms were exemplified using some typical appliances. The advantages of the new PWL representation for optimization procedures were demonstrated by the better performance (higher energy savings) in load scheduling and rescheduling using the proposed system.

The modular architecture of the sensor node facilitates the reuse of the same platform to develop edge nodes that measure environmental comfort variables and air quality, or nodes that provide the functionality of smart meters. This supports the integration of typical smart-home networks with energy-monitoring networks in a novel, easier, and affordable way. The use of mature technologies for communication and database systems combined with the scalability of the cloud-based approach suggests that the proposed solution is futureproof.

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References

1. Zhang, X.; Lovati, M.; Vigna, I.; Widén, J.; Han, M.; Gal, C.; Feng, T. A review of urban energy systems at building cluster level incorporating renewable-energy-source (RES) envelope solutions. *Appl. Energy* **2018**, *230*, 1034–1056. [CrossRef]
2. Köckemann, U.; Alirezaie, M.; Renoux, J.; Tsiftes, N.; Ahmed, M.U.; Morberg, D.; Lindén, M.; Loutfi, A. Open-Source Data Collection and Data Sets for Activity Recognition in Smart Homes. *Sensors* **2020**, *20*, 879. [CrossRef] [PubMed]
3. Pietila, A.J. Reducing the Magnitude and Reshaping the Temporal Distribution of Residential Electrical Loads Purposed to Achieve a Zero Peak House in a Southern Ontario Climate. Master's Thesis, Aerospace Engineering, Carleton University, Ottawa, ON, Canada, 2011.
4. Newsham, G.R.; Galasiu, A.D.; Armstrong, M.M.; Beausoleil-Morrison, I.; Szadkowski, F.; Sager, J.M.; Pietila, A.J.; Rowlands, I.H. The zero-peak house: Full-scale experiments and demonstration. *Energy Build.* **2013**, *64*, 483–492. [CrossRef]
5. Eunomia Research & Consulting Ltd. Heat Pump Manufacturing Supply Chain Research Project, Final Report. December 2020. Available online: https://www.gov.uk/government/publications/heat-pump-manufacturing-supply-chain-research-project (accessed on 15 March 2021).
6. Shukla, A.K.; Sudhakar, K.; Baredar, P. Recent advancement in BIPV product technologies: A review. *Energy Build.* **2017**, *140*, 188–195. [CrossRef]
7. Debbarma, M.; Sudhakar, K.; Baredar, P. Thermal modeling, exergy analysis, performance of BIPV and BIPVT: A review. *Renew. Sustain. Energy Rev.* **2017**, *73*, 1276–1288. [CrossRef]
8. Zhang, X.; Shen, J.; Lu, Y.; He, W.; Xu, P.; Zhao, X.; Qiu, Z.; Zhu, Z.; Zhou, J.; Dong, X. Active Solar Thermal Facades (ASTFs): From concept, application to research questions. *Renew. Sustain. Energy Rev.* **2015**, *50*, 32–63. [CrossRef]
9. Poppi, S.; Sommerfeldt, N.; Bales, C.; Madani, H.; Lundqvist, P. Techno-economic review of solar heat pump systems for residential heating applications. *Renew. Sustain. Energy Rev.* **2018**, *81*, 22–32. [CrossRef]
10. O'Shaughnessy, E.; Cutler, D.; Ardani, K.; Margolis, R. Solar plus: Optimization of distributed solar PV through battery storage and dispatchable load in residential buildings. *Appl. Energy* **2018**, *213*, 11–21. [CrossRef]
11. Alva, G.; Lin, Y.; Fang, G. An overview of thermal energy storage systems. *Energy* **2018**, *144*, 341–378. [CrossRef]
12. *Directive 2010/31/EU of the European Parliament and of the Council on the Energy Performance of Buildings*; Official Journal of the European Union: Luxembourg, 2010.
13. *Directive 2009/28/EC of the European Parliament and of the Council on the Promotion of the Use of Energy from Renewable Sources*; Official Journal of the European Union: Luxembourg, 2009.
14. Renovate Europe. Available online: https://www.renovate-europe.eu (accessed on 24 April 2021).
15. Vigna, I.; Pernetti, R.; Pasut, W.; Lollini, R. New domain for promoting energy efficiency: Energy Flexible Building Cluster. *Sustain. Cities Soc.* **2018**, *38*, 526–533. [CrossRef]
16. Li, X.; Wen, J. Net-zero energy building clusters emulator for energy planning and operation evaluation. *Comput. Environ. Urban Syst.* **2017**, *62*, 168–181. [CrossRef]
17. Zhu, T.; Huang, Z.; Sharma, A.; Su, J.; Irwin, D.; Mishra, A.; Menasche, D.; Shenoy, P. Sharing Renewable Energy in Smart Microgrids. In Proceedings of the ACM/IEEE International Conference on Cyber-Physical Systems (ICCPS), Philadelphia, PA, USA, 8–11 April 2013; pp. 219–228. [CrossRef]
18. Gajowniczek, K.; Ząbkowski, T. Electricity forecasting on the individual household level enhanced based on activity patterns. *PLoS ONE* **2017**, *12*, e0174098. [CrossRef] [PubMed]
19. Alajmi, T.; Phelan, P. Modeling and Forecasting End-Use Energy Consumption for Residential Buildings in Kuwait Using a Bottom-Up Approach. *Energies* **2020**, *13*, 1981. [CrossRef]
20. Gao, B.; Liu, X.; Zhu, Z. A Bottom-Up Model for Household Load Profile Based on the Consumption Behavior of Residents. *Energies* **2018**, *11*, 2112. [CrossRef]
21. Behm, C.; Nolting, L.; Praktiknjo, A. How to model European electricity load profiles using artificial neural networks. *Appl. Energy* **2020**, *277*, 115564. [CrossRef]
22. Barsanti, M.; Mussetta, M. Load Modeling and Scheduling Optimization for Energy Sharing in Prosumers Network. In Proceedings of the 2019 IEEE Milan PowerTech, Milan, Italy, 23–27 June 2019; pp. 1–6. [CrossRef]
23. Khan, M.A.; Javaid, N.; Arif, M.; Saud, S.; Qasim, U.; Khan, Z.A. Peak Load Scheduling in Smart Grid Communication Environment. In Proceedings of the 2014 IEEE 28th International Conference on Advanced Information Networking and Applications, Victoria, BC, Canada, 13–16 May 2014; pp. 1025–1032. [CrossRef]
24. Ullah, M.N.; Javaid, N.; Khan, I.; Mahmood, A.; Farooq, M.U. Residential Energy Consumption Controlling Techniques to Enable Autonomous Demand Side Management in Future Smart Grid Communications. In Proceedings of the 2013 Eighth International Conference on Broadband and Wireless Computing, Communication and Applications, Compiegne, France, 28–30 October 2013; pp. 545–550. [CrossRef]
25. Costanzo, G.T.; Zhu, G.; Anjos, M.F.; Savard, G. A System Architecture for Autonomous Demand Side Load Management in Smart Buildings. *IEEE Trans. Smart Grid* **2012**, *3*, 2157–2165. [CrossRef]
26. Tu, J.; Zhou, M.; Cui, H.; Li, F. An Equivalent Aggregated Model of Large-Scale Flexible Loads for Load Scheduling. *IEEE Access* **2019**, *7*, 143431–143444. [CrossRef]

27. Khan, Z.A.; Khalid, A.; Javaid, N.; Haseeb, A.; Saba, T.; Shafiq, M. Exploiting Nature-Inspired-Based Artificial Intelligence Techniques for Coordinated Day-Ahead Scheduling to Efficiently Manage Energy in Smart Grid. *IEEE Access* **2019**, *7*, 140102–140125. [CrossRef]
28. Nuchprayoon, S. Forecasting of daily load curve on monthly peak day using load research data and harmonics model. In Proceedings of the 6th IEEE International Conference on Control System, Computing and Engineering (ICCSCE), Penang, Malaysia, 25–27 November 2016; pp. 338–342. [CrossRef]
29. Çakmak, R.; Altaş, İ.H. Optimal scheduling of time shiftable loads in a task scheduling based demand response program by symbiotic organisms search algorithm. In Proceedings of the 2017 Saudi Arabia Smart Grid (SASG), Jeddah, Saudi Arabia, 12–14 December 2017; pp. 1–7. [CrossRef]
30. Sung, M.; Ko, Y. Machine-learning-integrated load scheduling for peak electricity reduction. In Proceedings of the 2015 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 9–12 January 2015; pp. 309–310. [CrossRef]
31. Li, J.; Zhao, Q.; Wang, H.; Wang, W.; Yang, Y.; Yan, C. Analysis of Deep Learning Control Strategy about Peak Load Regulation and Frequency Regulation with Distribution Thermal Storage Electric Boiler. In Proceedings of the 5th IEEE International Conference on Cloud Computing and Intelligence Systems (CCIS), Nanjing, China, 23–25 November 2018; pp. 461–464. [CrossRef]
32. Chimamiwa, G.; Alirezaie, M.; Pecora, F.; Loutfi, A. Multi-sensor dataset of human activities in a smart home environment. *Data Brief* **2021**, *34*, 106632. [CrossRef]
33. Park, J.; Jang, K.; Yang, S. Deep neural networks for activity recognition with multi-sensor data in a smart home. In Proceedings of the 2018 IEEE 4th World Forum on Internet of Things (WF-IoT), Singapore, 5–8 February 2018; pp. 155–160. [CrossRef]
34. Li, Q.; Gravina, R.; Li, Y.; Alsamhi, S.H.; Sun, F.; Fortino, G. Multi-user activity recognition: Challenges and opportunities. *Inf. Fusion* **2020**, *63*, 121–135. [CrossRef]
35. Ramos, D.; Teixeira, B.; Faria, P.; Gomes, L.; Abrishambaf, O.; Vale, Z. Use of Sensors and Analyzers Data for Load Forecasting: A Two Stage Approach. *Sensors* **2020**, *20*, 3524. [CrossRef] [PubMed]
36. Rafe Biswas, M.A.; Robinson, M.D.; Fumo, N. Prediction of residential building energy consumption: A neural network approach. *Energy* **2016**, *117*, 84–92. [CrossRef]
37. Hashizume, A.; Mizuno, T.; Mineno, H. Energy Monitoring System Using Sensor Networks in Residential Houses. In Proceedings of the 26th International Conference on Advanced Information Networking and Applications Workshops, Fukuoka, Japan, 26–29 March 2012; pp. 595–600. [CrossRef]
38. Rawi, M.I.M.; Al-Anbuky, A. Passive House sensor networks: Human centric thermal comfort concept. In Proceedings of the 2009 International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), Melbourne, Australia, 7–10 December 2009; pp. 255–260. [CrossRef]
39. Phand, A.; Bangar, R.; Dani, R.; Lohokare, J. A scalable home automation IoT ecosystem using open source technologies. In Proceedings of the 7th International Conference on Computing in Engineering & Technology (ICCET 2022), Online Conference, 12–13 February 2022; pp. 186–190. [CrossRef]
40. Hlaing, W.; Thepphaeng, S.; Nontaboot, V.; Tangsunantham, N.; Sangsuwan, T.; Pira, C. Implementation of WiFi-based single phase smart meter for Internet of Things (IoT). In Proceedings of the 2017 International Electrical Engineering Congress (iEECON), Pattaya, Thailand, 8–10 March 2017; pp. 1–4. [CrossRef]
41. Balikhina, T.; Maqousi, A.A.; AlBanna, A.; Shhadeh, F. System architecture for smart home meter. In Proceedings of the 2nd International Conference on the Applications of Information Technology in Developing Renewable Energy Processes & Systems (IT-DREPS), Amman, Jordan, 6–7 December 2017; pp. 1–5. [CrossRef]
42. Al-Ali, A.R.; Zualkernan, I.A.; Rashid, M.; Gupta, R.; Alikarar, M. A smart home energy management system using IoT and big data analytics approach. *IEEE Trans. Consum. Electron.* **2017**, *63*, 426–434. [CrossRef]
43. Cheo, Z.; Yang, H.; Kansala, K.; Maatta, K.; Rehu, J.; Chen, W. Smart Home/Building Energy Management System for Future Smart Grid Architecture with Automated Demand Response Applications. In Proceedings of the 1st EAI International Conference on Smart Grid Assisted Internet of Things, Sault Ste. Marie, ON, Canada, 11–12 July 2017. [CrossRef]
44. Machorro-Cano, I.; Alor-Hernández, G.; Paredes-Valverde, M.A.; Rodríguez-Mazahua, L.; Sánchez-Cervantes, J.L.; Olmedo-Aguirre, J.O. HEMS-IoT: A Big Data and Machine Learning-Based Smart Home System for Energy Saving. *Energies* **2020**, *13*, 1097. [CrossRef]
45. Moga, D.; Stroia, N.; Petreus, D.; Moga, R.; Munteanu, R.A. Embedded platform for Web-based monitoring and control of a smart home. In Proceedings of the 2015 IEEE 15th International Conference on Environment and Electrical Engineering (EEEIC), Rome, Italy, 10–13 June 2015; pp. 1256–1261. [CrossRef]
46. van der Veen, J.S.; van der Waaij, B.; Meijer, R.J. Sensor Data Storage Performance: SQL or NoSQL, Physical or Virtual. In Proceedings of the 2012 IEEE Fifth International Conference on Cloud Computing, Honolulu, HI, USA, 24–29 June 2012; pp. 431–438. [CrossRef]
47. Scislo, L.; Szczepanik-Scislo, N. Air Quality Sensor Data Collection and Analytics with IoT for an Apartment with Mechanical Ventilation. In Proceedings of the 11th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS), Cracow, Poland, 22–25 September 2021; pp. 932–936. [CrossRef]
48. Böhlen, M.H.; Dignös, A.; Gamper, J.; Jensen, C.S. *Temporal Data Management-An Overview*; Zurich Open Repository and Archive; University of Zurich ZORA: Zurich, Switzerland, 2017. [CrossRef]

49. Mehmood, N.Q.; Culmone, R.; Mostarda, L. Modeling temporal aspects of sensor data for MongoDB NoSQL database. *J. Big Data* **2017**, *4*, 8. [CrossRef]
50. Sumalan, R.L.; Stroia, N.; Moga, D.; Muresan, V.; Lodin, A.; Vintila, T.; Popescu, C.A. A Cost-Effective Embedded Platform for Greenhouse Environment Control and Remote Monitoring. *Agronomy* **2020**, *10*, 936. [CrossRef]
51. Stroia, N.; Moga, D.; Vitan, E.; Cosovici, G.; Lungoci, C.; Kovacs, I.; Mircea, M. Internet based SCADA platform for monitoring strategic hydrotechnical structures. In Proceedings of the 2016 IEEE International Conference on Automation, Quality and Testing, Robotics (AQTR), Cluj-Napoca, Romania, 19–21 May 2016; pp. 1–5. [CrossRef]
52. Stroia, N.; Moga, D.; Barabas, Z. Web based monitoring of solar power systems. *IFAC Proc. Vol.* **2013**, *46*, 131–136. [CrossRef]
53. Moga, D.; Petreus, D.; Stroia, N. A low cost architecture for remote control and monitoring of greenhouse fields. In Proceedings of the 7th IEEE Conference on Industrial Electronics and Applications (ICIEA), Singapore, 18–20 July 2012; pp. 1940–1944. [CrossRef]
54. STMicroelectronics. *EVALSTPM34, EVALSTPM33, EVALSTPM32 Evaluation Board*; UM1748; User Manual. Available online: https://www.st.com/resource/en/user_manual/um1748-evalstpm34-evalstpm33-evalstpm32-evaluation-board-stmicroelectronics.pdf (accessed on 12 July 2022).
55. Trodden, P.A.; Bukhsh, W.A.; Grothey, A.; McKinnon, K.I.M. Optimization-Based Islanding of Power Networks Using Piecewise Linear AC Power Flow. *IEEE Trans. Power Syst.* **2014**, *29*, 1212–1220. [CrossRef]
56. Oprea, S.-V.; Bâra, A.; Reveiu, A. Informatics Solution for Energy Efficiency Improvement and Consumption Management of Householders. *Energies* **2018**, *11*, 138. [CrossRef]
57. Silva, B.N.; Khan, M.; Han, K. Load Balancing Integrated Least Slack Time-Based Appliance Scheduling for Smart Home Energy Management. *Sensors* **2018**, *18*, 685. [CrossRef]
58. Caprino, D.; Della Vedova, M.L.; Facchinetti, T. Applying limited-preemptive scheduling to peak load reduction in smart buildings. In Proceedings of the IEEE 20th Conference on Emerging Technologies & Factory Automation (ETFA), Luxembourg, 8–11 September 2015; pp. 1–8. [CrossRef]
59. Shaban, A.; Maher, H.; Elbayoumi, M.; Abdelhady, S. A cuckoo load scheduling optimization approach for smart energy management. *Energy Rep.* **2021**, *7*, 4705–4721. [CrossRef]
60. Jamil, M.; Mittal, S. Hourly load shifting approach for demand side management in smart grid using grasshopper optimisation algorithm. *IET Gener. Transm. Distrib.* **2020**, *14*, 808–815. [CrossRef]
61. Vidal, A.R.S.; Jacobs, L.A.A.; Batista, L.S. An evolutionary approach for the demand side management optimization in smart grid. In Proceedings of the 2014 IEEE Symposium on Computational Intelligence Applications in Smart Grid (CIASG), Orlando, FL, USA, 9–12 December 2014; pp. 1–7. [CrossRef]
62. Sharma, A.K.; Saxena, A. A demand side management control strategy using Whale optimization algorithm. *SN Appl. Sci.* **2019**, *1*, 870. [CrossRef]
63. Naz, M.; Iqbal, Z.; Javaid, N.; Khan, Z.A.; Abdul, W.; Almogren, A.; Alamri, A. Efficient Power Scheduling in Smart Homes Using Hybrid Grey Wolf Differential Evolution Optimization Technique with Real Time and Critical Peak Pricing Schemes. *Energies* **2018**, *11*, 384. [CrossRef]
64. Tamilarasu, K.; Sathiasamuel, C.R.; Joseph, J.D.N.; Madurai Elavarasan, R.; Mihet-Popa, L. Reinforced Demand Side Management for Educational Institution with Incorporation of User's Comfort. *Energies* **2021**, *14*, 2855. [CrossRef]
65. Lezama, F.; Soares, J.; Canizes, B.; Vale, Z. Flexibility management model of home appliances to support DSO requests in smart grids. *Sustain. Cities Soc.* **2020**, *55*, 102048. [CrossRef]
66. Venkatesh, B.; Sankaramurthy, P.; Chokkalingam, B.; Mihet-Popa, L. Managing the Demand in a Micro Grid Based on Load Shifting with Controllable Devices Using Hybrid WFS2ACSO Technique. *Energies* **2022**, *15*, 790. [CrossRef]
67. Ullah, I.; Hussain, S. Time-Constrained Nature-Inspired Optimization Algorithms for an Efficient Energy Management System in Smart Homes and Buildings. *Appl. Sci.* **2019**, *9*, 792. [CrossRef]
68. Yang, X.-S. *Nature-Inspired Optimization Algorithms*; Elsevier: London, UK, 2014.
69. Giaconi, G.; Gunduz, D.; Poor, H.V. Privacy-Aware Smart Metering: Progress and Challenges. *IEEE Signal Processing Mag.* **2018**, *35*, 59–78. [CrossRef]
70. Silicon Laboratories. WGM160P Wi-Fi®Module Data Sheet. Available online: https://www.silabs.com/documents/public/data-sheets/wgm160p-datasheet.pdf (accessed on 29 September 2020).
71. STMicroelectronis. *EVALSTPM3x-3PH Evaluation Board and Graphical User Interface (GUI)*; UM1944; User Manual. Available online: https://www.digikey.in/htmldatasheets/production/3156012/0/0/1/EVALSTPM3X-3PH-GUI.pdf (accessed on 12 July 2022).
72. STMicroelectronis. *STPM32, STPM33, STPM34. ASSP for Metering Applications with up to Four Independent 24-Bit 2nd Order Sigma-delta ADCs, 4 MHz OSF and 2 Embedded PGLNA*; DS10272; Datasheet. Available online: https://www.st.com/resource/en/datasheet/stpm32.pdf (accessed on 12 July 2022).
73. STMicroelectronics. *EVALSTPM-3PHISO: Getting Started with the STPMS2 3-ph Full Shunt Evaluation Board*; UM2847; User Manual. Available online: https://www.st.com/resource/en/user_manual/um2847-evalstpm3phiso-getting-started-with-the-stpms2-3ph-full-shunt-evaluation-board-stmicroelectronics.pdf (accessed on 12 July 2022).
74. Sun, Q.; Li, H.; Ma, Z.; Wang, C.; Campillo, J.; Zhang, Q.; Wallin, F.; Guo, J. A Comprehensive Review of Smart Energy Meters in Intelligent Energy Networks. *IEEE Internet Things J.* **2016**, *3*, 464–479. [CrossRef]