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Full Length Article

Intelligent Load Management and Power Consumption Optimization in Smart Grid Systems Using Adaptive Control

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Abstract

Smart grids need load management that keeps feeder demand within its limit without relying on a model that stays accurate as weather and customer behavior change. This paper proposes a self-tuning adaptive controller for the aggregate demand of a population of thermostatically controlled loads. A recursive least squares (RLS) estimator identifies, online, how the aggregate flexible power responds to a broadcast thermostat setpoint shift, and a damped one-step-ahead control law uses the estimate to hold total feeder demand below a limit set at 90 % of the uncontrolled peak. The method is tested in a 24 h numerical model of 400 air-conditioning units and an inflexible base load, solved in Python, over five random populations. It is compared with no control and with a fixed-gain PI controller tuned on the nominal day. On the nominal day, the adaptive controller lowers the peak from 1000.8 kW to 913.7 kW, a reduction of 8.7 % against 6.3 % for the PI controller, and reduces the time above the limit from 163 min to about 1 min, with no measurable comfort cost. On a heat-wave day, in which the limit cannot be met without discomfort, both controllers reduce the peak by about 9 to 11 % and cause similar discomfort; the adaptive controller halves the time above the limit but not the energy above it. The study is simulation-based, uses assumed device parameters and a single class of flexible load, and does not include communication delays or customer participation behavior.

Keywords: *smart grid; demand response; adaptive control; recursive least squares; load management; thermostatically controlled loads*

Introduction

Demand response (DR) moves electricity use away from the hours when grid load and costs are highest, and it is an important tool for modern power systems [1]. Its practical value depends on control: the aggregate of many small flexible loads must be steered reliably, without reducing comfort beyond what customers accept. Studies on smart grids stress that effective DR also requires computational methods that keep the burden manageable [2].

Many control designs rely on a fixed model or fixed gains tuned for one operating condition. The flexibility of a population of loads is not fixed, however; for instance, air-conditioning demand depends on outdoor temperature, so the response to a control signal changes during the day and between days. A controller that cannot adapt may under-react in some conditions and over-react in others. Adaptive control, which identifies the response online, is therefore a natural candidate.

This paper develops and tests a self-tuning regulator for peak-demand limiting. The objectives are (i) to formulate an online-identified model of the aggregate flexible load, (ii) to design a control law that keeps total feeder demand below a limit by shifting thermostat setpoints, and (iii) to compare it with no control and with a fixed-gain PI controller in nominal and heat-wave conditions, using peak demand, time above the limit, load factor, energy and comfort indicators.

Section 2 reviews related work, Section 3 describes the models and controllers, Section 4 presents the results, and Section 5 concludes with future directions.

Literature Review

Reviews of demand response show a broad field. Stanelyte et al. described DR as a mechanism that redistributes consumption away from peak periods, and reviewed enabling technologies such as smart meters and the internet of things, ancillary services and the possible role of blockchain [1]. Binyet et al. reviewed DR for power reallocation, with attention to load scheduling, peak shaving, renewable integration and energy management systems [3]. Assad et al. reviewed computational methods for smart-grid DR and optimization, including intelligent algorithms, machine learning and quantum computing, and recommended reducing the computational burden of DR in future smart grids [2].

Application-oriented studies show what DR can deliver. Daminov et al. coupled DR with dynamic thermal rating to increase transformer reserve and lifetime, finding the minimum DR needed to allow

a load connection through an integrated management and sizing problem solved in YALMIP [4]. Jasim et al. connected electric-vehicle batteries to parallel distributed generators for demand management in smart microgrids, using an artificial neural network controller that acts on the demand curve and battery charge level to perform peak load shaving [5].

A large part of the control literature uses model predictive control (MPC). Joshal and Gupta reviewed MPC for microgrids, noting that the receding-horizon principle allows optimization under constraints [6]. Mannini et al. surveyed smart management of microgrids and reported that MPC is emerging as a competitive alternative to conventional methods, particularly for voltage and frequency regulation and distributed-resource management [7]. Pamulapati et al. reviewed microgrid energy management from the energy trilemma perspective, observing that multi-agent systems and MPC are widely used [8]. Moreno-Castro et al. reviewed MPC for the economic dispatch of microgrids [9], and Tumeran et al. reviewed MPC-based energy management for the integration of renewable sources [10].

The reviews indicate that predictive and intelligent methods are widely studied, and that their value depends on the quality of the underlying model and on computation. Few of the works summarized above, however, address how a controller can keep a demand limit when the response of the controlled load population itself changes with conditions. The present study approaches this by identifying a low-order aggregate model online with RLS, which keeps the computation light, and by testing the controller against a fixed-gain alternative under a change of weather.

Materials and Methods

The test system is a feeder serving 400 customers over 24 h. Each customer has an inflexible base load and one air-conditioning unit modelled as a thermostatically controlled load (TCL). Device parameters are drawn from uniform ranges (Table 1) and are assumed representative values, not measured data. The ambient temperature follows a sinusoid with a mean of 28 °C and an amplitude of 6 °C that peaks at 15:00 (34 °C); a heat-wave scenario adds 5 °C. The base-load profile has a morning peak and an evening peak around 19:30. The feeder limit is 904.0 kW, equal to 90 % of the uncontrolled nominal peak (1004.5 kW). The model follows Fig. 1 and was solved in Python 3 using NumPy with a 15 s step; control actions are updated every 60 s. All results are averages over five random populations (seeds 0 to 4); the limit and the PI gains are determined with seed 0. The block layout of Fig. 1 and Fig. 2 is Simulink-style.

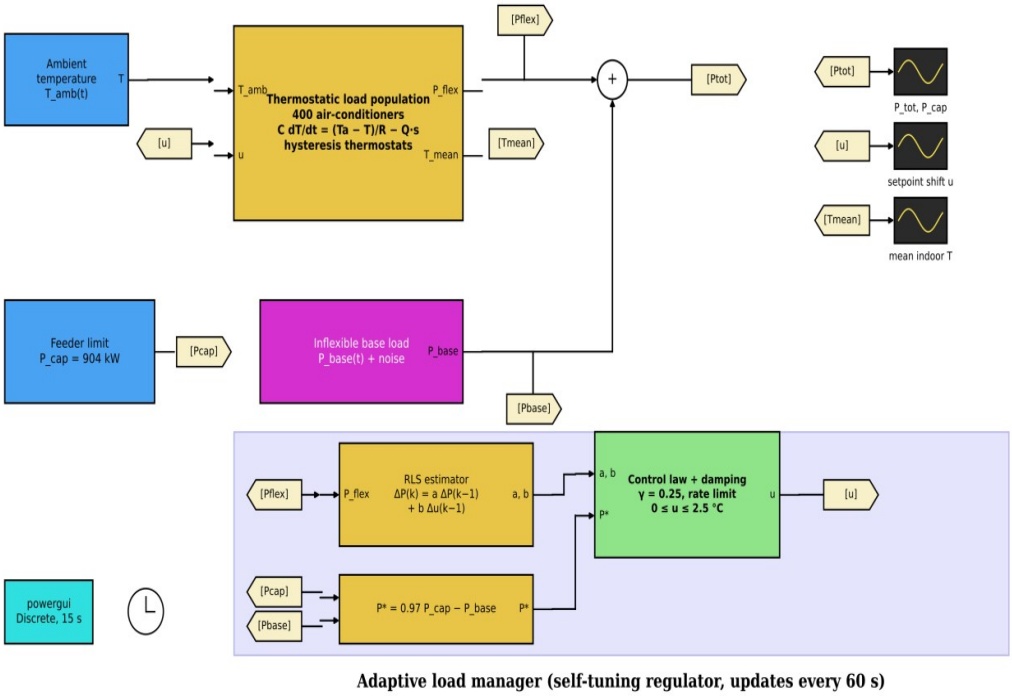

Fig. 1. Simulink-style block diagram of the feeder, thermostatic load population and adaptive load manager.

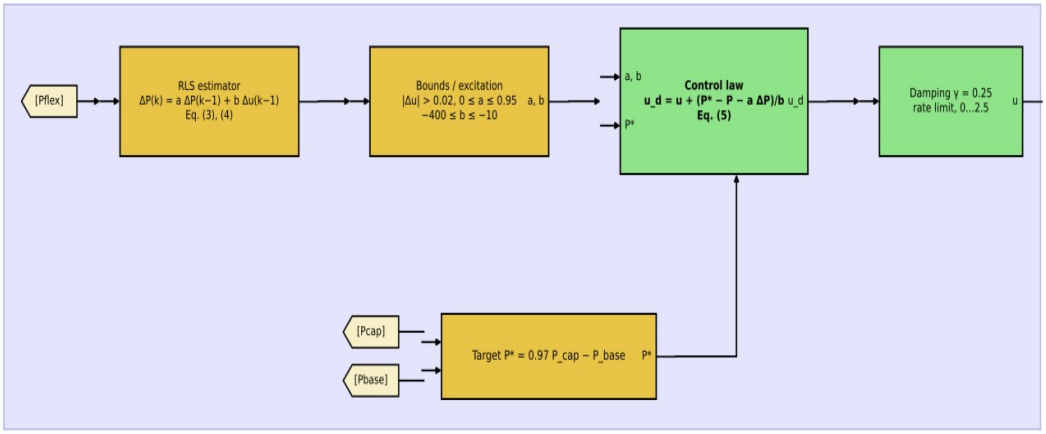

Fig. 2. Structure of the adaptive load manager: RLS identification and control law.

Procedures

Step 1: thermostatic load model. The indoor temperature T_i of unit i follows:

$$C_i \cdot dT_i/dt = (T_a - T_i)/R_i - Q_i \cdot s_i, \quad Q_i = COP \cdot P_i \quad (1)$$

where T_a is the ambient temperature, R_i and C_i the thermal resistance and capacitance, P_i the electrical rating and s_i the on/off state. The unit switches on when T_i exceeds the effective setpoint (22 °C + u) by the half dead band of 0.5 °C and off when it falls below it by the same amount. The aggregate flexible power and the total feeder demand are:

$$P_{flex}(k) = \sum_{i=1}^{400} P_i \cdot s_i(k); \quad P_{tot}(k) = P_{flex}(k) + P_{base}(k) \quad (2)$$

Step 2: online identification. The setpoint shift u is broadcast to all units. The aggregate response is described by an incremental first-order model, which removes the dependence on the absolute load level:

$$\Delta P_{flex}(k) = a \cdot \Delta P_{flex}(k-1) + b \cdot \Delta u(k-1) \quad (3)$$

where Δ denotes the change over one control period, a is a pole and b a gain (kW per °C, negative because a larger setpoint shift lowers power). The parameter vector θ = [a, b] is updated by recursive least squares with forgetting factor λ = 0.98 and covariance P_c:

$$K = P_c \cdot \varphi/(\lambda + \varphi^T \cdot P_c \cdot \varphi); \quad \theta(k) = \theta(k-1) + K \cdot (y - \varphi^T \cdot \theta(k-1)); \quad P_c = (P_c - K \cdot \varphi^T \cdot P_c)/\lambda \quad (4)$$

where φ = [ΔP_flex(k−1), Δu(k−1)] is the regressor and y = ΔP_flex(k) the measurement. To avoid covariance wind-up, an update is made only when |Δu| > 0.02 °C, the covariance is bounded, and the parameters are limited to 0 ≤ a ≤ 0.95 and −400 ≤ b ≤ −10 kW/°C.

Step 3: control law. The allowed flexible power is the target P* = 0.97·P_cap − P_base. The desired setpoint shift follows from the model, and the applied value is damped and limited:

$$u_d = u(k-1) + (P^* - P_{flex}(k) - a \cdot \Delta P_{flex}(k))/b; \quad u(k) = u(k-1) + \gamma \cdot (u_d - u(k-1)), \quad \gamma = 0.25 \quad (5)$$

with 0 ≤ u ≤ 2.5 °C and |Δu| ≤ 0.5 °C per period. The fixed-gain reference is a PI controller acting on the error P_tot − P_cap with gains K_p and K_i selected from a small grid by minimizing the energy above the limit plus a comfort penalty on the nominal day; they are then frozen. Both controllers use the same signal u and the same measurements.

Analysis

Indicators are the peak demand, the load factor (mean divided by peak), the peak-to-average ratio (PAR = peak/mean), the time and the energy above the feeder limit, the total energy consumed, and comfort measures: the mean temperature excess above the upper dead-band limit (22.5 °C) and the share of unit-time with the indoor temperature more than 2 °C above that limit. Results are reported as means over the five populations.

Results and Discussion

Fig. 3 shows the uncontrolled system. Demand peaks at 1004.5 kW at about 18:00, when air-conditioning demand and the rising evening base load overlap; the 904.0 kW limit is exceeded for about 163 minutes.

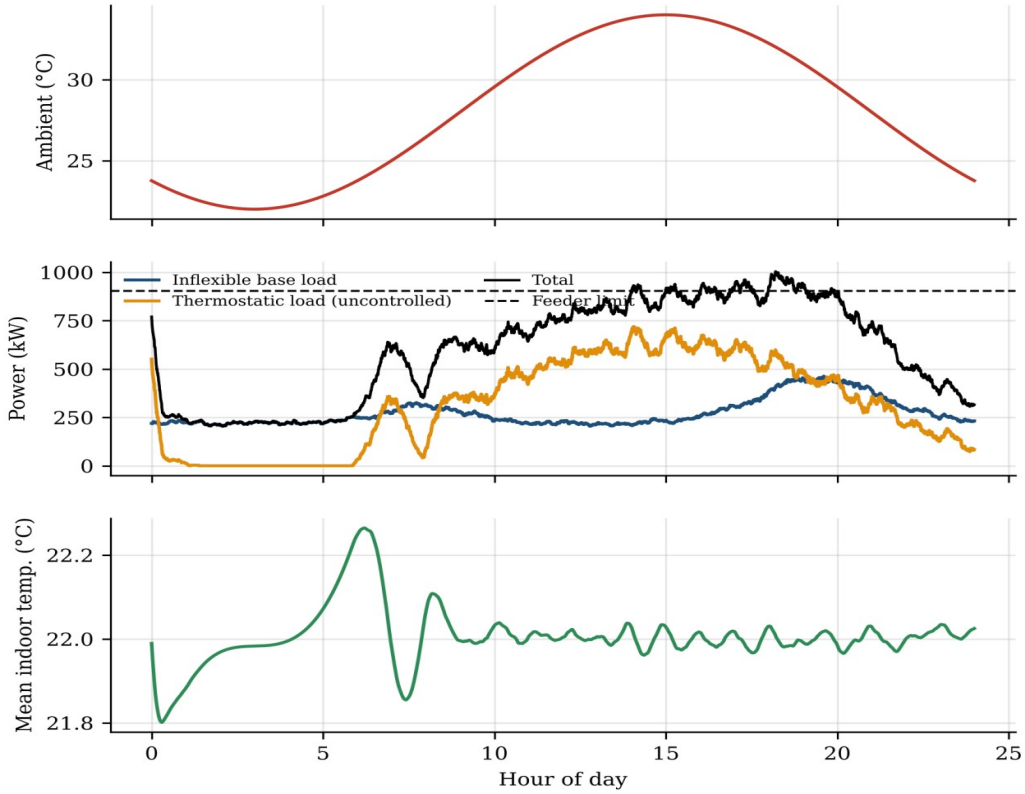

Fig. 3. Simulated 24 h feeder: ambient temperature, base load, thermostatic load and total demand without control.

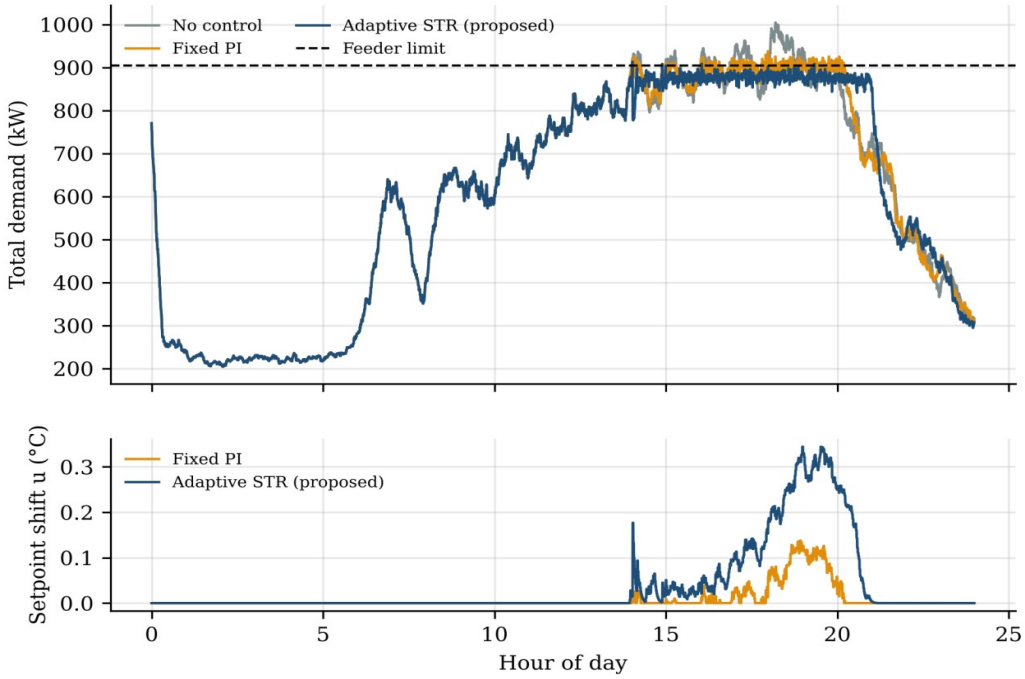

Fig. 4. Nominal day: total demand and setpoint shift under each controller.

Fig. 4 and show the nominal day. The PI controller reduces the peak to 938.0 kW but remains above the 904.0 kW limit for 124 minutes, because its gains, selected for a smooth, comfortable response, are low. The adaptive controller brings the peak to 913.7 kW and keeps demand under the limit except for about one minute, with an energy excess of 0.12 kWh against 14.4 kWh for the PI controller. The

load factor improves from 0.59 to 0.65 and the peak-to-average ratio from 1.68 to 1.54. The comfort cost is negligible, with a mean temperature excess of 0.01 °C. The small drop in daily energy (about 0.4 %) arises because part of the cooling that is postponed has not yet been recovered by midnight, and it should not be read as a genuine saving. The adaptive result stays about 10 kW above the limit at the peak because of the 3 % safety margin and the 60 s control period.

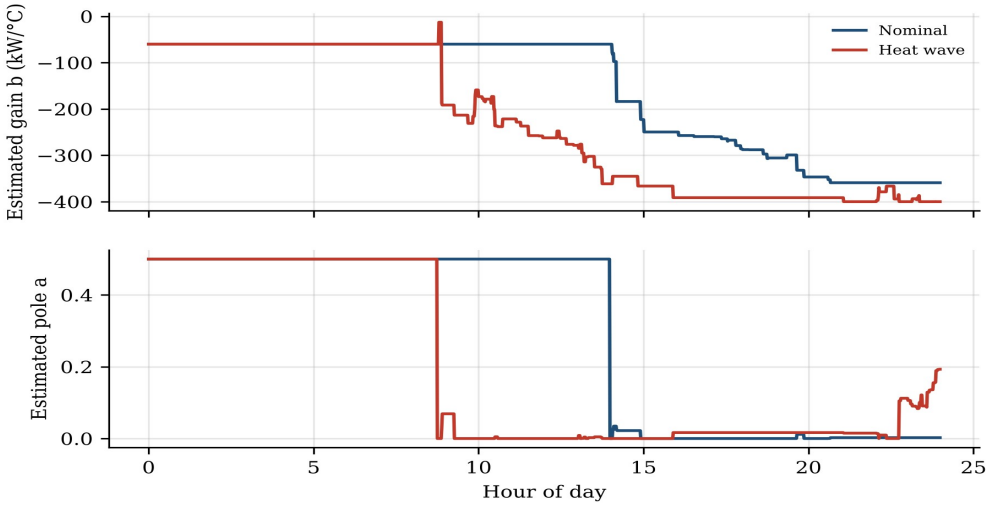

Fig. 5. Online RLS estimates of the aggregate gain b and pole a.

Fig. 5 shows how the estimated gain b and pole a evolve. While the controller is active, the gain averages about −290 kW/°C on the nominal day and about −345 kW/°C on the heat-wave day, where it also reaches its lower bound of −400 kW/°C. The pole stays close to zero (mean of 0.00 to 0.02), which means that the aggregate power reacts to a setpoint change almost within one control period. The estimates therefore track a change in the response of the population, which is the behavior the adaptive design is intended to exploit. Identification is only updated when the control signal moves, so the estimates hold their last value while the limit is not binding.

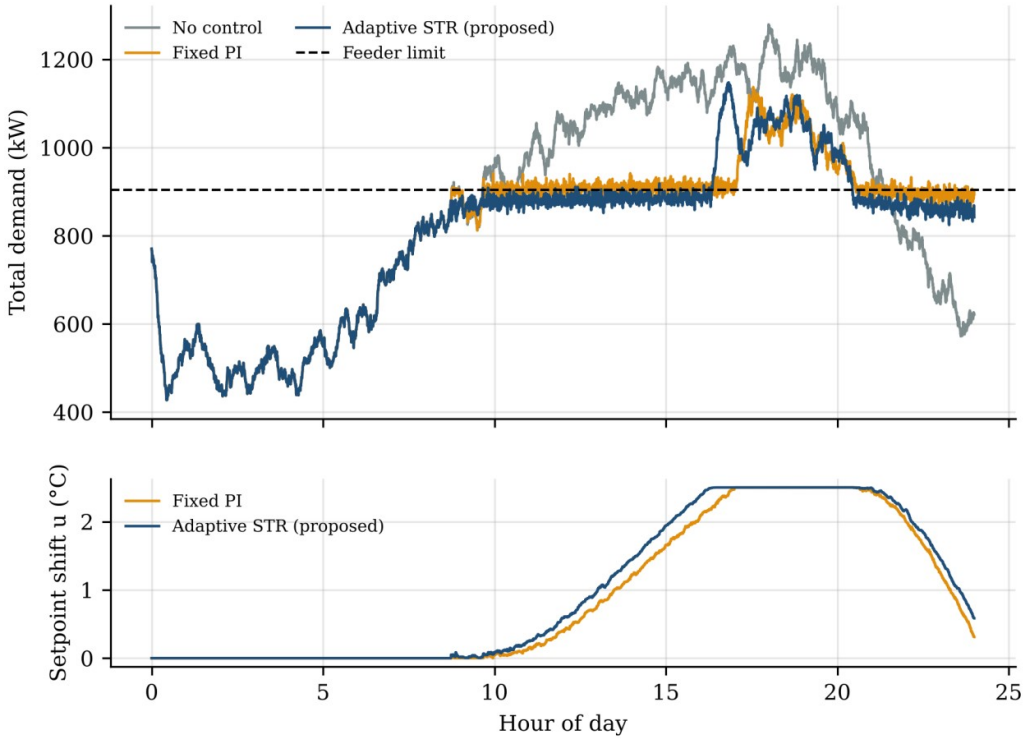

Fig. 6. Heat-wave day: total demand and setpoint shift under each controller.

The heat-wave day is a different situation: the same 904 kW limit is physically out of reach without substantial discomfort, because the uncontrolled air-conditioning demand alone reaches about 897 kW at the evening peak, close to the 904 kW limit. Both controllers therefore saturate the setpoint shift. The adaptive controller gives a lower peak (1129.2 kW against 1152.5 kW) and cuts the time above the limit from 556.5 to 269.1 minutes, but the energy above the limit is slightly higher (557.5 against 508.3 kWh) and discomfort is slightly worse (12.5 % of unit-time more than 2 °C above the band, against 10.7 %). Thus, on the heat-wave day, the adaptive design is not clearly better than the PI controller; the benefit is confined to the time above the limit and the peak. The result also shows that a feeder limit must be accompanied by a rule about acceptable comfort loss, because no controller can create flexibility that does not exist (Fig. 7).

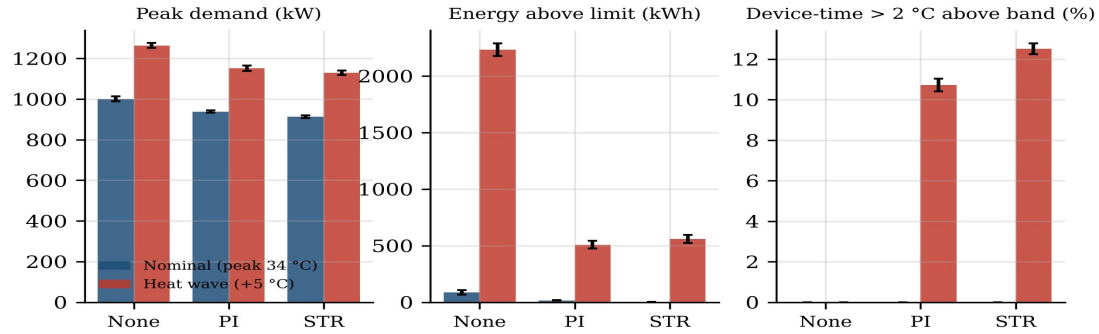

Fig. 7. Summary indicators over five random populations (mean ± standard deviation).

The behavior is consistent with the view in the reviews that DR is useful for peak shaving but depends on available flexibility [1], [3]. The light computation of the RLS-based law (a two-parameter update every minute) is in line with the recommendation of Assad et al. to reduce the computational burden of DR [2], and is far simpler than the optimization-based MPC schemes surveyed for microgrids [6], [7], [9]. A numerical comparison with those works or with the artificial neural network controller of Jasim et al. [5] is not possible, because systems and metrics differ. The conclusions are limited by the single type of flexible load, the broadcast signal without communication delay, perfect measurement of aggregate power, and the assumed device parameters.

Conclusion and Future Work

A self-tuning adaptive controller based on online RLS identification of the aggregate response of thermostatic loads was developed to keep feeder demand below a limit. On a nominal day it reduced the peak demand by 8.7 % (against 6.3 % for a tuned PI controller), lowered the time above the limit from 163 to about 1 minute, and improved the load factor from 0.59 to 0.65, without measurable loss of comfort. On a heat-wave day, where the limit cannot be met without discomfort, the two controllers performed similarly, with the adaptive controller showing a lower peak and less time above the limit but a slightly higher energy excess and discomfort.

The contribution is a light, model-free-in-practice controller and an honest account of where it helps and where it does not. Future work should include other flexible resources such as electric-vehicle charging and storage, a comfort-aware limit that relaxes under extreme conditions, communication delays and partial participation, forecasting of base load, and comparison with MPC and with field data from real feeders.

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