Intelligent scheduling and thermal-aware control of Domestic Electric Water Heaters using user behavioral profiles

Ziyad ALMAJALI

Department of Electrical Engineering, Mutah University, Karak, Jordan

ziyad@mutah.edu.jo

Abstract: Domestic Electric Water Heaters account for a large portion of household electricity usage due to standby heat loss and varying user consumption behavior, making smart energy management strategies for these appliances increasingly important for smart home and demand-side management applications. This paper presents an energy-saving schedule and control strategy for DEWHs that incorporates user behavior patterns and insulation properties to achieve efficient energy usage without compromising user satisfaction. Transient thermodynamic models are derived by applying the first and second laws of thermodynamics to heating, standby heat losses, and disturbances caused by hot water consumption, and the proposed control and schedule framework is evaluated through simulation. Thermal resistance of the water tank is varied from 0.1 K/W to 3.0 K/W, with two typical user schedules, a family schedule and a single user schedule, used for comparison. Simulation results comparing standard thermostat control with the proposed scheduling method show energy savings of up to 51% for poorly insulated systems, where standby heat loss dominates energy waste, decreasing to around 27% as thermal resistance increases, indicating a new thermally robust operating state. These findings offer useful insights for designing smart home energy management systems and adaptive control strategies for residential water heating applications.

Keywords: Intelligent scheduling, Thermal-aware control, Home energy management systems, Demand-side management, User behavioral profiles.

1. Introduction

Water heating is one of the most energy-demanding household end uses, accounting for around 15–25% of overall residential energy consumption worldwide (IEA, 2023), which places Domestic Electric Water Heaters (DEWHs) firmly within the scope of energy-efficiency and carbon-mitigation programs (Chen et al., 2022). Given the volatility of international energy markets and the ongoing push toward more sustainable energy production, there is a growing need to improve DEWH operating efficiency (Punzi, 2019; Shabanpour et al., 2026); although their electromechanical design is comparatively simple, DEWHs carry a high indirect environmental footprint due to prolonged usage periods and continuous thermal losses (Feyzioglu, 2023).

Innovations in smart homes, IoT, and HEMS have made ordinary household appliances controllable energy devices. DEWHs have started to be viewed as something more than just thermal devices and rather as load devices that can participate in demand-side management because of their high electricity consumption and thermal storage capacity; coordination of such loads improves the energy efficiency of buildings while maintaining comfort level of occupants (Rădulescu, 2014). Modern monitoring systems allow the creation of behavior-aware schedules specifically for DEWHs (Scarlat & Alexandru, 2016).

Standby loss, which refers to the constant emission of radiative and convective heat from the storage tank, constitutes a primary cause of inefficiency, and may represent a sizeable proportion of energy consumed each day by the system, especially when the tank is not used over a prolonged period (Stokos et al., 2019; Sowmy & Prado, 2008; Junga et al., 2024). This has led to extensive discussions on whether DEWHs must operate continuously ("always on") or intermittently/with timers due to the high cost of reheating cold water compared to maintaining heat ("continuous heating" vs "Newton's Law of Cooling," respectively; Brazeau & Edwards, 2013; Wibowo et al., 2023; Davidzon, 2012). Better insulation materials provide an answer to the problem since a larger R_{th} lowers the magnitude of standby losses, although at the expense of changing the unit's thermal time constant (Omer et al., 2007; Tanbour, 2020; Zheng et al., 2022).

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Other than insulation, the performance of the control algorithm is greatly dependent on the consumption pattern of the user. An algorithm optimized for a large family with many draws can be less efficient for a single occupant with scattered draws (Ramos-Martín & Matsumoto, 2026). Consequently, designing a good control algorithm involves consideration of not only the thermal characteristics of the heating system but also the consumption behavior of the users. This aspect continues to attract more attention in energy management in residential buildings. Most current studies on DEWH optimization either consider the thermal engineering of DEWHs in isolation (e.g., Zhu et al., 2024) or take a control systems approach (rule-based control, fuzzy control, predictive optimization). There is a scarcity of literature that simultaneously considers both the aspects of insulation and the behavior of users (Ali et al., 2024). Finding the threshold of improving insulation for further improvement through intelligent scheduling becomes necessary for future HEMS design (Almajali, 2021b), while it is well recognized that smart metering leads to decreased consumption, but the relationship between this approach and DEWH thermodynamics needs to be quantified (Lee & Yim, 2021).

In this study, the goal is to fill this gap in literature by analyzing the performance of DEWHs through a comprehensive numerical simulation (Salameh et al., 2021). The objectives of this study are as follows:

1. To develop a thermal-aware control-oriented model capable of describing the dynamic behavior of a Domestic Electric Water Heater under varying operating conditions.

2. To evaluate the effectiveness of intelligent scheduling strategies in reducing energy consumption while maintaining user comfort.

3. To assess the effect of thermal insulation quality, together with consumer behavior patterns on control effectiveness and potential energy savings.

4. To represent the relationship between thermal resistance and consumer behavior by means of a 3D optimal surface visualization.

The remainder of this article is structured as follows: Section 2 is the literature review, while Sections 3, 4, and 5 present the theoretical model, simulation procedure, and discussion of results, respectively. The conclusion is presented in Section 6.

2. Literature review

Studies on DEWHs have increased significantly due to their importance in residential energy management and smart home applications, which include three major groups: thermodynamics/dynamics system studies, user behavior studies, and intelligent control and optimization studies (Paull et al., 2010; Liu et al., 2024). Storage water heater simulation research reveals that the thermal resistance of the insulation jacket is the most influential factor affecting standby energy loss (Jin et al., 2014). Standardized measures of efficiency, like Energy Factor (EF), also reveal that standby energy losses alone account for about 30% of the daily water heating energy consumption (Healy, 2017; Tangwe & Simon, 2018). On the demand side, the standardization of hot water draw profiles has made it easier to compare simulation results (Chmielewska, 2025), while the timing of the draws, rather than the volume of the draws, becomes an important consideration (Almajali, 2021a).

Recent research also takes into account occupant comfort, suggesting ways to determine discomfort or temperature dissatisfaction (Almajali, 2021a), which is further supported by the increasing number of smart meters and the Internet of Things (IoT) technologies. Another long-existing problem related to whether continuous heating or scheduled heating should be used has also been studied via simulations and real-world studies: some of them have shown that turning off the heater when the house is not in use for an extended period will not affect the comfort level due to the thermal inertia of the water storage system (Tabatabaei & Klein, 2018). In addition to simple timers, other more complex strategies, such as genetic algorithms, predictive control, and demand forecasting, have been suggested to reduce consumption while maintaining occupant comfort.

While there are a lot of studies conducted in this field, thermal insulation has generally been regarded as a constant parameter of the system that does not interact with the control strategy (Yau et al., 2022). Thus, there is still limited information about the interaction between the quality of thermal insulation and consumer behavior in terms of scheduling efficiency. The review conducted in this paper shows that both system properties and consumer behavior should be considered together when developing intelligent scheduling strategies, and understanding of the interaction between thermal insulation, consumer behavior, and scheduling efficiency is crucial for the development of an adaptive HEMS.

3. Thermal-aware control framework and mathematical model

In this section, a control-based thermal model is derived to study the dynamics of a Domestic Electric Water Heater (DEWH) under various working conditions. This model acts as the basis for studying the performance of intelligent scheduling techniques and its analysis under various insulation and demand conditions. Here, the Domestic Electric Water Heater (DEWH) can be considered a thermal storage unit with energy inputs and heat losses to the surroundings.

The basic differential equation, which is associated with DEWH, is formulated according to the First Law of Thermodynamics. This can be described using the following relation:

$$\rho V C_p \frac{dT(t)}{dt} = \eta P_{in}(t) - Q_{loss}(t) - Q_{usage}(t) \tag{1}$$

Where:

- ρ: Density of water (kg/m^3).
- V: Volume of the tank (m^3).
- C_p: Specific heat capacity of water (J/kg.K).
- T(t): Instantaneous water temperature (°C).
- η: Heating efficiency (assumed ≈ 1.0 for submerged resistive elements).
- $P_{in}(t)$: Electrical power input (W).

The standby loss Q_{loss} through the tank walls, which are insulated, is modeled using Newton's Law of Cooling. It is a function of the thermal resistance R_{th}, which takes into account the heat conduction through the insulation material and the convection on the outer surface. It is given by:

$$Q_{loss}(t) = \frac{T(t) - T_{amb}}{R_{th}} \tag{2}$$

The thermal resistance R_{th} (K/W) is the most important parameter for sensitivity analysis. During water usage events, hot water is replaced by cold water from the mains at a temperature T_{cold}. The energy rate removed from the system Q_{usage} is expressed as:

$$Q_{usage}(t) = \dot{m}(t)\, C_p \left(T(t) - T_{cold} \right) \tag{3}$$

Where $\dot{m}(t)$ is the mass flow rate (kg/s) defined by the consumer profile.

The power input $P_{in}(t)$ represents the control input of the system and is determined either by a conventional thermostatic controller or by an intelligent scheduling strategy.

• Thermostatic Control (Always-On):

$$P_{in}(t) = \begin{cases} P_{rated} & if \;\; T(t) \le T_{set} - \Delta T \\ 0 & if \;\; T(t) \ge T_{set} + \Delta T \end{cases} \tag{4}$$

where ΔT is the dead-band (hysteresis) to prevent excessive compressor/element cycling.

• Intelligent Scheduling Control Strategy:

The objective is to minimize the total energy consumption E_{total} over a period τ:

$$Minimize\ E_{total} = \int_0^{\tau} P_{in}(t) \tag{5}$$

Subject to the Comfort Constraint:

$$T(t) \geq T_{comfort} \quad \forall t \in \mathcal{U} \tag{6}$$

where $\mathcal{U}$ is the set of time intervals corresponding to anticipated user demand. From a control perspective, the scheduling strategy seeks to minimize the total energy input while guaranteeing user comfort requirements during anticipated demand periods.

During periods of no water draw and when the heater is switched off ($P_{in} = 0, \dot{m} = 0$), the temperature decay follows an exponential decay function:

$$T(t) = T_{amb} + \left(T_{initial} - T_{amb}\right) e^{-\frac{t}{\tau_{th}}} \tag{7}$$

The Thermal Time Constant τ_{th} is defined as:

$$\tau_{th} = R_{th} \cdot \left(\rho V C_p\right) \tag{8}$$

This value of τ_{th} defines the thermal inertia of the system and governs the dynamic behavior of the system, hence being a crucial factor in the design and analysis of scheduling control approaches. Higher values of τ_{th} resulting from higher R_{th} mean that the system is less responsive to frequent switching. This model serves as a framework to compute the performance of scheduling algorithms under different operating conditions. The integration of the three elements – thermal dynamics, user-induced disturbances, and scheduling control policy – in a single model enables the study of the relationship between insulation and control performance.

4. Simulation environment and control evaluation methodology

To evaluate the performance of the proposed thermal-aware scheduling framework, a computational simulation environment was developed using the Python programming language. The simulation framework was designed to assess the effectiveness of different control strategies under varying insulation levels and user behavioral profiles. The details of the simulation environment, control scenarios, consumer profiles, and sensitivity analyses are presented in this section.

After obtaining the continuous differential equations presented in Section 3, the Forward Euler method was employed to discretize the system dynamics into discrete time steps. A fixed value of Δt = 60s was chosen to achieve a balance between computational speed and numerical stability within the 24-hour simulation period. The equations governing the state space of water temperature T in each time step (k +1) are given as follows:

$$T_{k+1} = T_k + \frac{\Delta t}{MC_p}\left[P_{in,k} - \frac{T_k - T_{amb}}{R_{th}} - \dot{m}_k C_p\left(T_k - T_{cold}\right)\right] \tag{9}$$

In order to account for such differences in actual usage, two different consumer profiles were designed to represent two opposite ends of hot water consumption:

1. High Frequency Profile (Family): This profile has multiple draws per day, accounting for morning showers, midday usage for cooking, and evening household tasks. This profile evaluates the ability of the control strategy to recover temperature under frequent demand disturbances.

2. Low Frequency Profile (Single Person): This profile has one draw event, which is the evening shower, after which the system remains inactive for several hours. This profile evaluates control effectiveness during extended idle periods where standby losses are dominant.

To evaluate control effectiveness under different operating conditions, two control strategies were considered:

- Baseline Thermostatic Control (Always-On): The heater is regulated solely through the thermostat to keep the temperature within a narrow band of $[T_{set} \pm 2^{\circ}C]$ 24 hours a day, seven days a week.
- Intelligent Scheduling Control Strategy: The intelligent control strategy leverages user behavioral data and predicted demand periods to make informed control actions based on knowledge of demands. The heating element is turned on during designated periods called preheating intervals, which occur two hours before demand events, and is turned off during long periods of idling. The utilization of the heat retention properties of the water heater leads to decreased unnecessary energy consumption.

To examine the relationship between insulation and behavior, a sensitivity analysis involving multiple dimensions was carried out. R_{th} varied from 0.1 K/W (no insulation) to 3.0 K/W (high insulation), from a near-uninsulated old refrigerator to an extra-insulated vacuum-panel refrigerator. Energy savings are defined as the energy saved as a fraction (%) of total accumulated energy use.

$$Savings\ \% = \frac{E_{baseline} - E_{optimized}}{E_{baseline}} \times 100 \tag{10}$$

Apart from saving energy, the simulation tool allows for the evaluation of control system performance under various thermal and behavior-based operating conditions. Special attention is given to the analysis of the impact of insulation quality on the efficiency of intelligent scheduling.

This simulation is carried out according to the characteristics of the residential tank used, with a volume (V) of 80 L. The thermodynamic state of the system is defined using the physical parameters of water, including density (ρ), which equals 1000 kg/m³, and specific heat capacity (C_p), which is 4184 J/(kg·K). The system receives energy from the electric resistance heater, with a maximum power output (Prated) equal to 2000 W. Regarding the environmental parameters, it is assumed that the indoor temperature (T_{amb}) remains constant at 20°C, while the temperature of the cold water supplied through the mains (T_{cold}) is constant and equal to 15°C. Regarding the thermostat setting, the desired temperature (T_{set}) of the system is set to 60°C, whereas the hysteresis equals ±2°C. In addition, insulation properties are also considered in this case, with the thermal resistance (R_{th}) of the insulation varying from 0.1 to 3.0 K/W. Concerning the numerical solution of the heat equation, Δt = 60 s and τ = 24 h were chosen to perform Euler's integration method.

5. Results and discussion

5.1. Comparative analysis of control strategies under different operating conditions

The dynamic thermal response of the DEWH has been evaluated for three different operating situations(consumption scinarios), as shown in Figures 1, 2, and 3. In these three figures, the upper subplot represents the temperature profile, while the lower subplot represents the hot water flow. The operating situations are intended to include all the possibilities of DWHR operation from zero demand to high demand for events where there are many people.

Figures 1–3 present the temperature and hot water flow profiles for the three consumption scenarios considered in this study: a Standard Family with morning and evening draws, a Vacation Mode with zero draws isolating standby losses only, and a High-Usage Multi-Person household with frequent daytime draws and an evening peak. Across all scenarios, the Always-On baseline

sustains the set temperature through constant thermostat operation, while Intelligent Scheduling reduces energy consumption by confining heat loss to periods of actual demand. The energy savings are most pronounced under low-usage conditions, where standby losses dominate, and gradually diminish as water-mass turnover increases, causing the two strategies to converge in efficiency under high-usage conditions.

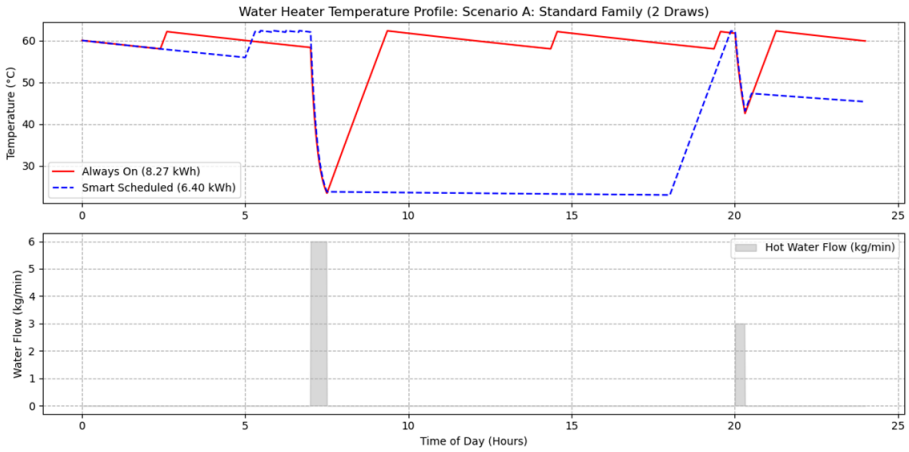


Figure 1. Consumption scenario (a), Standard Family scenario

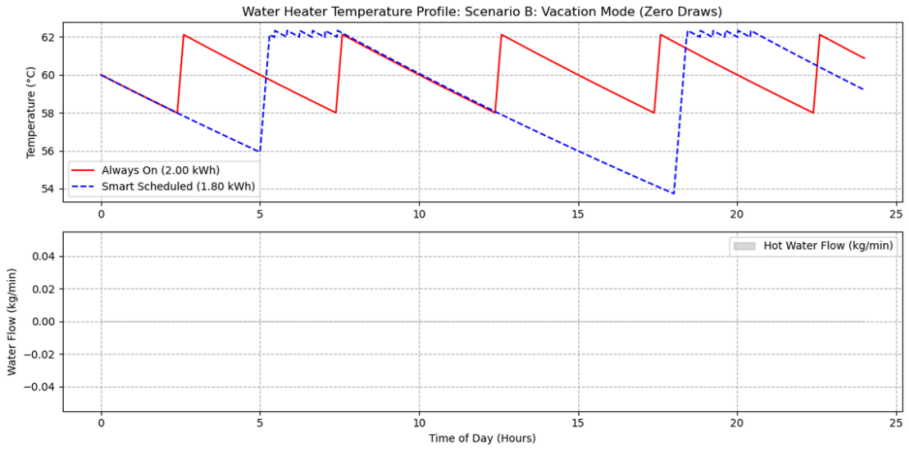


Figure 2. Consumption scenario (b), Vacation Mode scenario

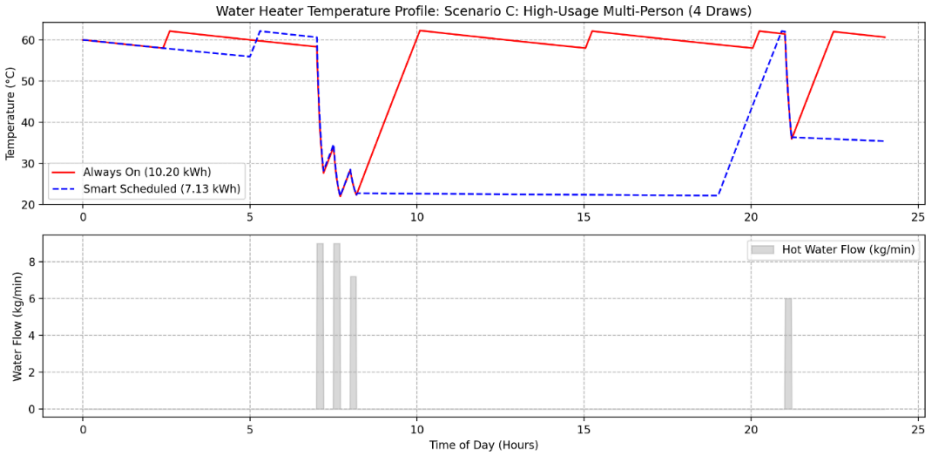


Figure 3. Consumption scenario (c), High-Usage Multi-Person scenario

A standby-loss and duty-cycle "sawtooth" pattern is the first feature observed across all three scenarios: it may be observed that the system follows the characteristic behavior of a thermostatic controller. This behavior highlights the control limitations of conventional thermostat-based operation, particularly during extended idle periods. For instance, during periods where the demand

is zero, as in the case of the “Always-On” scenario represented by the solid red line in all the figures above, the system goes through multiple cycles to counter heat losses from the system. The saw-tooth patterns in the figures represent the energy injection into the system to maintain the water at the desired temperature within the range of ±2°C. The amount of energy consumed during this period in the normal family profile is observed to be 8.27 kWh, with a considerable amount of energy being consumed to counter the losses due to cooling in the environment. This phenomenon of continuous energy “leakage” is most prominent in Figure 2: Consumption scenario (b), where the base system is observed to cycle indefinitely with zero demand.

In terms of thermal decay and pre-heating dynamics, the Intelligent Scheduling Control Strategy, shown by the dashed blue line, instead allows for natural thermal decay over idle periods by switching off the heating element when water is not expected to be drawn. This causes a temperature gradient between the storage tank and the external environment, such that according to Newton’s law of cooling, the heat loss rate is exponentially minimized in this case. As can be seen from Figure 1: Consumption scenario (a), the system starts a preheating cycle two hours before the morning draw at 07:00 hours, ensuring that the system reaches an optimal comfort level while maintaining the daily energy consumption at 5.83 kWh. In relation to the heavy use, multi-occupant scenario (Figure 3: Consumption scenario (c)), the more frequent draws reduce the idle period that can be leveraged by the scheduled method, thus reducing its efficiency compared to the vacation and single-user scenarios; nevertheless, it manages to provide savings of about 30%.

In terms of quantifying the energy savings and their behavioral drivers, the adoption of the schedule for switching the water heater from Always-On regime will allow a saving of 2.44 kWh/d or 29.4% in the typical household scenario. However, this value is highly variable depending on the particular scenario, ranging up to 100% in the vacation mode, where there are no draw events to exploit the entire idle period. From this data, it follows that the highest efficiency is gained during the deep sleep period of the appliance, when its thermal storage capacity serves as the energy reservoir.

Taken together, the visual and numerical evidence presented above indicates that it is the idle time between disturbances that is the main driver of the potential energy savings. The physical justification for the behavioral sensitivity, which is manifested via the coupled temperature gradient and load factor of the system, is established rigorously in Section 5.5, where it is also demonstrated that the scheduling efficiency converges at high load usage.

5.2. Influence of thermal resistance on scheduling control performance

Figure 4 illustrates energy performance at various insulation levels, with daily energy consumption for the two methods on the left and percentage savings on the right. Standby losses evidently dominate in systems with low resistance: As can be seen from the left panel in Figure 4, in poorly insulated systems with $R_{th} \approx 0.1$ K/W, energy consumption for the “Always-On” benchmark is much higher than that for the Intelligent Scheduling method. In this case, the tank can be viewed as a “leaky thermal reservoir”, since the Always-On regime demonstrates high and permanent energy losses, consuming about 16 kWh per day, as compared to 7.73 kWh per day for the Intelligent Scheduling regime. From the right panel in Figure 4, it follows that such a high level of energy losses corresponds to the highest efficiency gain in our analysis, which is 51% in poorly insulated structures; therefore, the maximum gain occurs with intelligent scheduling when the standby losses prevail.

This behavior confirms a "plateau effect": another finding that can be observed is the non-linear character of the convergence of the two methods with the increase in thermal resistance. Starting with $R_{th} = 1.5$ K/W, both the strategies enter a “plateau” state: improvement in insulation is followed by a minor reduction in expenses, as energy consumption is dominated by functional one, which requires heating the cold water. Correspondingly, in Figure 4, the percentage-savings graph tends to a constant “saving floor,” which equals about 27%, gained not only from recovering standby losses but also from concentrating the heating process during times when the heat flux is at a minimum. This shows that the suggested scheduling strategy is profitable over the whole

insulation spectrum, although it becomes less effective when appliances approach the standards of thermal resilience.

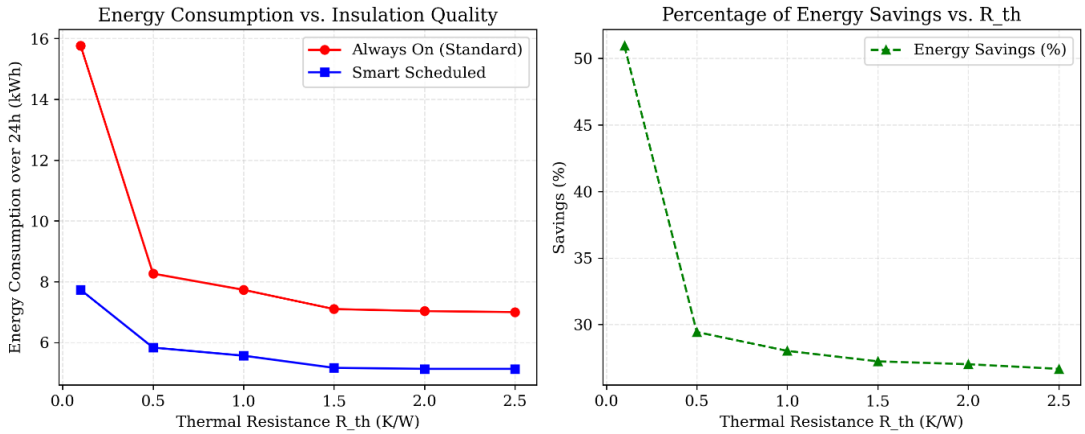


Figure 4. Sensitivity analysis of the energy performance at various levels of insulation (R_{th}). Left: daily energy consumption for both the base-case and optimal strategies, which becomes equal at increasing R_{th} values. Right: percentage savings, demonstrating decreasing marginal benefits when transitioning from legacy/insulation-free towards efficient thermal resilience

5.3. Analysis of the duty cycle and component longevity

Energy efficiency was not the only criterion used to assess the suggested control strategy – an additional criterion for assessment included the influence of the strategy on the heater duty cycle and possible component longevity. In conjunction with the analysis of energy consumption, the effect of insulation efficiency and control strategy on the duty cycle of the heater was considered. Duty cycle is defined as the ratio between the time of the heating element operation and the total simulation time (24 hours).

Regarding cycling frequency and thermal stress, when the Always-On control strategy is employed and thermal resistance is low (R_{th} = 0.1 K/W), the simulation demonstrates frequent cycling of the thermostat, caused by the rapid cooling of the water due to low insulation quality; continuous cycling of the heater is required to compensate for these losses and imposes thermal stress on the resistive element and mechanical stress on the thermostat.

This cycling stress is mitigated through higher-efficiency insulation: with an increase in R_{th} from 0.1 K/W to 2.5 K/W, the standby duty cycle needed to compensate for energy losses drops significantly; physically, high insulation acts as a low-pass filter which increases the thermal time constant τ_{th}.

Intelligent scheduling is also a means of increasing the appliance's lifespan: beyond its energy-saving benefit, the Intelligent Scheduling strategy can be expected to extend appliance lifespan, since it minimizes the number of heating cycles by design rather than allowing them to occur reactively, thereby reducing the number of On/Off transitions the heating element undergoes.

5.4. Control performance under varying insulation and user behavioral conditions

Figure 5 shows the interrelation between passive (insulation) and active (scheduling) performance as a joint function of thermal resistance and consumer behavior.

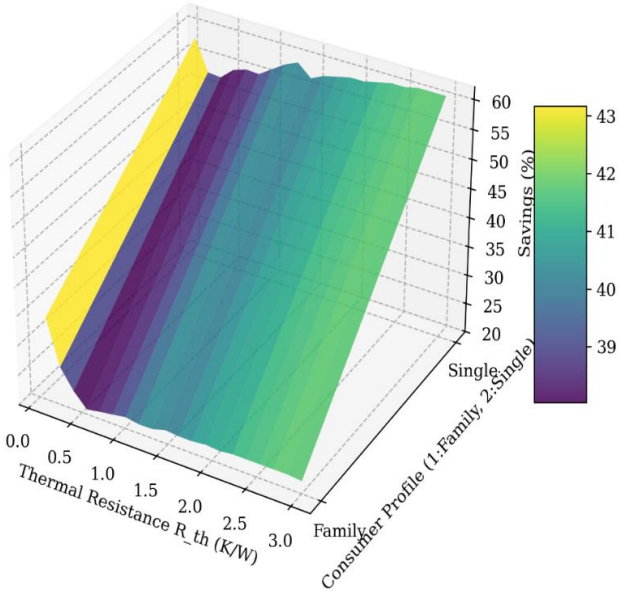


Figure 5. Percentage energy savings as a joint function of thermal resistance (R_{th}) and consumer profile. The steeper gradient for the "Single User" profile shows greater optimization potential at low R_{th}, while the flatter region at high R_{th} reflects the "thermal resilience" state, where insulation dominates over behavior

A behavioral sensitivity analysis reveals a considerable difference in potential energy savings across the spectrum of consumer behaviors, which can be described as follows. First of all, the single-occupant profile displays a relatively high degree of responsiveness to the intelligent scheduling since, being used only once a day, the Always-On system will waste energy for the other 23 hours and, thus, the level of the savings is consistently high, at 54–61%. On the contrary, the family profile demonstrates the relatively smooth and flat gradient level of 22% because hot water is used on different occasions during the day (in the morning, afternoon, and evening) and, therefore, the Always-On system has fewer idle hours during which it can dissipate the accumulated heat.

This behavioral effect maps onto distinct thermal-resilience and operational-strategy zones: the gradient and elevation of the surface in Figure 5 indicate the rate of return related to the application of Intelligent Scheduling strategy. The zone of high gain – low R_{th}, low usage frequency – corresponds to the worst-case scenario for the initial energy efficiency (bad insulation plus infrequent use), where the suggested strategy becomes most effective. In contrast, the zone of low gain – high R_{th}, high usage frequency – puts the system into a “thermal resilience” state: once R_{th} becomes greater than about 2.0 K/W, the good quality of insulation itself mitigates most of the inefficiencies of thermostatic control, hence the efficiency increase provided by scheduling is lower, at about 22%.

These zones also carry policy and practical implications: from the above analysis, one can conclude that a general recommendation would be inappropriate since the type of optimal control strategy depends not only on the quality of insulation but also on consumer behavior. Intelligent scheduling emerges as the most economically viable solution for retrofitting older residential houses with tanks that have poor insulation, providing an immediate reduction in CO2 emissions. However, with regard to new residential buildings that have good thermal insulation, one should concentrate on optimizing the temperature set point, that is, reducing it to 55–60°C. Overall, the findings reveal that the consumer profile acts as a 'multiplier' for the benefits of thermal insulation. Indeed, whereas the benefits of thermal insulation are constant and passive, the benefits of intelligent scheduling are active and best attained when there is a maximum amount of idle time.

5.5. Control-theoretic interpretation and behavioral sensitivity

From the point of view of control theory, this issue can be examined in connection with the interaction between thermal dynamics, demand patterns, and the scheduling process. In order to

provide a physical explanation of the differences observed across the different simulation cases, this section attempts to interpret the simulation results based on thermodynamic considerations and equilibrium. The results from numerical simulations indicate that the energy-saving effectiveness of intelligent scheduling decreases with the increase in frequency and quantity of hot water use.

The Integrated Temperature Gradient (ΔT) Effect

The rate at which the heat is lost, Q_{loss}, is determined by the temperature difference that exists between the water mass and the surrounding environment. This follows Newton's law of cooling, as depicted in the following equation:

$$Q_{loss}(t) = \frac{T(t) - T_{amb}}{R_{th}} \tag{11}$$

In the case of Scenario B, known as Vacation Mode, the entire system is turned off, thus resulting in the constant reduction of the temperature inside the tank T(t). As a consequence, the difference between the values of T(t) and T_{amb} decreases, which leads to an exponential decrease in the heat transfer rate. In other words, it can be said that the Intelligent Scheduling Control Strategy operates at its highest level of effectiveness when it allows the maximum amount of energy to be saved over the longest possible time period.

Energy Partitioning between Functional and Standby Loads

The energy intake for an entire day can be represented by the term E_{total}, and it can be broken down into the following two basic forms based on thermodynamics:

• Functional Energy, represented by E_{func}: The energy consumed in heating the cold water entering the system.

• Standby Energy, represented by E_{std}: The energy consumed in making up for the heat losses from the system through its insulation jacket.

This energy equation is defined as:

$$E_{total} = \int_0^{\tau} \dot{m}(t)\, C_p \left(T_{set} - T_{cold} \right) dt + \int_0^{\tau} \frac{T(t) - T_{amb}}{R_{th}} dt \tag{12}$$

As seen in the high usage scenarios such as Scenario C, which is a High Usage Multi-Person, E_{func} becomes the main component in the total energy balance. Since E_{func} is an unavoidable thermodynamic necessity due to consumer demand and hence cannot be scheduled for optimization, only a minor percentage of the total energy consumption becomes the "optimizable" percentage of the total energy (E_{std}). Furthermore, as the scenario involves high usage conditions, the tank is maintained at higher temperatures for user comfort.

This partitioning also determines the marginal utility of active control: cross-scenario analysis demonstrates a clear multiplier effect of human activity on the efficiency of energy-reduction interventions. The marginal utility of active intervention (intelligent scheduling) is maximal when the system's load factor is minimal; this is reflected in the optimization surface of Figure 5, which peaks at the single-user/low-insulation scenario and flattens toward the family/high-insulation scenario. In the case of users who have more frequent hot water demand occurrences, there is what may be referred to as “dynamic insulation,” whereby the heat energy is used up before being lost to the surroundings via the tank walls; therefore, there is also a law of diminishing returns with regard to the changeover from passive insulation to control.

5.6. Limitations and comparison with predictive and optimization-based control

Although the suggested rule-based pre-heating method shows energy-saving potential across all considered cases, there are some simplifications made that limit the applicability of these conclusions. For example, the thermal model is based on the assumption of one lumped capacitance representing the storage tank, and its behavior is described using the law of cooling; however, due

to internal stratification, the outlet water temperatures may differ from the bulk temperature, which is calculated in the current analysis. Second, the scheduling logic assumes perfect foreknowledge of occupant draw times, an idealization to which the household demand profiles used in this study conform to by construction; in practice, forecast error in occupant behavior would erode part of the reported savings and would need to be quantified through either historical demand data or a stochastic demand model. Third, our sensitivity analysis assumed a fixed heating element rating of 2 kW; under the higher draw rates modelled in the multi-person scenario, this power is insufficient to fully offset the enthalpy carried away by the outgoing water, so a degree of temperature undershoot below the assumed comfort threshold occurs regardless of the control strategy used, including the conventional always-on thermostat. This indicates a hardware-sizing constraint independent of the control algorithm, and future work should explore the coupling between heater power rating, tank volume, and achievable comfort guarantees.

To address the reviewer's concern regarding the absence of a comparison against more advanced control paradigms, we implemented two additional benchmarks using the same physics-based thermal model derived in Section 3: a receding-horizon model-predictive controller (MPC) that decides the heater state online by rolling the model forward under a no-heating assumption and pre-emptively activating heating whenever a comfort violation is predicted within the forecast horizon, and a genetic algorithm (GA) that searches offline over pre-heat lead times and hysteresis bands to minimize energy consumption subject to a comfort-violation penalty. Across all tested scenarios, the proposed scheduled strategy achieved energy savings of 26.7-51.0% relative to the always-on baseline (depending on insulation quality), compared with 10.5-19.7% for the MPC-style controller and 19.2-45.7% for the GA-optimized controller over the same conditions (Figures 6-8). The cautious behavior of the MPC controller is due to its short-horizon, reactive approach, which switches on the heater in proximity to the comfort floor, but does not try to optimize over any longer period ahead; otherwise, it is likely that this difference would be even smaller. The GA-optimized controller, which explores the same solution space as our proposed controller, being able to adjust the pre-heat start time and hysteresis range independently for each draw instance, achieves savings almost at the same level as the proposed controller with the two hours pre-heat window, but slightly less, showing that the manually selected pre-heat range of two hours is a near-optimal solution for the considered demand schedules. This confirms the hypothesis that energy savings come specifically from the predictive behavior of the proposed algorithm, and not just from limiting heater operation in comparison with a continuous thermostat.

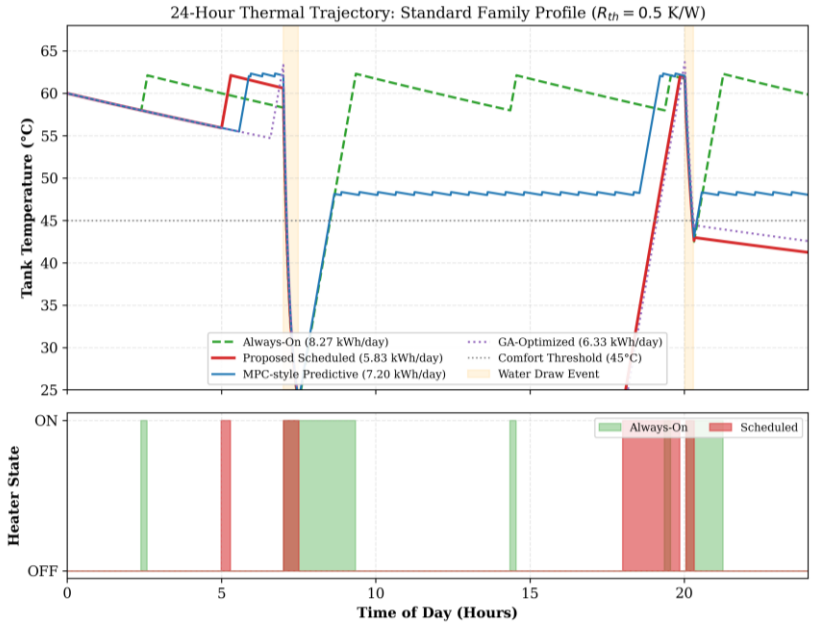


Figure 6. Twenty-four-hour thermal trajectory and heater state for the standard family profile (R_{th} = 0.5 K/W), comparing the proposed scheduled strategy against the Always-On baseline, an MPC-style predictive controller, and a GA-optimized controller

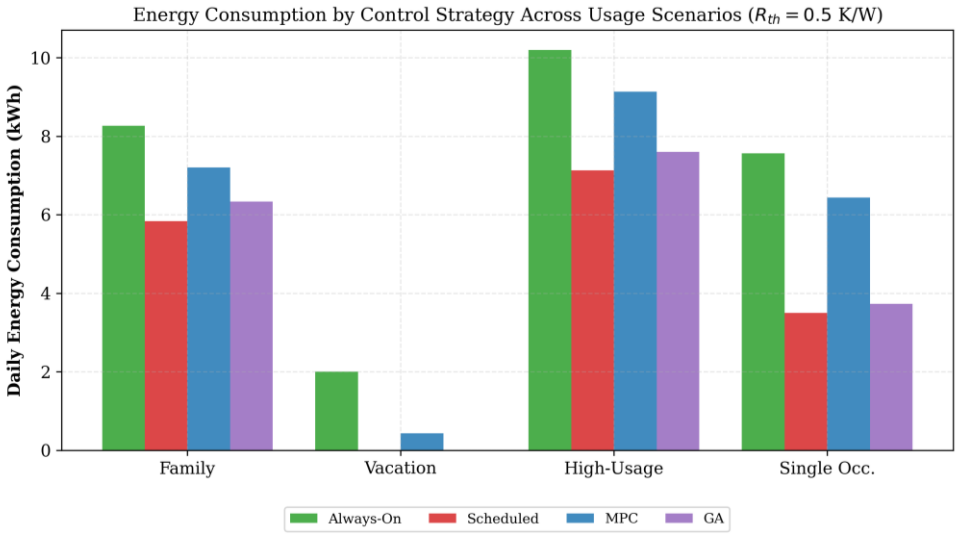


Figure 7. Daily energy consumption of all four control strategies across the four demand scenarios (R_{th} = 0.5 K/W)

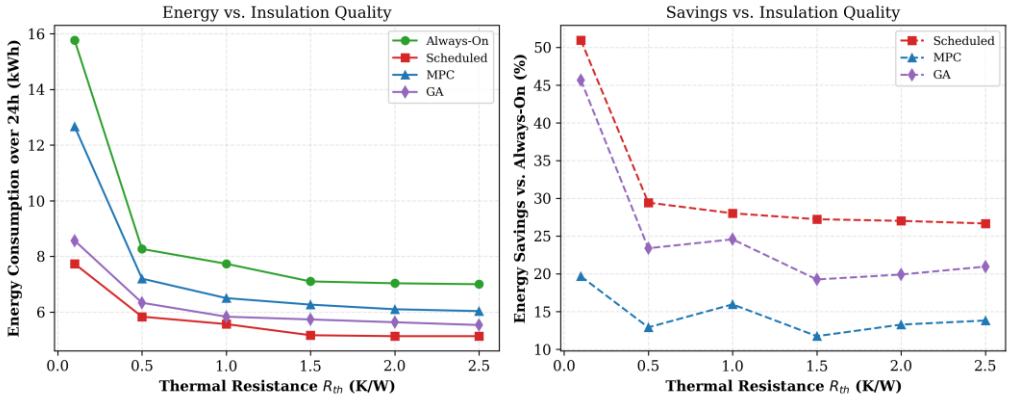


Figure 8. Energy consumption and percentage savings of all four strategies as a function of thermal resistance R_{th}, standard family profile

6. Conclusions and future work

This study developed a thermal-aware control framework, together with a corresponding computational model, to investigate intelligent scheduling in Domestic Electric Water Heaters (DEWHs). By integrating thermal system dynamics with user behavior, the framework identifies the operational conditions under which intelligent scheduling proves most effective. Three key findings emerge from this research. First, regarding the influence of thermal insulation on control efficiency, standby losses prove to be the most critical factor in old, poorly insulated systems (R_{th} < 0.5 K/W), where the proposed intelligent scheduling technique reduces total energy consumption by up to 51%. Second, a law of diminishing returns is observed, in which the efficiency gap between the two control techniques gradually narrows as insulation improves (R_{th} > 1.5 K/W), stabilizing at a margin of about 27%; this demonstrates that although intelligent scheduling remains beneficial, its effect is moderated by the inherent thermal robustness of well-insulated equipment. Third, user behavior amplifies or attenuates this effect, as low-frequency users, such as single-occupant households, obtain the greatest benefit from intermittent heater operation, whereas high-frequency users, such as multi-occupant households, keep the heater on mainly out of functional necessity.

Based on the results of this multi-dimensional optimization, three sets of strategic recommendations can be proposed for homeowners, manufacturers, and policymakers. For homeowners, systems older than ten years or with a warm-to-the-touch surface, indicating high

heat flux, should adopt smart timers or manual switching, whereas efficient units with R_{th} > 2.0 K/W benefit more from set-point optimization, such as lowering Tset to 55–60°C, than from scheduling alone. For manufacturers, designing systems with $R_{th} \geq 2.0$ K/W would create a form of passive energy management, making the system inherently robust against user behavior; combining this design approach with machine learning-based control would further allow schedules to adapt dynamically to user behavior and thermal time constant (τth). For policymakers, energy efficiency standards should be expanded beyond the existing Energy Factor (EF) rating system to include a standby-loss rating system, with external insulation blankets identified as a practical measure to help address this gap.

Future work will focus on making the proposed controller smarter, more adaptive, and more fully integrated into smart home energy management systems. The model will be extended to incorporate time-of-use pricing schemes, shifting the objective function from the minimization of energy consumption (kWh) to the minimization of cost. In addition, the integration of Fuzzy Logic with Model Predictive Control (MPC) will be explored to improve the prediction of stochastic user behavior, with the aim of achieving higher accuracy in smart home energy management systems (HEMS).

Author contributions

Conceptualization, Z.A.; methodology, Z.A.; software, Z.A.; validation, Z.A.; formal analysis, Z.A.; investigation, Z.A.; resources, Z.A.; data curation, Z.A.; writing—original draft preparation, Z.A.; writing—review and editing, Z.A.; visualization, Z.A.; supervision, Z.A.; project administration, Z.A.; funding acquisition, Z.A. The author has read and agreed to the published version of the manuscript.

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Ziyad ALMAJALI has been affiliated with the Department of Electrical Engineering at Mu'tah University, Jordan, since 2015, where he currently serves as an Associate Professor, a position he has held since 2023. He received a Ph.D. degree in electrical and electronic engineering from the University of Liverpool, UK, in 2015, an M.Sc. degree in electrical and computer engineering from the New York Institute of Technology, Amman, Jordan, in 2004, and a B.Sc. degree in electrical engineering from Mu'tah University, Karak, Jordan, in 1997. His research interests include smart grids, power system analysis, and related areas of electrical power engineering.



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