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RESEARCH ARTICLE

Usage-centered, efficient, and sustainable: an IoT-driven transformation of water heaters

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Abstract

In developing countries, a significant amount of natural gas is used for household water heating, accounting for roughly 50% of total usage. Legacy systems, typified by large water heaters, operate inefficiently by continuously maintaining a large volume of water at a constant temperature, irrespective of demand. With dwindling domestic gas reserves and rising demand, this increases dependence on expensive energy imports.

We introduce a novel Internet of Things (IoT)-inspired solution to understand and predict water usage patterns and only activate the water heater when there's a predicted demand. This retrofit system is maintenance-free and uses a rechargeable battery powered by a thermoelectric generator (TEG), which capitalizes on the temperature difference between the heater and its environment for electricity. Our study shows a notable 70% reduction in natural gas consumption compared to traditional systems. Our solution offers a sustainable and efficient method for water heating, addressing the challenges of depleting gas reserves and rising energy costs.

Impact statement

This work presents an innovative Internet of Things (IoT)-based retrofit solution for tank-based water heaters, addressing energy inefficiencies prevalent in developing countries. By integrating a thermoelectric generator (TEG) powered by waste heat, and employing machine learning to predict hot water demand, this system significantly reduces natural gas consumption by about 70%. Its real-world application demonstrates a sustainable, cost-effective method for enhancing water heating efficiency, offering a significant impact on energy conservation and cost reduction for households, while also addressing the challenges posed by depleting gas reserves and the environmental impact of traditional energy sources.

1. Introduction

Numerous developing nations face an intensifying energy crisis, driven by rising dependence on imported natural gas and significant inefficiencies in the residential sector, primarily due to the widespread use of storage tank-based water heaters (Awan and Knight, 2020; Zahid et al., 2022). These devices, a notable contributor to residential gas consumption, operate around the clock, using up energy to maintain the temperature of water that often remains unused. While instant heaters present a potential alternative, market preferences lean toward tank-based heaters. Their large capacity, utility during power outages, and the economic challenges tied to the installation of multiple instant heaters make them more desirable. This trend transcends geographical boundaries, from developing nations to developed countries like the United States, the United Kingdom, Canada, New Zealand, and Australia, where natural gas-driven, tank-based water heating is dominant (Xie et al., n.d.).

A key contributor to the inefficient operation of tank-based water heaters is the persistent use of legacy mechanical thermostats, designs of which have seen little to no change since the 1970s (Zaheen Machines, 2023). Given these inefficiencies, retrofitting solutions that aim to bolster the efficiency of water heating systems emerge as a viable approach. Addressing these challenges, our research endeavors to present advancements in retrofitted hardware and software solutions, specifically targeting the replacement of these outdated mechanical thermostats.

From a hardware standpoint, we developed a retrofit *thermal controller* to replace traditional controls in storage tank-based water heaters, enhancing control and leveraging machine learning for adaptable operation based on user schedules or water usage patterns. Given the power challenges in developing regions and the impracticality of using batteries in typical heater locations, such as backyards or side alleys (due to safety reasons), we incorporated a thermoelectric generator (TEG) into the controller. Leveraging the Seebeck effect, the TEG transforms the heater's waste heat into electricity, guaranteeing continuous and sustainable operation.

The software component of our solution is built around the *intelligence hub*, which is placed indoors to utilize main power sockets for its functionality. The hub, equipped with BLE and Wi-Fi for communication, focuses mainly on data collection and processing. By receiving data from the thermal controller, the intelligence hub uses machine learning to study patterns in hot water consumption. The insights obtained from this preliminary analysis are sent back to the thermal controller, potentially aiding in refining its operations. In addition to these analytical tasks, the intelligence hub also acts as an interface between users and the system. It incorporates an Android application server, which offers users an opportunity to view their consumption data and, if desired, adjust their heating preferences from a distance.

Overall, we make the following concrete contributions.

- **Innovative system architecture**: This research presents a holistic system design that combines hardware and machine learning techniques, refining energy management in tank-based water heaters.
- **Sustainable energy via TEGs**: Addressing power consistency issues, this study integrates a TEG into the system, tapping into waste heat for electricity generation and enhancing system resilience.
- **Empirical validation**: The paper undertakes a comprehensive empirical evaluation, comparing the proposed system's efficacy against conventional water-heating methods.

We designed our solution in accordance with industrial standards, ensuring that a trained installer can set up the system on-site in less than an hour. Local industries in the water-heating sector have swiftly taken interest in our innovation, initiating studies on its technical and economic feasibility through an early adopters program. Should these evaluations prove positive, we anticipate a swift rollout.

2. Related work

Numerous solutions have been proposed and developed to enhance the energy efficiency of water-heating systems. However, these solutions have not effectively replaced legacy water-heating systems, mainly due to their failure to address the unique challenges faced by developing countries, such as Bangladesh, India, and Pakistan. One significant challenge is the large average household size in these countries, which ranks among the highest globally (Bongaarts, 2001). The economic viability of legacy water heaters with their large storage tanks remains favorable for the majority of the population. Attempts to replace them with smaller instant water heaters have proven unsuccessful, primarily due to the capital costs associated with providing the same level of comfort for typical households. Moreover, instant water heaters often suffer from low water pressure, further complicating their adoption.

Solar water-heating systems have been introduced as an alternative to fossil fuel reliance for water heating. Extensive research (Ibrahim et al., 2014; Jamar et al., 2016; Minoli et al., 2017) has explored various solar power-based water-heating solutions. These range from passive designs that directly harness solar heat to active designs that utilize photovoltaic panels to convert solar energy into electricity for water heating. The latter approach offers the advantage of energy storage for use during periods when solar power is unavailable, such as at night or on cloudy days. However, these designs typically involve high initial costs and may not be feasible for existing structures. Additionally, the efficiency of solar collectors and the economic viability of utilizing incident solar energy for water heating remain areas of concern (Gautam et al., 2017).

Numerous studies have focused on minimizing energy consumption for hot water provision during winter. One example is the Circulo system (Frye et al., 2013), which learns patterns of hot water usage within a household and circulates hot water only when it is most likely to be used. This approach has shown a 30% reduction in hot water circulation costs without increasing water wastage. However, such circulation rates require energy-intensive devices like water circulation pumps, leading to significant annual energy costs (Deck, 2023). Consequently, water circulation pumps are not a practical option in the regions considered in this paper.

Similarly, the concept of a smart water heater (SWH) (Sun et al., 2015) has been proposed to minimize heat losses through piping by delivering lower-temperature water whenever possible. By learning models for each fixture, the SWH system solves an optimization problem to determine when and at which temperature water should be delivered, aiming to reduce energy consumption without compromising user thermal comfort. SWH has demonstrated energy cost reductions of 8 to 14% in residential water heating.

Considering the enduring prevalence of tank-based water heating systems, our proposed solution recognizes the need for retrofitting these legacy systems at an affordable price to enhance their efficiency and mitigate the impact of rising energy prices on households.

3. Background: tank-based water heater

Figure 1 illustrates the basic architecture of a typical water heater, commonly referred to as storage water heaters or geysers. Used extensively for residential and commercial purposes worldwide, these water heaters operate by storing a large volume of water and keeping it heated to a desired temperature over an extended period.

In a typical setup, cold water enters the tank through a water inlet, while hot water is discharged through an outlet when a hot water tap is opened by the user. The water temperature is maintained by a manually configured mechanical thermostat, which controls the gas supply to the burner based on the set temperature. A pilot flame is always lit, providing the ignition source for the burner when it needs to be activated, typically when the water temperature falls below the set point.

While these systems are effective in providing a steady supply of hot water, their operation is predominantly mechanical and heavily reliant on user intervention. Users manually configure the mechanical thermostat, often controlled using an analog dial with vague temperature descriptions. This lack of precision and responsiveness to changes in household consumption patterns leads to energy inefficiencies. Moreover, considering their design to accommodate large households, the water heaters feature substantial storage tanks. Maintaining the water temperature in these extensive tanks, irrespective of the immediate hot water demand, can potentially contribute to significant energy wastage.

The problem is exacerbated when these heaters are installed in areas with limited power availability, such as backyards, where there is no easy access to power sockets. This limits the potential for incorporating more efficient and intelligent electronic control systems.

The challenge, therefore, lies in devising a solution that can address these inefficiencies in a cost-effective and sustainable way, specifically for tank-based water heaters. A solution that can intelligently adjust the water heater's operations based on usage patterns and minimize wastage, while also being resilient to power availability challenges, could significantly improve the efficiency of energy consumption in the residential sector.

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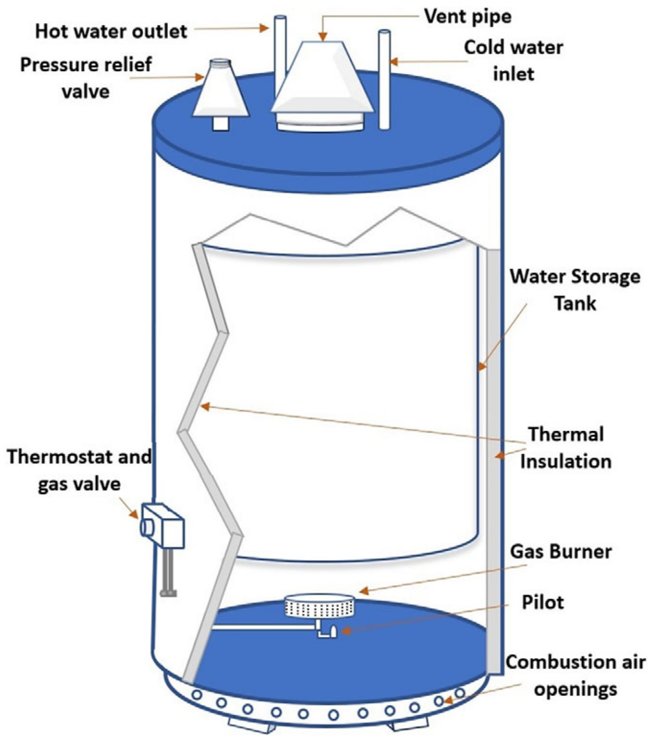

Figure 1. *Architecture of a conventional, tank-based water heater.*

4. System design and implementation

Our system aims to develop an intelligent, cost-effective, and energy-efficient solution for managing traditional tank-based water heaters. It employs an Internet of Things (IoT)-based retrofit controller that learns a household's water usage patterns using sensor data to optimize energy consumption. The architecture of this solution is centered around two key modules: the *thermal controller* and the *intelligence hub*, as shown in Figure 2.

4.1. Thermal controller

The thermal controller system is based on the ARM Cortex nRF51 System-on-a-Chip (SoC) (ARM Cortex nRF51, 2023), which acts as the central unit for data processing and communication. All sensors and actuators in the system are linked to this microcontroller, enabling it to sense important parameters, analyze them, and make decisions accordingly. These parameters are measured by four distinct sensors integrated into the system. The first sensor is a thermocouple probe, specifically designed to measure the temperature of the water tank. The MAX6675 digital amplifier (MAX6675, 2023), interfacing through the Serial Peripheral Interface (SPI), is connected to this probe. These amplifiers enhance the accuracy of the temperature measurements, and SPI, a well-established protocol for data communication, allows for a higher data transfer rate.

In addition to temperature monitoring, our system also integrates a water-flow sensor designed to learn the water usage pattern by measuring the water flow rate. It does so by recording the rate at which water is consumed, which is then used to anticipate future water usage patterns.

The safety of the system is fortified by a natural gas leakage detector, the MQ5 sensor (Zainuddin et al., 2022). This sensor can identify gas leaks and also detect a complete loss of gas pressure. Upon detecting a gas concentration that exceeds the safe limit, the system autonomously shuts down the gas supply to prevent any potential mishaps. Additionally, a flame sensor (IR Sensor, 2023) is incorporated to detect the

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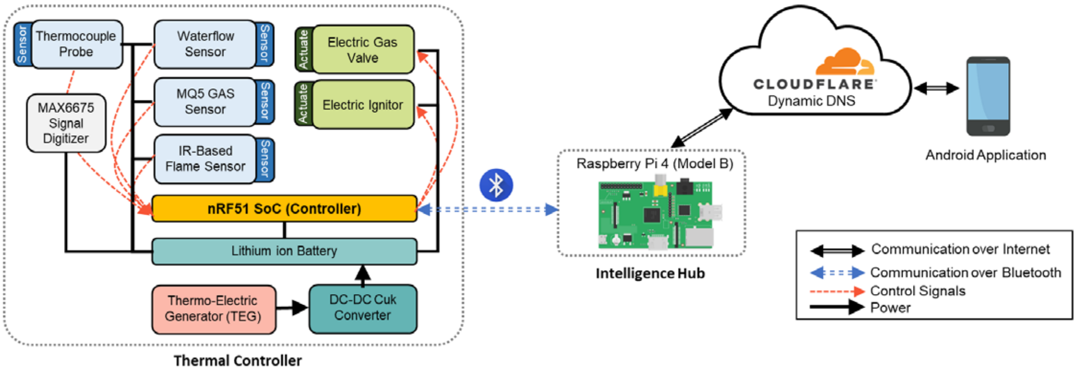

Figure 2. *System architecture diagram highlighting interaction and data flow between the thermal controller and intelligence hub, sensor/actuator connections, and enabling of remote monitoring via internet and Android app.*

presence of a flame. Once a flame is detected, indicating that the burner has been ignited, a set of predefined actions is initiated to ensure the system is functioning as intended.

4.1.1. Power optimization and wake-up strategies

The nRF51 SoC employs a duty-cycled operation strategy to optimize power consumption. It, along with sensor nodes and the RF radio, is activated only when necessary and transitions to a low-power or sleep state during periods of inactivity, especially when no active BLE connection is present.

To wake up the nRF51 from its sleep state, our system employs a multi-pronged wake-up strategy. First, the nRF51 uses the *directed advertising* mechanism in the BLE protocol. Here, the nRF51 intermittently wakes up to broadcast its availability via advertising events. If the intelligence hub wants to establish a connection during one of these advertising events, it sends a connection request, prompting the nRF51 to fully wake up and establish the connection. Second, the integrated sensors operate in a low-power monitoring mode, ensuring they consume minimal power while still being responsive to significant events. For instance, the water flow sensor can trigger an interrupt when water flow is detected, waking up the SoC. Third, for scheduled events like turning on the burner, we use a timer-based wakeup. A timer is configured to wake up the nRF51 SoC at specific times based on the learned schedule.

4.1.2. Thermal energy harvesting and conversion

Battery is the component with the shortest lifespan and highest maintenance requirement in most similar systems. They typically require regular maintenance, replacement, and recycling, which can be a significant hassle and an environmental hazard due to battery waste. In our design, we have minimized the reliance on frequent battery replacements, thus significantly reducing maintenance needs and environmental impact. We have integrated an energy-harvesting system using a TEG that leverages the Seebeck effect (Chen et al., 2018; Jouhara et al., 2021). Inside the water heater's chamber, we placed a 5-W TEG module (SP1848-27145 TEG Peltier Module, 2023) with both heating and cooling blocks. The hot side of the TEG faces the burner, while we connect its cold side to a heat sink. This setup provides a 5.2-W output that efficiently charges the onboard Li-ion battery. We use a DC-DC Ćuk converter to process this power, with the converter being controlled by the microcontroller employing the maximum power point tracking (MPPT) algorithm (Omairi et al., 2017). We chose the Ćuk converter for its ability to handle continuous current, ensuring optimal power delivery to the 3.6 V Li-ion battery (Haq et al., 2021).

The output power generated by the TEG depends on the temperature difference ($\Delta T = T_h - T_c$) between the hot (T_h) and cold (T_c) sides of the module, exhibiting a nonlinear I-V characteristic. Figure 3 illustrates the relationship between ΔT and the generated output power. The average T_h in our deployment fluctuates around 250°C, while T_c is maintained at 30°C, resulting in an average output power of 4 W.

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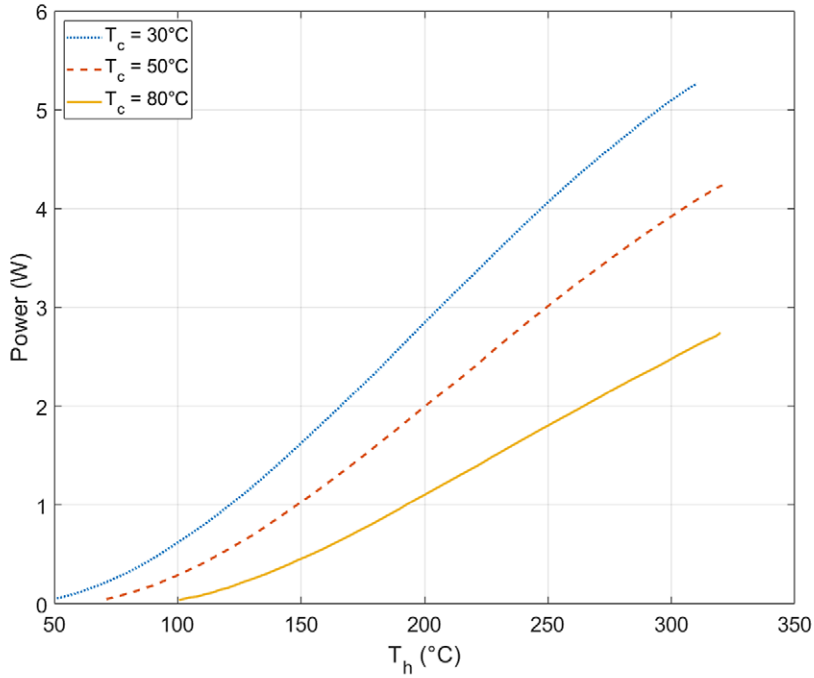

Figure 3. *The power output of the TEG plotted against the temperature difference (T_h) under various cold-side temperatures (T_c). The curve demonstrates the nonlinear nature of the TEG's power output.*

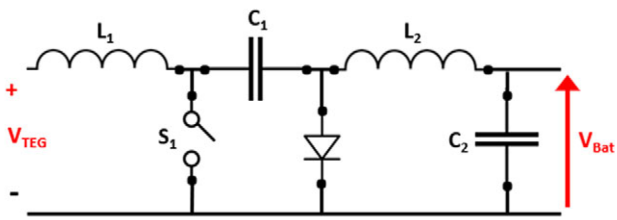

Figure 4. *The circuit diagram of the Ćuk converter used in our system for power conversion.*

4.1.3. MPPT using the P&O algorithm

The implementation of the proposed system involves utilizing a DC-DC Ćuk converter to extract electrical energy from the TEG module. This converter operates in the continuous conduction mode and integrates the MPPT algorithm. A switch, denoted as S_1, is responsible for the frequency switching at 50 kHz. The schematic diagram of the Ćuk converter is depicted in Figure 4.

We use the perturbation and observation (P&O) method as our MPPT algorithm (Femia et al., 2004). This method perturbs the TEG's terminal voltage to find its optimal operating point based on the derivative of power with respect to voltage (dP/dV). If $dP/dV > 0$, the algorithm moves closer to the maximum power point; if $dP/dV < 0$, it reverses direction. We illustrate this in Figure 5, where the parameter N represents the modulation value for the duty cycle or pulse width.

The P&O algorithm offers simplicity, leading to reduced design costs and minimal computational demands during runtime. Despite its limitations, such as slow responses to dynamic changes and oscillations during steady-state operation (Brambilla et al., 1999; Femia et al., 2004), they do not impact our use case, which focuses on battery charging. The combination of the TEG-to-DC converter and the P&O MPPT algorithm is vital to our system, facilitating efficient energy harvesting and charging.

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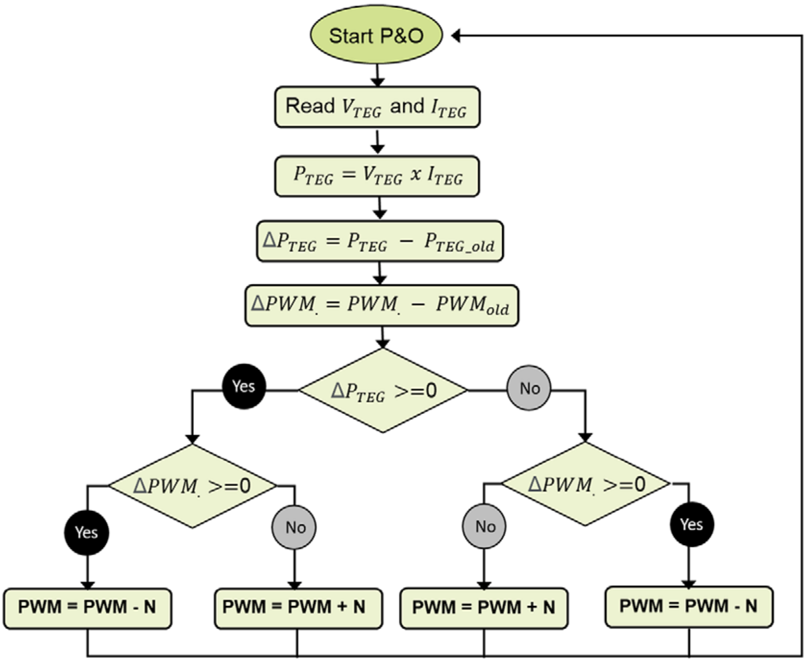

Figure 5. *Flowchart illustrating the P&O-based MPPT algorithm. This algorithm is used to optimize the operation of the Ćuk converter and maximize power delivery from the TEG to the battery.*

A practical representation of the thermal controller's implementation can be seen in Figure 6, which shows the retrofit controller installed on a water heater at the deployment site.

4.2. Intelligence hub

This module serves as the brain of our system. It is based on the Raspberry Pi 4 Model B (Rasperry Pi 4 (model B), 2019), which offers both BLE and Wi-Fi connectivity, enabling our system to serve as a bridge between the thermal controller and the internet. With the intelligence hub acting as a server for the accompanying Android application, users can remotely monitor and control their water heaters.

The hub operates as a server with a registered domain name, employing a DDClient to routinely update the domain name to point toward Cloudflare's DNS (Cloudflare, 2023). This ensures a reliable and continuous connection between the hub and the internet, providing an efficient way for users to remotely interact with the system.

Additionally, we have developed an accompanying Android application, enabling users to remotely monitor their water heaters and update schedules according to their needs, as shown in Figure 7. The intelligence hub serves as the server for this application, facilitating two-way communication for real-time control and monitoring.

The intelligence hub further harnesses the power of machine learning to anticipate future hot water demand based on household water usage patterns and the time of day. The system incorporates a dual approach to scheduling to meet the varied user preferences, employing both automatic and manual scheduling features.

4.2.1. Automatic scheduling

The automatic scheduling mechanism is built around a machine learning model known as the Mixture of Gaussian Hidden Markov Models (MoGHMM). This algorithm studies water usage patterns based on two inputs: instantaneous water usage and corresponding time of day. Designed to adapt to diverse water

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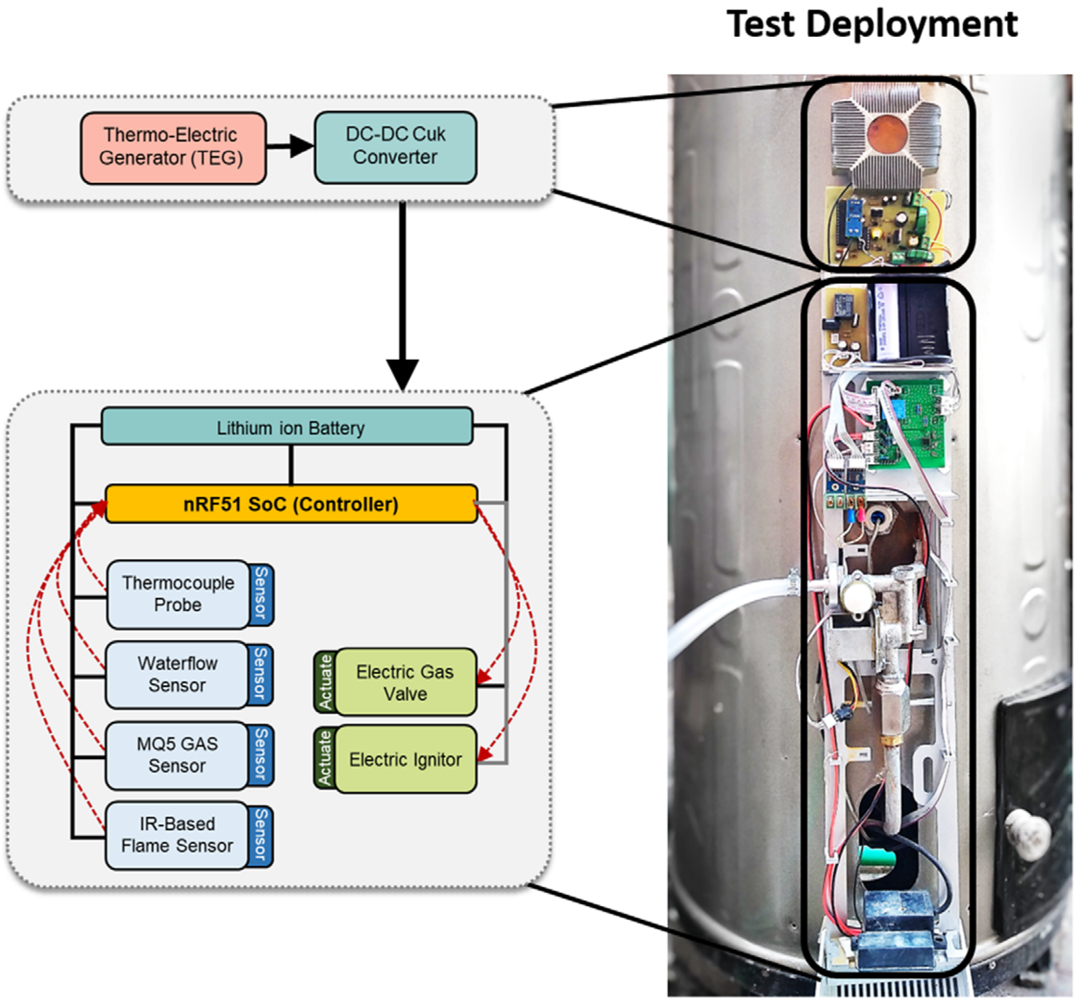

Figure 6. *Deployment of the retrofit thermal controller on a tank-based water heater at the site.*

usage patterns, the MoGHMM algorithm works with two states: a dormant state (D_s) and an active state (A_s). The dormant state corresponds to periods of minimal water usage, typically from midnight to early morning, while the active state represents periods of increased water usage throughout the rest of the day, as illustrated in Figure 8.

Within the MoGHMM, we differentiate between a routine pattern (M_r), which signifies a commonly observed usage pattern, and an abnormal pattern (M_a), representing rarely observed patterns. The classification between M_r and M_a is performed by a Hidden Markov Model (HMM) classifier, which computes the matching probability of the current water usage (D) with both M_r and M_a. The classifier's output is given as follows:

$$model = \underset{m \in \mathcal{M}_a, \mathcal{M}_r}{\arg\max}\ (D|m)$$

This approach ensures that abnormal patterns do not adversely affect system performance, as the system can intelligently distinguish and adapt to different usage scenarios. Our automatic scheduling mechanism has demonstrated an accuracy exceeding 90% after a two-week training period (Abbas et al., 2020), ensuring efficient anticipation of hot water demand.

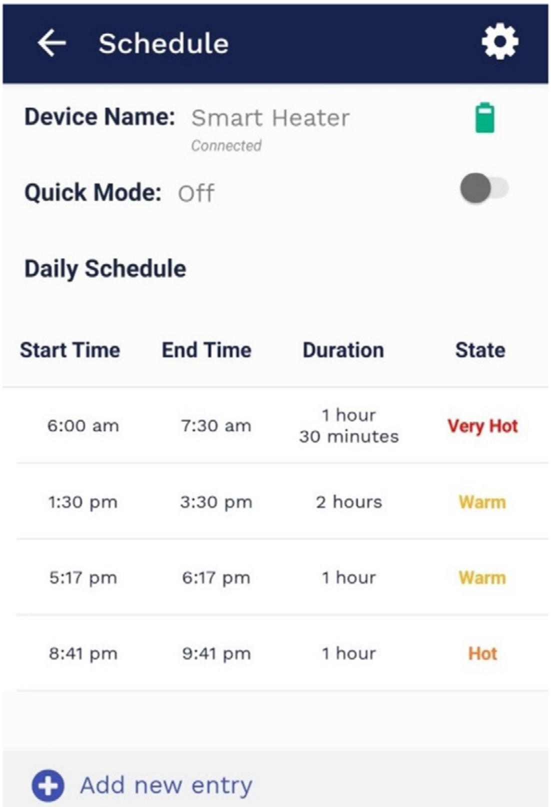

Figure 7. *Android application.*

4.2.2. Manual scheduling

The manual scheduling feature provides users with an option to override the MoGHMM models and manually set their preferred water temperature for different days and times of the week. This feature acknowledges the nondeterministic nature of hot water usage in some households (Abbas et al., 2020). The manual schedule, along with an optional "hard start" feature for unexpected hot water needs, can be configured within the smartphone application and uploaded to the controller.

In summary, these scheduling algorithms allow our system to offer user-friendly, efficient, and intelligent control of water heaters, catering to varied usage patterns and user preferences.

We estimate the total cost of implementing the proposed system to be less than $50. This estimate encompasses the expenses related to individual components, sensors, the microcontroller, as well as the aggregate bulk printed circuit board (PCB) manufacturing cost. The per-unit price of each component is based on an assumed bulk order of 1000 units. Moreover, the total cost considers the expenses related to the TEG system. In contrast, instant water heaters start at a price point of $80, lack the smart features offered by our system, often exhibit lower water pressure, and may not provide sufficient hot water for prolonged activities such as bathing, thus reaffirming the cost-effectiveness and utility of our proposal.

5. Modelling TEG

We developed and simulated a model of the TEG using MATLAB Simulink to evaluate its feasibility for charging the system battery. We applied the MPPT algorithm to the model's output to transfer maximum power from the TEG to the load, which is the system battery in this context.

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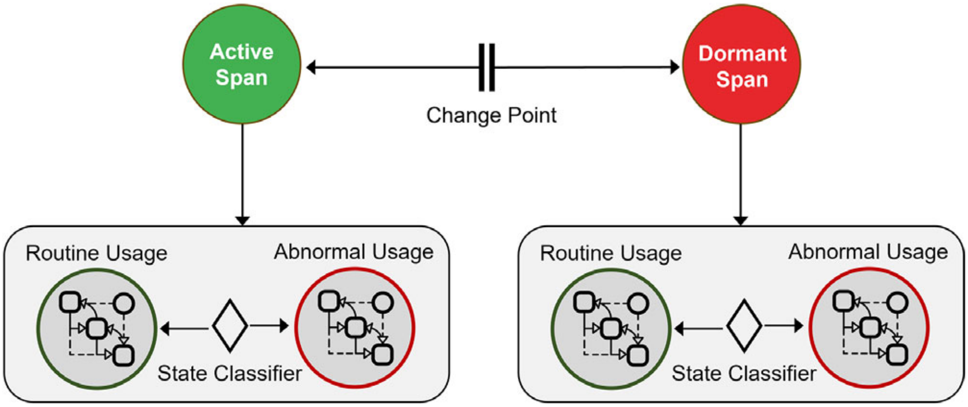

Figure 8. *Illustration of MoGHMM algorithm, which forecasts and distinguishes between dormant and active states, corresponding to periods of minimal and increased water usage, respectively.*

5.1. The TEG model

We modeled the TEG using a temperature-dependent voltage source and a resistor, representing its internal resistance, as recommended in (Mamur and Coban, 2020). Maximum power transfer from the TEG module to the load occurs when their impedances match.

The input parameters for the TEG model include the temperatures of its hot and cold sides, the Seebeck coefficient, and the number of TEG modules, with the latter set to one for our implementation. The Seebeck coefficient measures the thermoelectric sensitivity of a material, denoting the voltage change due to the temperature difference (T_h - T_c) (Mamur and Coban, 2020).

With these parameters, we effectively modeled the TEG's behavior, enabling a thorough analysis of its performance within our system.

5.2. The charging system

We direct the TEG's output to a DC-DC Ćuk converter, which operates continuously at a 50 kHz switching frequency. The converter's duty cycle leverages the MPPT algorithm. We chose the Ćuk converter for its continuous input and output currents, reducing strain on the attached 3.6 V Li-ion cell.

We direct the output from the TEG module to the Ćuk converter and utilize the MPPT algorithm to optimize power transfer to the battery. For comparison purposes, as detailed in the work (Mamur and Coban, 2020), we incorporate a fixed resistance load. In our analysis, we assume that the TEG's cold side remains at a steady 25°C, representing ambient temperature. Meanwhile, its hot side is in contact with a metal surface consistently maintained at 200°C. This temperature differential is crucial for the TEG's power generation.

To investigate the impact of temperature difference on the power output of the TEG, we maintain a constant load and cold side temperature while uniformly increasing the hot side temperature. This is achieved by activating the burner to heat the water in the tank. As the temperature difference between the hot and cold sides of the TEG increases, the power delivered to the fixed resistance load exhibits a corresponding increase, as depicted in Figure 9a. This observation aligns with the relationship between input and output power.

Figures 9b and 9c illustrate the simultaneous increase in voltage and current as the temperature difference across the TEG increases. The MPPT algorithm plays a crucial role in extracting maximum power from the TEG by regulating the voltage, which subsequently controls the current flowing through the fixed load connected to the converter's output.

The temperature differences examined in Figure 9 can also be indirectly linked to evaluate seasonal and environmental variations. During the summer, the temperature difference between the surface of the water

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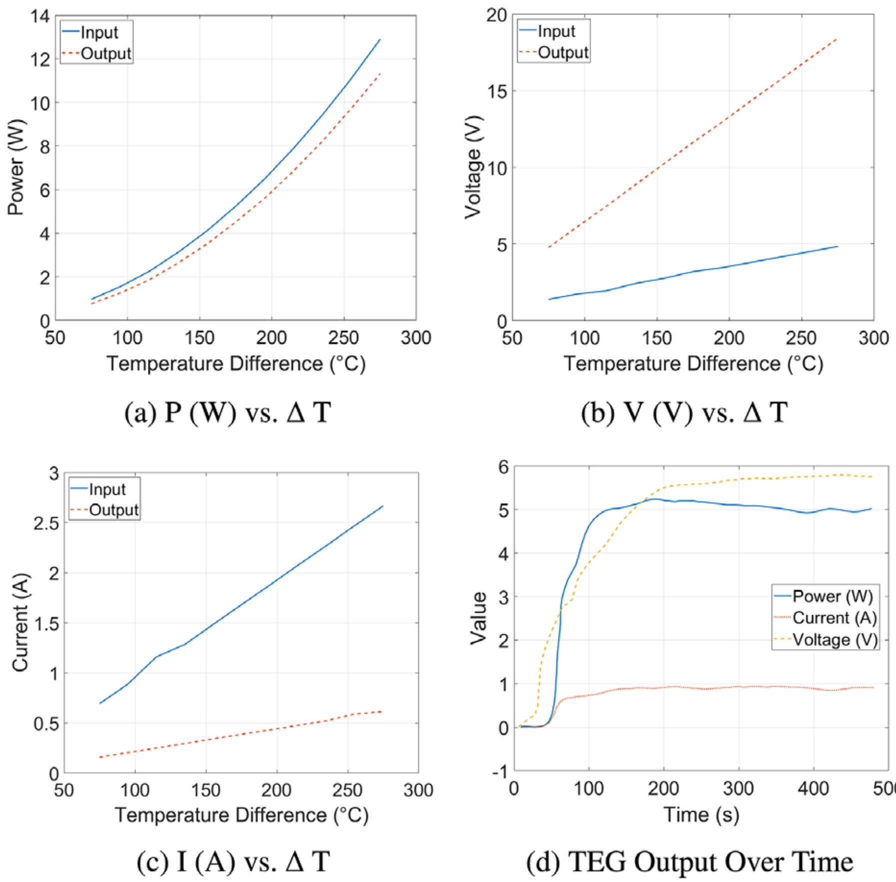

Figure 9. *Comprehensive analysis of TEG performance: correlations of power, voltage, and current with temperature difference (Δ T), and time-series depiction of TEG output.*

heater and the environment is relatively small because both the water heater surface and the surrounding environment are hot. Consequently, the TEG produces less energy. However, this is balanced by the reduced demand for hot water during the summer months.

In contrast, during the winter, the temperature difference increases significantly as the environment is much colder than the surface of the water heater. This greater temperature differential enhances the TEG's efficiency, resulting in higher energy generation. This increase in energy production aligns with the higher demand for hot water during the colder months.

Our initial result demonstrates that the system can effectively adapt to varying environmental conditions, maintaining consistent need-based performance throughout the year. The analysis of TEG efficiency under different temperature differences provides a solid foundation for understanding its performance across different seasons.

6. Experimental results

We evaluate the performance of our proposed solution for legacy water-heating systems by deploying a prototype in a real household. To do this, we gathered data about usage characteristics based on a household's typical hot water requirements. Although each household may exhibit unique usage patterns, we have validated the machine learning algorithm and found it to predict usage with high accuracy in diverse settings (Abbas et al., 2020).

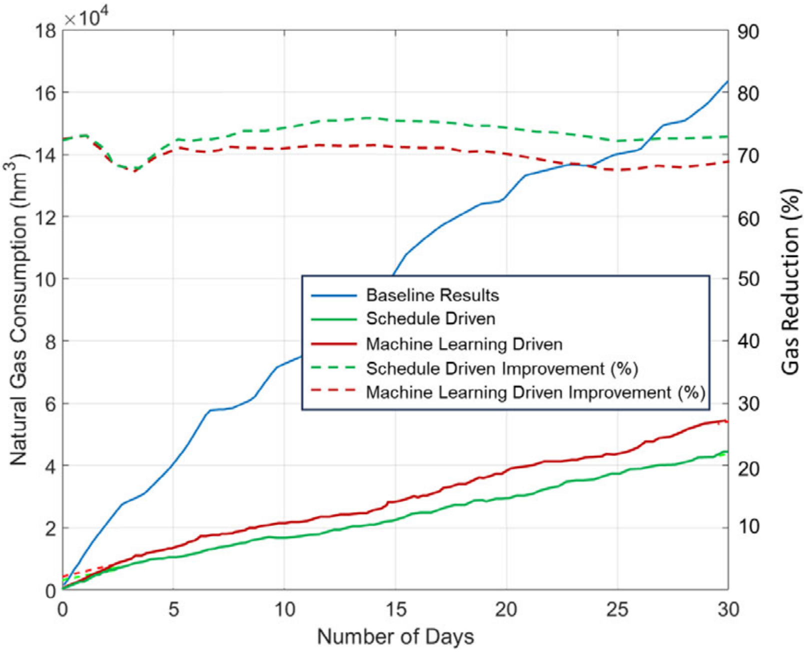

Figure 10. *Comparison of cumulative gas consumption by the proposed system operating under different modes with the baseline. The retrofit controller reduces gas consumption by around 70%.*

Figure 6 illustrates the integration of the retrofit controller into a standard gas-powered water heater, serving as our experimental setup to gauge our system's efficacy. In this section, we share the results, emphasizing the controller's effect on natural gas consumption for water heating and maintaining the household's water comfort. We also offer insights into our controller's power consumption and the TEG's effectiveness in recharging the system battery, aiming for long-term, maintenance-free operation.

6.1. Impact on gas consumption

We collected gas consumption data for a typical water heater equipped with a traditional mechanical thermostat over a one-month period. This serves as our baseline data, representing the gas consumption of standard water heaters commonly used in households across Pakistan.

The smart controller has two modes: user-defined schedules and machine learning. For these modes, we derived the gas consumption data from the baseline data, rather than using our smart system in a live setting. The rationale behind this approach was to establish equal grounds for comparison. Testing each mode over its own distinct one-month period would introduce variability due to inherent differences in consumption behavior. Hence, we measured the on/off times of both the user-provided schedule and the machine-learning (MoGHMM) predicted timings to infer gas consumption. Given the consistent gas flow during the on-time, which we previously quantified, this allows precise gas consumption measurement and comparisons.

In Figure 10, the daily natural gas consumption for all three scenarios over a one-month period is depicted. The dotted lines indicate reductions in gas consumption as percentages. Notably, the curves for both the user-defined and MoGHMM-learned schedules align closely, underscoring MoGHMM's proficiency in accurately learning and mirroring household water usage patterns.

Figure 10 also showcases the cumulative natural gas consumption across the designated days. It is evident from the results that our smart controller achieves a reduction in natural gas consumption by roughly 70%. This significant reduction can be attributed to the controller's ability to discern household water usage patterns, activating the water heater precisely when hot water demand is anticipated.

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Table 1. *Energy consumption of the proposed system with and without power optimizations*

Modes of operation		Current (A)	Before power optimization Energy (Wh)	After power optimization Energy (Wh)
System ON	Active mode	0.42	1.26	0.08
	Sleep mode	0.013		
System OFF	Active mode	0.031	0.093	0.003
	Sleep mode	0		

It is important to note that gas savings might differ among households, as water usage patterns can vary considerably. While our system realized significant gas savings in the studied household settings, variations in water usage patterns imply that not every household might achieve the same level of savings.

6.2. The system's power consumption

We deem it essential to analyze the power consumption of the proposed system, especially given its intended use in environments without tethered power access, depending solely on rechargeable batteries. We determined the system's power requirements by monitoring the input current across different operational modes, both with and without power optimizations.

Without power optimizations, the device always remains in the *active* mode, where both the radio and sensor nodes function continually. However, when we introduce power optimizations, the device switches between *active* and *sleep* modes, utilizing a very low duty cycle. Specifically, the system activates every 30 seconds for a brief moment to execute necessary tasks and then reverts to the *sleep* mode. In this *sleep* mode, we deactivate all sensors and the radio. It's also important to highlight that we consistently set the radio transmit power to 0 dBm.

Table 1 presents the device's power consumption results. The data reveal substantial power savings, achieved by eliminating superfluous processing and operating the device at low duty cycles. These power optimizations extend the battery life, assuring the system's continuous operation over extended durations.

By integrating the TEG into our system, we can recharge the system's battery, extending its lifespan without the need for manual recharging via external power. However, it remains crucial to ensure that the TEG, with the designed MPPT converter, produces power sufficient to either match or exceed the battery's discharge rate.

Figure 9d displays the results derived from the TEG in conjunction with a Ćuk converter. We initiated the system at time t = 0 secs and recorded the current and voltage readings from the converter's output. As the temperature difference (*Th* - *Tc*) grows, the power the TEG module produces increases proportionally. The temperature differential peaks at 190°C, at which the TEG output can support the controller system's power needs throughout the season, removing the need for any extra charging. Our implementation of the MPPT algorithm maximizes power extraction from the TEG module, efficiently charging the system battery.

Table 1 shows that during the water heater's active function, the device's controller draws a maximum current of 0.42A, which covers the power needs of all sensors and peripherals. The TEG's power output, as depicted in Figure 9d, sufficiently powers our system, erasing the need for extra charging during the entire operational season. This outcome underscores the efficiency of our TEG integration, guaranteeing the system's continuous and self-sufficient operation.

7. Limitations and future work

Our study's primary objective was to establish a proof of concept and demonstrate the system's feasibility. However, we acknowledge that our evaluation was limited to a single household and a specific model of

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water heater, which may not represent the diversity of usage patterns and heater designs found in broader populations. Additionally, we emulated different climatic conditions for evaluation, which may not capture the actual seasonal or geographic variations that could impact the efficiency of the TEG. Future research should include a more diverse range of households and water heater models to better understand the system's adaptability, with longer field trials conducted in various climates to assess the TEG's performance across different temperature differentials.

Our system also introduces data privacy and security concerns that can affect user acceptance and trust. Users may be apprehensive about the potential misuse of their water usage data, underscoring the need for robust data protection measures. Although our initial prototype did not focus on security, developing strong data security protocols to protect user information and enhance privacy will be critical. Educating users about these measures can build trust and encourage system adoption.

8. Conclusion

In this paper, we tackled the energy inefficiencies of tank-based water heaters by introducing an innovative retrofit controller that integrates machine learning for adaptive monitoring and control. The introduction of a TEG ensures sustainability by converting waste heat into electrical energy, addressing the challenges of intermittent power availability in certain heater placements. The Intelligence Hub, placed indoors, streamlines data collection, analysis, and communication, facilitating informed decision-making for the thermal controller. Our real-world deployment results validate the system's enhanced energy efficiency while ensuring user comfort. This work paves the way for modern, efficient, and user-friendly water-heating solutions, with potential avenues for future optimization and integration.

Author contribution. Conceptualization, investigation, methodology, validation, visualization, and writing—original draft, review, and editing: all authors. All authors approved the final submitted draft.

Data availability statement. Data availability is not applicable to this article as no new data were created or analyzed in this study.

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