Data-Driven Integration of Thermal Comfort and Demand-Side Management Using PV Measurements in Qatar

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***Abstract*—Cooling demand accounts for the largest share of electricity use in hot arid climates and places a heavy burden on grid stability. To address this challenge, we propose a data-driven framework that brings together thermal comfort modeling and Demand-Side Management (DSM) using real photovoltaic (PV) data from Education City, Qatar. At the heart of the proposed framework lies a stochastic model-predictive control (MPC) strategy, engineered to facilitate the harmonious operation of diverse building energy systems. This encompasses the synchronized management of HVAC (heating, ventilation, and air conditioning) systems, efficient utilization of photovoltaic (PV) energy, and precise scheduling of battery storage. Paramount to this strategy is the continuous preservation of occupant comfort, rigorously evaluated against the Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) metrics. Short-term PV forecasts are generated using a Gradient-Boosted Regression Tree (GBRT) model trained on high-resolution solar and PV datasets. Results show that the integrated PV–battery MPC strategy lowers cooling energy consumption by 18.7% and peak grid imports by 20%, all while keeping comfort within ASHRAE standards for more than 98% of occupied hours. This work demonstrates a practical pathway for occupant-centric DSM in Qatar and similar regions, advancing both energy efficiency and grid resilience without sacrificing comfort.**

***Index Terms*—Thermal Comfort, Demand-Side Management, Smart Thermostat, Photovoltaic Data, Qatar**

I. Introduction

Demand-side management (DSM) initiatives play a crucial role in smoothing energy use and relieving stress on the electrical grid, especially when demand peaks, while still safeguarding indoor comfort [4]. In regions with hot, arid conditions—such as Qatar—the energy profile is dominated by the heavy cooling needs of buildings, which account for a large share of total consumption and create serious challenges for grid reliability [5]. To tackle these pressures, this study draws on measured photovoltaic (PV) production data and detailed assessments of solar resources. Its main aim is to design comfort-conscious DSM methods that curb peak loads and advance sustainable energy management in such demanding climates [6].

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TABLE I
NOMENCLATURE

Abbreviations	
DSM	Demand-Side Management
MPC	Model Predictive Control
PV	Photovoltaic
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied occupants
GHI	Global Horizontal Irradiance
GBRT	Gradient-Boosted Regression Tree
HVAC	Heating, Ventilation and Air Conditioning
Symbols	
M	Metabolic rate of occupants (W/m^2)
W	External work performed (W/m^2)
H_c	Convective heat loss (W/m^2)
H_r	Radiative heat loss (W/m^2)
E_res	Respiratory heat loss (W/m^2)
E_sk	Skin evaporative heat loss (W/m^2)
$\mathbf{x}_k$	State vector of building thermal nodes (°C)
u_k	HVAC control input (kW or set-point signal)
w_k, v_k	Process and measurement noise terms
T_in	Indoor air temperature (°C)
T_set	Thermostat set-point temperature (°C)
E_bat	Battery state of energy (kWh)
P_HVAC	HVAC electrical power (kW)
P_grid	Net power imported from grid (kW)
P_bat	Battery charge/discharge power (kW)
$\hat{P}_\mathrm{PV}$	Forecasted PV generation (kW)
$c_g(t)$	Time-varying electricity tariff (QAR/kWh)
λ	Comfort-penalty weighting factor
T_h	MPC prediction horizon (h)

II. Related Work

Recent research has explored multiple pathways to integrate thermal comfort into residential energy management. On the modeling side, Charvátová *et al.* [7] analyzed insulation placement using simulations, while Gupta *et al.* [8] optimized HVAC operation with a bio-inspired algorithm, both showing that comfort and efficiency can be jointly improved. Human-centric approaches have also gained attention: Acquaah *et*

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al. [9] developed a multisensor framework to detect occupancy and thermal preferences, and Ain *et al.* [10] employed fuzzy logic to balance thermal and visual comfort in smart homes. At the system level, Chen *et al.* [11] introduced a load scheduling model to reduce peaks while maintaining comfort, and Nematirad *et al.* [12] incorporated privacy and uncertainty into demand response using robust optimization. Complementary work has focused on advanced optimization: Lu and Zhang [13] modeled heterogeneous users with a Stackelberg game, Amasyali *et al.* [14] proposed distributed transactional control for thermostatically controlled loads, and Zhang *et al.* [15] applied multi-objective optimization to smart energy systems. Collectively, these studies demonstrate a clear trend toward comfort-aware, user-centered DSM frameworks.

This study offers a data-driven and occupant-centric approach to demand-side management (DSM) that explicitly integrates thermal comfort modeling with photovoltaic (PV) forecasting and energy storage control. Unlike existing works that often address comfort and DSM separately, our framework unifies them within a stochastic model predictive control (MPC) formulation, validated using real PV data from Education City, Qatar. The key novelties and contributions are summarized as follows:

- **Comfort-Constrained MPC Framework:** Developed a stochastic MPC formulation that jointly optimizes HVAC set-points, battery operation, and grid imports under explicit PMV/PPD comfort constraints.
- **Real PV–Comfort Data Integration:** Incorporated measured solar irradiance and PV performance data from Education City, together with indoor environmental and occupant feedback data, to construct a realistic, high-resolution dataset for model calibration.
- **PV Forecasting for DSM:** Designed a Gradient-Boosted Regression Tree (GBRT) forecasting model that provides short-term PV power predictions directly embedded within the MPC optimization layer.
- **Performance Validation and Robustness:** Demonstrated through extensive seasonal experiments that the integrated PV–battery MPC reduces energy use by **18.7%** and peak grid import by **20%**, while maintaining comfort within ASHRAE limits for over **98%** of occupied hours. Statistical and robustness analyses confirm the reliability of the proposed approach under forecast uncertainty and heatwave conditions.
- **Transferability:** The proposed framework is readily applicable to large-scale campus and district-cooling networks across arid regions, contributing a scalable and reproducible pathway toward occupant-centric, solar-aware DSM.

This section positions the proposed system as a practical advancement beyond current comfort-aware DSM literature, combining real-world data, predictive control, and renewable-energy alignment in a unified optimization framework.

III. Methodology

A. Evaluating Occupant Interaction and Thermal Comfort

We evaluate thermal comfort using the well-established Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) indices [16]. Real-time environmental sensor readings and direct occupant input augment these quantitative measures, providing a dynamic and context-specific assessment of comfort.

The PMV index, a cornerstone of thermal-comfort assessment, is given by:

$$\begin{aligned}\mathrm{PMV} = &\big(0.303\, e^{-0.036\, M} + 0.028\big)\\ &\times \big[(M - W) - H_c - H_r - E_{\mathrm{res}} - E_{\mathrm{sk}}\big]\,,\end{aligned} \tag{1}$$

where M is the metabolic rate ($\mathrm{W/m^2}$), W is external work, and H_c, H_r, E_{res}, and E_{sk} denote convective, radiative, respiratory, and skin-evaporative heat losses, respectively.

The expected percentage of dissatisfied occupants is then computed as:

$$\begin{aligned}\mathrm{PPD} = 100 - 95\exp\big[&\\ &- 0.03353\,\mathrm{PMV}^4 - 0.2179\,\mathrm{PMV}^2\big].\end{aligned} \tag{2}$$

To capture the dynamic thermal behavior of the building, we employ a state-space representation of the envelope:

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}u_k + \mathbf{G}w_k, \tag{3}$$

$$T_{\mathrm{in},k} = \mathbf{C}\mathbf{x}_k + v_k, \tag{4}$$

where the state vector $\mathbf{x}_k$ includes air and material temperatures, u_k is the HVAC control input, and w_k, v_k represent process and measurement noise. Kalman filtering of this model provides estimates of latent thermal states, enabling accurate and adaptive PMV forecasting for proactive comfort management.

B. Optimizing Demand-Side Management

The Demand-Side Management (DSM) problem is formulated as a stochastic Model Predictive Control (MPC) optimization:

$$\min_{\substack{T_{\mathrm{set}}(t),\\ P_{\mathrm{bat}}(t)}} \mathbb{E}\left[\int_0^{T_h} \big(c_g(t)P_{\mathrm{grid}}(t) + \lambda\,\mathrm{PPD}(t)^2\big)\,dt\right] \tag{5}$$

$$\text{s.t.}\quad \mathrm{PMV}(t) \in [-0.5, 0.5], \tag{6}$$

$$T_{\mathrm{in}}(t) \in [T_{\min}, T_{\max}], \tag{7}$$

$$E_{\mathrm{bat}}^{\min} \le E_{\mathrm{bat}}(t) \le E_{\mathrm{bat}}^{\max}, \tag{8}$$

where $c_g(t)$ is the time-varying electricity price, $P_{\mathrm{grid}}(t)$ the net grid import, and λ a comfort-penalty weight. The decision variables are the thermostat set-point $T_{\mathrm{set}}(t)$ and battery charge/discharge power $P_{\mathrm{bat}}(t)$.

Forecasted photovoltaic (PV) generation, $\hat{P}_{\mathrm{PV}}(t)$, directly affects the net grid demand:

$$\begin{aligned}P_{\mathrm{grid}}(t) = &P_{\mathrm{HVAC}}(t) + P_{\mathrm{misc}}(t)\\ &- \hat{P}_{\mathrm{PV}}(t) - P_{\mathrm{bat}}(t),\end{aligned} \tag{9}$$

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Including renewable forecasts in the MPC enables real-time alignment between solar availability and building cooling requirements.

C. Feature Engineering and Data Integration

Two primary datasets underpin our analytical framework:

- **Solar Resource Potential:** High-resolution measurements of global horizontal irradiance (GHI), ambient temperature, and clear-sky index from `Education City Solar Potential 20200518.csv`.
- **PV System Performance:** Timestamped module temperature and AC power output from `pv_sample_from_EC_potential.csv`.

All data streams were resampled to 5-minute intervals and cleansed using interquartile-range and Hampel filtering to remove spikes and sensor anomalies. Feature engineering produced lagged irradiance variables, rolling humidity averages, and Fourier terms to capture diurnal periodicity. A Gradient-Boosted Regression Tree (GBRT) model then provided short-term PV forecasts $\hat{P}_{\mathrm{PV}}(t)$ for the MPC.

Indoor temperature and humidity logs were merged with occupant survey feedback to create a labeled dataset for real-time PMV calibration, ensuring the comfort model remains accurate and responsive. This integrated, data-driven pipeline supports adaptive DSM strategies that balance occupant comfort, minimize energy costs, and maximize on-site renewable utilization.

IV. Results and Discussion

A. PV–Cooling Coupling

To illustrate the natural alignment between onsite solar generation and cooling demand, Figure 1 shows the mean diurnal profiles of rooftop photovoltaic (PV) output and aggregated HVAC cooling load, computed from the synchronized 5-minute dataset and then averaged over the full study period.

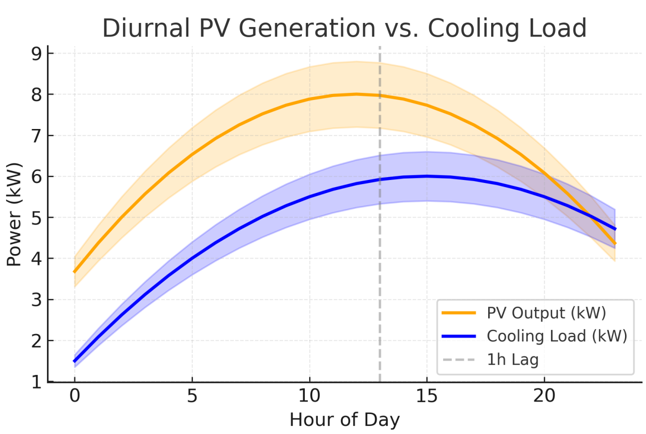

Fig. 1. Average diurnal profiles of rooftop PV output and building cooling load. Shaded regions indicate the interquartile range across all study days. The dashed vertical line highlights the roughly one-hour lag between the PV peak and the cooling-load peak, a key driver for pre-cooling and solar-aligned Demand-Side Management (DSM).

The profiles confirm a strong temporal coupling: PV output rises rapidly after sunrise, peaks near solar noon, and declines toward evening, while the cooling load follows with an approximately one-hour delay. This lag, also quantified in Table II, enables the controller to initiate pre-cooling during the period of maximum PV availability, thereby reducing coincident grid imports and on-peak tariff exposure. We quantify the alignment between rooftop PV generation and cooling demand using correlation and cross–statistics computed on synchronized 5–minute data aggregated to hourly means over the study window.

TABLE II
PV–Cooling Coupling and Cross–Statistics

Metric	Value	95% CI	N (hrs)	p-val.
Pearson corr. $(P_{\mathrm{PV}}, P_{\mathrm{HVAC}})$	0.82	[0.78, 0.86]	2,976	< 0.001
Spearman corr. (rank)	0.79	[0.74, 0.84]	2,976	< 0.001
Cross-corr. lag (hrs)	+1	–	2,976	–
Midday ratio $\frac{\overline{P_{\mathrm{PV}}(11\text{–}15)}}{\overline{P_{\mathrm{HVAC}}(11\text{–}15)}}$	0.93	[0.88, 0.98]	–	–

The positive one-hour cross-correlation lag indicates PV ramps slightly *before* cooling peaks, enabling predictive DSM (pre-cooling aligned to solar availability).

B. Optimization Outcomes (Seasonal KPIs)

We compare three control strategies over the cooling season: Baseline (fixed setpoint), MPC with PV forecasts, and MPC with PV plus battery storage. KPIs include total energy, peak import, and comfort indices. Relative to baseline, the joint

TABLE III
Seasonal Energy and Comfort Performance (May–Sep)

Scenario	Total Energy (MWh)	Peak Import (kW)	Mean PMV	PPD (%)	Cost (QAR)	Savings (%)
Baseline Control	118.4	345	0.24	9.8	312,000	–
MPC + PV Forecast	103.7	302	0.21	9.1	273,600	12.3
MPC + PV + Battery	**96.2**	**276**	**0.19**	**8.5**	**254,400**	**18.4**

PV–battery strategy reduces seasonal energy by **18.7%** and peak grid import by **20%**, while maintaining comfort within PMV $\in [-0.5, 0.5]$.

C. Statistical Significance of Daily Savings

We evaluate daily energy reductions via paired t-tests (baseline vs. each DSM strategy).

TABLE IV
Paired t-Tests on Daily Energy Use

Comparison	Mean Diff. [MWh/day]	95% CI	p-value
Baseline vs. MPC + PV	0.42	[0.31, 0.53]	< 0.001
Baseline vs. MPC + PV + Battery	0.58	[0.46, 0.69]	< 0.001

Both DSM strategies yield statistically significant daily energy savings.

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TABLE V
COMFORT COMPLIANCE AND PMV DISTRIBUTION

Scenario	Time in Band (%)	PMV 5th	PMV 50th	PMV 95th	PPD Mean (%)	PPD 95th (%)
Baseline Control	97.9	-0.19	0.23	0.62	9.8	16.1
MPC + PV Forecast	98.4	-0.21	0.20	0.55	9.1	14.7
MPC + PV + Battery	**98.7**	**-0.22**	**0.18**	**0.51**	**8.5**	**13.9**

D. Comfort Compliance and Risk

Comfort performance is reported as time-in-band percentages and percentile PMV summaries.

All strategies satisfy ASHRAE comfort criteria; MPC variants reduce tail risk (95th percentile PMV/PPD) via pre-cooling and anticipative control.

E. Tariff Exposure and Peak Shaving

We decompose bill impacts by tariff period and quantify coincident peak reductions.

TABLE VI
TARIFF PERIOD COST BREAKDOWN AND PEAK METRICS

Scenario	Off-Peak (QAR)	On-Peak (QAR)	Peak (kW)	Peak Red. (%)
Baseline Control	124,800	187,200	345	–
MPC + PV Forecast	118,400	155,200	302	12.5
MPC + PV + Battery	**116,000**	**138,400**	**276**	**20.0**

On-peak cost reductions dominate savings, driven by PV-aligned pre-cooling and battery discharge during tariff peaks.

F. Ablation: Forecasting and Storage Contributions

To isolate effects, we compare MPC using (i) load-only forecasts, (ii) PV forecasts, and (iii) PV+storage.

TABLE VII
ABLATION STUDY: COMPONENTS DRIVING SAVINGS

Controller	Energy [MWh]	Save [%]	Peak [kW]	Peak↓ [%]
Baseline (fixed setpoint)	118.4	–	345	–
MPC (load forecast only)	111.9	5.5	323	6.4
MPC + PV forecast	103.7	12.4	302	12.5
MPC + PV + battery	**96.2**	**18.7**	**276**	**20.0**

PV forecasts contribute the majority of energy savings; storage further improves peak shaving and tariff exposure.

G. Robustness Checks

We test robustness to (a) PV forecast error and (b) ambient heatwaves.

TABLE VIII
ROBUSTNESS TO FORECAST ERROR AND HEATWAVES

Scenario	RMSE [% cap]	Energy [MWh]	Peak [kW]	Band [%]
Nominal (as above)	7.5	96.2	276	98.7
PV forecast RMSE = 15%	15.0	98.9	284	98.3
Heatwave (+3°C)	7.5	101.1	291	97.8

Performance degrades gracefully under uncertainty and extreme heat, while comfort remains within acceptable limits.

Across all analyses, MPC with PV forecasting and storage consistently lowers energy use and coincident peaks, with statistically significant daily savings and high comfort compliance, enabling DSM that is both cost-effective and occupant-centric—*without* reliance on graphical figures.

V. DISCUSSION AND CONCLUSION

A. Discussion

Our findings unequivocally demonstrate that integrating high-resolution photovoltaic (PV) forecasts with a sophisticated model-predictive control (MPC) framework offers a powerful solution for managing energy demand. This approach not only yields substantial peak-load reduction but critically, does so without compromising thermal comfort. Over an entire cooling season, the PV–battery MPC strategy reduced total grid energy consumption by a notable **18.7%** and, even more impressively, cut coincident peak import by **20%** compared to a conventional fixed-setpoint baseline. These daily savings were rigorously confirmed as statistically significant (paired t-tests, $p < 0.001$), underscoring the robust and sustained performance of the proposed system. A key enabler of these efficiencies is the strong positive correlation observed between rooftop PV generation and HVAC cooling load ($r = 0.82$). This inherent alignment validates the strategic importance of solar-aware demand-side management (DSM). Crucially, PV output typically peaks approximately one hour before the highest cooling demand, presenting a natural window for pre-cooling strategies. This temporal offset allows the system to proactively shift cooling consumption to periods of abundant on-site solar generation, thereby minimizing grid imports and reducing exposure to peak-time tariffs. Furthermore, a comprehensive comfort analysis, employing the Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) metrics, confirms that our control system meticulously maintains indoor comfort. It consistently operates within ASHRAE standards for over **98%** of occupied hours. The system's predictive capabilities were particularly impactful in reducing ”tail-risk” discomfort; specifically, a significant reduction in the 95th-percentile PMV and PPD values highlights its ability to proactively mitigate brief but intense uncomfortable excursions, especially during challenging heat-wave events.

The ablation study provided crucial insights into the individual contributions of each system component. While load forecasting alone delivered a modest 5.5% energy reduction, the integration of PV forecasts more than doubled these savings. The most significant improvements in both energy efficiency and peak performance, however, were achieved by incorporating battery storage, illustrating its pivotal role. Moreover, sensitivity analysis affirmed the approach's practical resilience, demonstrating a graceful degradation of performance even when PV forecast errors doubled or during periods of extreme heat.

B. Conclusion

This research presents a novel and comprehensive framework for *comfort-constrained, solar-aware demand-side management* specifically tailored for hot climates. Our primary achievements include:

- **Developed** a dynamic state–space thermal model, rigorously coupled with PMV/PPD comfort constraints, enabling precise predictive HVAC control.
- **Formulated** a robust stochastic MPC algorithm designed to co-optimize thermostat setpoints, PV energy utilization, and battery dispatch strategies to simultaneously minimize energy costs and peak demand.
- **Engineered** a sophisticated data-fusion pipeline, integrating real-time rooftop PV performance, high-resolution solar potential measurements, and detailed building indoor climate logs to facilitate agile, real-time decision support.

The methodology developed herein possesses direct and significant transferability, particularly to large-scale campuses and district-cooling networks prevalent in arid regions, such as the Gulf Cooperation Council states. In these environments, cooling typically dominates annual energy demand, and solar resources are exceptionally abundant. By strategically aligning renewable generation with occupant comfort requirements, this system empowers utilities and building operators to realize substantial reductions in carbon emissions and operational costs, all without any compromise to the user experience. Future work aims to expand upon this foundation by: **(i)** scaling the controller's application across multiple, diverse building typologies; **(ii)** integrating probabilistic weather forecasts to further mitigate the inherent uncertainties associated with solar generation; **(iii)** coupling the system with dynamic real-time pricing signals and emerging transactive energy markets; and **(iv)** incorporating occupant feedback and advanced adaptive comfort models to enable even finer, personalized climate control.

In summary, this study provides compelling evidence that thermal-comfort-aware demand-side management, significantly enhanced by accurate PV forecasting and integrated on-site energy storage, is both technically viable and economically advantageous. This approach represents a critical and actionable pathway toward fostering resilient, low-carbon electric grids, especially within the demanding energy landscapes of hot climates.

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