OPTIMIZATION OF ENERGY CONSUMPTION IN REAL TIME SYSTEMS USING IOT DEVICES

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ABSTRACT
The increasing electricity demand necessitates innovative solutions to optimize energy consumption. This research delves into the realm of Real-Time Operating Systems deployed in Internet of Things (IoT) devices, aiming to develop energy-efficient algorithms. The focus is on balancing the multifaceted needs of IoT applications, including low latency, energy efficiency, and optimal resource utilization. The objective is to enhance IoT systems' overall performance and responsiveness while minimizing power consumption. This study introduces an energy-efficient scheduling framework that combines data-driven methods, machine learning, and real-time scheduling. Machine learning identifies consumption patterns. Energy-efficient scheduling algorithms, like DVFS and predictive scheduling, are explored to reduce energy use while meeting real-time demands. The findings of this research would help develop smart cities, offering a practical framework for optimizing energy consumption in IoT devices.
KEY WORDS Dynamic Voltage and Frequency Sharing, Home Energy Management System, Demand Response.

1 Introduction

In the foreseeable future, global electricity demand is anticipated to surge, growing at an accelerated rate of 3% annually. This uptick is primarily driven by the escalating electricity consumption in emerging markets and developing economies (EMDEs). As the world gradually recovers from the energy crisis, the growth in global electricity demand is poised to jump from 2.6% in 2023 to an average of 3.2% during 2024-2025. This robust growth surpasses the pre-pandemic rate of 2.4% observed between 2015 and 2019. By the year 2025, the demand is projected to soar by a staggering 2,500 TWh compared to 2022 levels [1]. This surge in demand has elevated the costs associated with energy consumption, particularly for individuals. The majority of this electricity consumption emanates from larger cities, now often referred to as smart cities. Given this pressing scenario, there is an urgent need to implement a comprehensive strategy to conserve electric energy effectively.

In response to this challenge, our initiative focuses on the development of smart cities by deploying an innovative energy awareness task scheduling framework. This framework harnesses sophisticated task scheduling algorithms and analyzes the intricate energy consumption patterns of diverse devices and systems within the smart city infrastructure. By embracing this forward-thinking approach, we aim to optimize energy usage, especially during peak demand periods. Through intelligent scheduling and a deep understanding of energy consumption patterns, our framework not only ensures efficient allocation of tasks but also mitigates unnecessary energy wastage. This proactive measure not only curtails costs for individuals but also contributes significantly to the overall energy conservation efforts. In essence, our approach stands at the forefront of sustainable urban development, aligning with the evolving needs of our communities and the environment. By leveraging cutting-edge technology and insightful data analysis, we are paving the way towards a more energy-efficient future for smart cities worldwide.

1.1 Objectives

The main objective of this research is to optimize task scheduling algorithms designed explicitly for RTOS deployed in IoT devices. These algorithms must balance the diverse requirements of IoT applications, such as low latency, energy efficiency, and effective utilization of limited resources, to enhance the overall performance and responsiveness of IoT systems. Integrate energy-awareness into scheduling algorithms, ensuring tasks are executed to minimize power consumption without compromising real-time requirements. This involves optimizing task execution sequences and leveraging low-power status effectively.

1.2 Contributions

Energy-aware scheduling can be approached using various algorithms. Here we are listing contributions of this paper:

1.2.1 Dynamic Voltage and Frequency Scaling (DVFS)

DVFS adjusts the operating frequency and voltage of processors dynamically to minimize energy consumption while meeting performance requirements [2, 3]. These are commonly used in processors and computing systems to optimize energy usage without sacrificing performance significantly.

1.3 Dynamic Power Management (DPM)

DPM is an effective strategy to curb static power consumption by capitalizing on idle intervals during task execution. When the duration of idle time reaches a predefined threshold, often referred to as the break-even time [4, 5], the processor is transitioned into a low-power sleep mode. This proactive approach significantly diminishes the processor's static power usage, optimizing energy efficiency without compromising performance.

1.3.1 Energy Efficient Load Balancing

Distributes tasks evenly across computing resources to balance the workload and avoid overloading specific resources, which can lead to increased energy consumption. They are Used in various distributed computing environments to optimize energy usage while ensuring high system performance.

1.3.2 Predictive Energy-aware Scheduling

Utilizes predictive models to forecast energy consumption and adapt task scheduling strategies proactively. It is beneficial in scenarios where energy usage patterns exhibit predictability, allowing tasks to be scheduled optimally in anticipation of future energy demands. These algorithms often involve a combination of traditional scheduling techniques with energy-specific optimizations to strike a balance between energy efficiency and task performance.

2 Ensuring IoT devices operate with minimal energy consumption

2.1 Challenges

Generally, optimizing or reducing energy consumption in real-time systems is quite challenging, some of those challenges include:

Real-Time Requirements Many smart city applications, such as traffic management and surveillance, require real-time data processing. Balancing the need for energy efficiency with the stringent latency requirements of these applications is a challenge. Delayed processing due to energy optimization techniques could impact the effectiveness of real-time systems.

Data Privacy and Security Smart city applications often deal with sensitive data, such as citizen information and surveillance footage. Ensuring data privacy and security while optimizing energy consumption adds complexity to the design of scheduling algorithms. Encryption and secure data transmission are essential but can introduce computational overhead.

Scalability Smart cities generate vast amounts of data from various sources. Energy-aware scheduling algorithms must be scalable to handle the increasing volume of data and the growing number of connected devices. Scalability challenges can arise in both algorithm design and system architecture.

Dynamic Workload Smart city workloads are highly dynamic, with fluctuations in demand based on factors such as time of day, events, and emergencies. Designing scheduling algorithms that can adapt to these dynamic workloads in real-time and make energy-efficient decisions is a challenge.

2.2 Case Study

Dynamic Voltage and Frequency Scaling (DVFS), as well as algorithms for adaptive power management and sleep mode optimization, are employed to conserve energy in IoT devices. These algorithms ensure devices operate in low-power states when idle and adapt their power consumption based on workload.

Home Energy Management System Global energy demand is rising, driven by the integration of renewable sources. Aging grid infrastructure needs upgrading for safe, reliable, and clean energy. Consequently, the smart grid concept has emerged, in which all players in the grid network connect and interact with each other through information and communication technologies (ICTs) to improve stability, resource efficiency, and sustainability in energy production, transmission, and distribution fields [6]. Residential demand-side management (DSM), within this concept, tackles challenges by optimizing energy use in households, responsible for 26.9% of global electricity consumption.

In recent times, researchers have directed their attention toward the development of Home Energy Management Systems (HEMSs) to address various challenges and innovations in the energy sector. The focal point of this study is also the creation of a HEMS designed for application in residential buildings. The primary objectives are to facilitate Demand Response (DR) mechanisms and enhance self-consumption. The aim is to empower households with a system that efficiently manages energy usage, responds to dynamic energy demands, and promotes increased self-sufficiency.

Currently, space heating and cooling contribute to over 50% of the total electricity consumption in residential settings [7]. Ensuring comfort in indoor temperature is crucial, especially since discomfort is a significant obstacle to adopting Demand Response programs. In addressing this, the study suggests incorporating a smart thermostat into a Home Energy Management System (HEMS). This integration aims to achieve efficient DR for air-conditioning while enhancing the overall thermal comfort of residents.

A Home Energy Management System (HEMS) empowers users to efficiently monitor, control, and automate an increasing array of smart appliances with minimal effort and time, requiring minimal human intervention [8]. This system is designed to optimize electricity bill savings through Demand Response (DR), self-consumption, and energy arbitrage. The comprehensive approach of HEMS helps avoid demand charges and ensures compliance with peak limits.

Recent research has focused on HEMS for Demand Response, exploring scheduling for shiftable appliances in smart homes. However, this alone resulted in limited bill savings. Another study optimized load scheduling for various appliances, including a dishwasher, washing machine, clothes dryer, and plug-in hybrid electric vehicle (EV), under Real-Time Pricing (RTP). Despite achieving peak limiting to prevent additional peaks, pre-cooling/heating for air conditioning (AC) and electric water heater (EWH) during peak hours was not considered.

An algorithm-based HEMS, developed in another study, factored in load priority and user comfort preferences using AC, EWH, EV, and clothes dryer. The system imposed a peak limit on household energy consumption, ensuring demand curtailment during peak hours. However, the study did not incorporate pre-cooling/heating for AC and EWH.

Smart Home Appliances in residential Demand Response Generally, smart home appliances compatible with residential Demand Response fall into three categories:

Time-shiftable Appliances: These appliances have lower energy consumption compared to others. They operate with fixed power patterns and cannot be interrupted once started. Examples include washing machines, dishwashers, and clothes dryers.

Thermostatically Controlled Appliances: These appliances have the ability to store thermal energy in a designated medium through precooling or preheating. They enable precise temperature adjustments within defined thermal boundaries. Examples of such appliances include air conditioners, electric water heaters, and refrigerators.

Power Shiftable Appliances: These appliances refer to devices that allow for flexibility in their power consumption patterns, enabling users to shift or adjust the timing of their energy usage. These appliances can be controlled to operate during periods of lower electricity demand or when renewable energy sources are more abundant, contributing to better grid management and energy efficiency. Examples of such appliances includes Electric Vehicles (EVs).

2.2.1 Smart Thermostats

Achieving the desired level of Demand Response adoption may face challenges, particularly concerning potential violations of end-user comfort. One notably concerning violation is related to thermal comfort.

[9] handled air conditioners (ACs) were managed as curtailable loads, with curtailment achieved through kilowatt (kW) reduction. However, the absence of a thermal model capable of accurately predicting the household's thermal behavior poses a risk. This method is prone to causing thermal comfort violations as it fails to capture temperature changes effectively.

Several studies have introduced a smart thermostat based on fuzzy logic for residential heating and air conditioning (HVAC) systems [10]. In contrast to conventional thermostats, the suggested model employs a fuzzy inference system (FIS) to adapt the set-point temperature based on variations in electricity prices, occupant presence, and outdoor temperature. However, the decision-making process did not assess the potential presence of a small-scale photovoltaic (PV) system or a Battery Energy Storage System (BESS) within the household.

[11] Suggested a model based on MATLAB-TRNSYS that offers pre-cooling/heating capabilities and the ability to switch between an electrical Air Source Heat Pump (ASHP) and a natural gas mini boiler. The switching is contingent on the thermal demand of a house and prevailing electricity/gas prices.

2.2.2 Current Focus

Our current focus lies in the development of Thermostatically Controlled Appliances using Internet of Things (IoT) devices. The primary objective is to integrate a Home Energy Management System (HEMS) with a smart thermostat to enhance the efficiency of Demand Response (DR) for Electric Water Heaters (EWH) while ensuring a heightened level of thermal comfort for end-users.

In contrast to conventional thermostats with fixed set-points, we are planning to introduce a smart thermostat that dynamically adjusts the initialized set-point based on changing conditions, including electricity prices, solar radiation, and occupant presence. This approach allows for flexible Demand Response implementation for EWH. For instance, during on-peak hours, the thermostat sets a higher set-point within the American Society of Heating and Air-Conditioning Engineers [12] limits for EWH to reduce electricity costs. However, the set-point varies for different occupancy levels. In situations of high occupancy, the smart thermostat prioritizes thermal comfort, leading to a lower set-point compared to scenarios with less or no occupancy. Moreover, the adjustments to the EWH set-point also consider the state of photovoltaic (PV) generation at home. Planning to implement Fuzzy logic as the preferred method for considering multiple factors in this dynamic system. Ultimately, the integration of a smart thermostat with a HEMS ensures a sophisticated and adaptive approach to DR for EWH, aligning with varying occupancy levels and PV generation states while prioritizing both energy efficiency and thermal comfort.

Implementation for Thermostatically Controlled Appliances (TCAs) A gray-box model utilizing a first-order lumped capacitance 1R1C configuration is employed. This model, widely acknowledged in various studies, is deemed sufficiently reliable for capturing the thermal behavior of the house, Electric Water Heater (EWH) tank, and refrigerator cabinet [13].

Eq. (1) formulates the EWH model. Here, the EWH tank is assumed to be located in a part of the house that is under the effect of AC operation, thus represents the day-ahead ambient set-point temperatures imposed by the smart AC thermostat. uc vector defines the hot water usage times. When hot water is used, it is replaced by inlet water. EWH does not allow the water temperature to drop below the minimum allowed temperature. Eq. (2) denotes the allowed hot water temperature limits inside the EWH tank. Eq. (3) gives the electrical power consumption of the EWH.

$$
\begin{aligned}
T_t^{hw} = & \\
& \frac{(T_t^{amb} + c^{EWH}.R^{EWH}.T_t^c.uc_t + R^{EWH}.COP^{EWH}.P^{EWH}.x_t^{EWH})}{(1 + c^{EWH}.R^{EWH}.uc_t)}) \\
& +(T_{t-1}^{hw} - (\frac{(T_t^{amb} + C^{EWH}.R^{EWH}.COP^{EWH}.P^{EWH}.x_t^{EWH})}{(1 + c^{EWH}.R^{EWH}.uc_t)}). \\
& e^{\frac{-(1+c^{EWH}.R^{EWH}.wc_t).\nabla t}{R^{EWH}.c^{EWH}}}, \forall t
\end{aligned} \tag{1}
$$

$$
T^{hw,min} \leq T_t^{hw} \leq T^{hw,max}, \forall t \tag{2}
$$

$$
P^{EWH} = P^{EWH}.x_t^{EWH}, \forall t \tag{3}
$$

- T_t^{hw} – EWH hot water temperature [Celsius]
- T_t^{amb},T_{t-1}^{amb} – Ambient temperature [Celsius]
- C^{EWH} – Constant amount of water heat flow capacity in a single time-step[kW/K]
- R^{EWH} – EWH thermal Resistance [Celsius/kW]
- T_t^c – EWH intel water temperature [Celsius]
- uc_t – daily cold-water usage times
- $(COP)^{EWH}$ – EWH coefficient of performance
- P^{EWH},P_t^{EWH} – EWH power[kW]
- x_t^{EWH} – Decision variable between 0-1 defining EWH usage
- T_t^{hw} – EWH hot water temperature [Celsius]
- T_t^{amb},T_{t-1}^{amb} – Ambient temperature [Celsius]
- C^{EWH} – Constant amount of water heat flow capacity in a single time-step[kW/K]
- R^{EWH} – EWH thermal Resistance [Celsius/kW]
- T_t^c – EWH intel water temperature [Celsius]
- $(uc)_t$ – daily cold-water usage times
- COP^{EWH} – EWH coefficient of performance
- P^{EWH}, P_t^{EWH} – EWH power[kW]
- x_t^{EWH} – Decision variable between 0-1 defining EWH usage

3 Conclusion

In this investigation, we propose a novel architecture for Home Energy Management Systems based on Mixed Integer Linear Programming. The primary objective is to minimize daily electricity costs within Electric Water Heater by optimizing both Demand Response (DR) strategies and self-consumption. Our proposed algorithm efficiently schedules tasks for a variety of manageable electrical loads, encompassing Time-Shiftable Appliances, Temperature-Controlled Appliances, and Programmable Switching Appliances. To enhance the accuracy of Photovoltaic (PV) power output prediction, our HEMS integrates a solar model designed for tilted PV arrays. This integration enables the HEMS to translate solar radiation forecasts into precise estimates of PV power output, accounting for variables such as array tilt angle and outdoor temperature impact on power generation efficiency.

The pivotal advancement of this research lies in the fusion of a smart thermostat into the framework of a Home Energy Management System (HEMS). Departing from the conventional thermostat paradigm, which relies on fixed set-points, the innovative approach proposed here adopts a fuzzy logic-based smart thermostat. This dynamic thermostat adjusts its set-point in real-time, responding to a spectrum of evolving conditions including fluctuating electricity prices, varying solar radiation levels, and the presence of occupants within the premises. What sets this system apart is its ability to delineate distinct set-points for each temporal interval, thereby offering a nuanced and adaptable approach to Demand Response (DR) for Electric Water Heater operation. By seamlessly integrating the smart thermostat within the overarching HEMS infrastructure, it transcends the conventional notion of the thermostat as a standalone device. Instead, it

becomes an intrinsic element of the holistic energy management ecosystem.
This integration yields manifold benefits. Firstly, it ensures that the EWH's participation in day-ahead optimization is harmoniously synchronized with other electrical loads present within the household. Consequently, the allocation of stored solar energy among various appliances is optimized, while simultaneously adhering to predefined peak power constraints. In essence, by ingeniously melding cutting-edge thermostat technology with the overarching HEMS framework, this study pioneers a comprehensive and highly efficient approach to residential energy management.

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