SASBE 2025 aims to encourage the international exchange of innovative ideas between researchers from academia and industry. In addition to knowledge dissemination, the conference offers a valuable platform for professional networking, particularly benefiting university professors, graduate students, and postdoctoral researchers.

Research Article

A Building Programming Method for Energy and Economic Efficiency in Hotels

Yadel Elbaz[1], Shabtai Isaac[1]

[1] Ben-Gurion University of the Negev, Beer-Sheva, Israel
Correspondence: isaacsh@bgu.ac.il

Abstract

This study develops an innovative building programming method to enhance the energy and economic efficiency of mechanical and electrical systems in hotels, with a focus on water heating systems and electric vehicle charging systems. The programming method is designed to tailor system planning to the dynamic needs of users, reduce resource waste, and maintain optimal service quality. The method includes a techno-economic analysis aimed at evaluating the energy and economic performance of the systems. It integrates a technological analysis of system efficiency and output with an economic analysis of operational costs, maintenance, and environmental impact. The process involves data collection from commercial buildings, usage pattern analysis, and system characterization based on varying factors such as seasonality and occupancy rates. The study employs innovative methodologies, statistical tools, and advanced technological applications to propose solutions for maximizing energy efficiency while minimizing costs and improving the environmental contributions of buildings.

Keywords: Building programming; Hotels; Sustainability; Optimization.

Highlights

- This study develops an innovative building programming method for mechanical and electrical systems.
- The method maximizes energy efficiency while life cycle minimizing costs.
- It is applied in hotels, with a focus on water heating and electric vehicle charging systems.

1 Introduction

Rapid growth in global energy demand, combined with climate change and resource constraints, has intensified the need for efficient, context-aware energy planning in the built environment. Within this landscape, hotels combine accommodation, food service, laundry, wellness facilities, and increasingly also electric-vehicle (EV) charging, resulting in complex and variable energy use.

Hotels exhibit pronounced temporal variability in demand due to shifting occupancy levels, daily activity cycles, and seasonality. Yet, many mechanical and electrical (M&E) systems are sized and operated around infrequent peak scenarios, creating persistent oversupply, unnecessary standby losses, and elevated capital and maintenance costs. A more accurate characterization of service requirements and usage patterns is needed to align capacity, control logic, and infrastructure with actual demand (Zanni et al., 2016; Hakkinen & Belloni, 2011).

In this study, a structured building programming method is proposed and applied for hotel M&E systems. The approach is demonstrated on two high-impact services: domestic hot water (DHW) supply and EV-charging infrastructure. Treating them together highlights common needs, such as demand modeling, capacity allocation, and control under uncertainty, as well as system-specific constraints. The decision to focus on these two specific systems was driven by a desire to test the proposed methodology across services that differ both in their maturity and design context. EV charging represents a relatively novel and emerging feature within hotel infrastructure, with limited available research or standardized planning guidelines. In contrast, DHW systems are well-established and widely implemented, with a substantial existing knowledge base. Nonetheless, it was important to apply the methodology to both systems: the innovative and the conventional. This dual-system approach allowed for a comprehensive evaluation of the method's adaptability and practical value in both cutting-edge and traditional M&E contexts.

For DHW, key design challenges include reconciling peak-hour draw with diurnal variability, minimizing thermal losses in storage and distribution, and ensuring temperature stability and safety. For EV charging, hotels must determine the appropriate mix of Level 2 AC charging (suited to overnight dwell times) and DC fast charging (suitable for short-stay or rapid-turnover use cases) while respecting electrical capacity constraints and demand charges. Without building energy management system (BEMS)-based load management, ad-hoc provision of high-power charging can create unexpected peaks and elevated costs (Park et al., 2018; Lotf et al., 2022).

The central premise is that a rigorous, early-stage characterization of needs and constraints can prevent systematic oversizing and enable effective operational control. The proposed building programming method comprises: (1) demand profiling; (2) capacity and topology mapping; (3) control integration; (4) performance metrics; and (5) sensitivity analysis.

Paper structure: Section 2 consolidates the literature review with the research objectives. Section 3 details the methodology, including data collection, data processing, requirements characterization, and translation to design and control for DHW and EV-charging systems. Section 4 presents the results of a theoretical application and of a practical application to a specific hotel. Section 5 provides discussion and conclusions.

2 Research Gaps and Objectives

2.1 Previous Research

Early-stage, data-informed planning is widely emphasized in literature, with BIM-enabled workflows that support shared models, coordinated analysis, and traceability of assumptions (Zanni et al., 2016; Hakkinen & Belloni, 2011). Evidence also documents systematic oversizing, particularly in HVAC, stemming from peak-based rules that overlook temporal diversity and part-load operation, with penalties in efficiency and cost (Djunaedy et al., 2011; Stanescu et al., 2019; Khan et al., 2019). For EV charging in buildings, research integrates forecasting, EMS coordination, and multi-objective optimization to respect user needs and operator constraints (Park et al., 2018; Lotf et al., 2022). Forecasting methods range from linear trends to diffusion models, with low-data approaches offering transparent planning inputs when rich covariates are unavailable (Kamis & Abraham, 2024; Pham, 2021). Modularity supports staged capacity growth and maintainability in related domains (Kumar et al., 2024; Eisele & Kohler, 2023). Standards inform measurement and performance definitions relevant here (EN 14511; SI 5281).

2.2 Research Gaps and Opportunities

Prior research leaves several needs unaddressed. There is limited guidance on translating user-service requirements and occupancy or dwell-time patterns into the required specifications of capacity, topology, and control for DHW and EV charging in hotels, rather than treating services in isolation (Zanni et al., 2016; Park et al., 2018). Methods for occupancy analytics and EV demand prediction exist, but they are infrequently embedded directly in auditable sizing rules and BEMS parameters that hotel engineers can implement and maintain (Kamis & Abraham, 2024; Pham, 2021; Lotf et al., 2022). Despite growing availability of monitoring data, designs still default to conservative, simultaneous-peak assumptions; procedures for calibrating design to the observed diversity and for quantifying part-load penalties in DHW and EV infrastructure are underspecified (Djunaedy et al., 2011; Stanescu et al., 2019; Khan et al., 2019). At the same time, high-fidelity EV-adoption models often require covariates that are unavailable at hotel scale, underscoring the value of defensible, low-data forecasting approaches that can directly inform charger mix, managed charging, and electrical-capacity decisions (Kamis & Abraham, 2024; Pham, 2021). Modularity is frequently advocated but rarely operationalized with concrete rules for partitioning DHW and distribution loops or for staging EV-charger deployment in line with seasonal occupancy (Kumar et al., 2024; Eisele & Kohler, 2023). Finally, the translation of standards into hotel-specific KPIs and verification plans, such as waiting probability for charging, DHW temperature stability, or restart energy, requires clearer templates that connect requirement statements to measurement and reporting (EN 14511; SI 5281).

2.3 Research Objectives

In response, the research aims to develop a building-programming method that links user needs, such as EV-charging availability windows and DHW comfort and hygiene constraints, with occupancy or dwell-time patterns. The output of this workflow is system specifications covering capacity, topology, and control (Zanni et al., 2016; Park et al., 2018). The study specifies auditable sizing rules for EV charging based on urgency classes, adopting a Level 2-first strategy with limited DC fast-charging as contingency in a manner compatible with electrical capacity limits and managed charging. For DHW, it defines design parameters that reflect realistic concurrency and diversity and sets out modular partitioning guidelines so that contiguous subsystems can be idled seasonally with controlled restarts and quantified energy and cost effects (EN 14511; SI 5281). The study also provides a low-data EV-forecasting pathway (linear trend with scenario bounds) that remains transparent and adaptable as data quality improves and demonstrates how forecast choices map to charger mix and load-management policies (Kamis & Abraham, 2024; Pham, 2021). BEMS control strategies such as load shifting, demand limiting, temperature setbacks, and dynamic prioritization, are integrated into the requirement-to-design translation with parameterization intended for routine use by hotel engineers (Lotf et al., 2022). To evaluate outcomes consistently, the research establishes standards-aligned KPIs and a verification plan, which covers the share of EV users served within the declared window, DHW temperature stability, energy or cost per occupied room, and restart energy. It demonstrates the applicability of the method across two services (DHW and EV charging) and two levels of evidence (theoretical scenarios and a practical hotel case), to ensure transferability.

2.4 Scope and Assumptions

The scope centers on hotels with variable occupancy and mixed service profiles. The EV-charging component emphasizes Level 2 service for overnight stays, with DC fast-charging provision sized to urgent demand and local electrical constraints. The DHW component emphasizes diversity-based flow sizing and modularization for seasonal idling. The approach prioritizes transparency and auditability over model complexity and assumes the availability of basic occupancy records and access to BEMS configuration (Park et al., 2018; Lotf et al., 2022).

3 Methodology

This study develops a requirements-driven workflow for two hotel M&E services EV charging and domestic hot water (DHW). The method links data collection and processing to explicit requirement statements and then to design, topology and BEMS-aligned control. Throughout, assumptions are stated in simple, auditable terms so that engineers can reproduce and adapt the steps without specialized software.

The methodology is staged to remain auditable with limited data and to connect requirement statements directly to sizing, topology, and BEMS control. Once the hotel’s service scope (DHW, EV charging), seasonal operating modes, and constraints (electrical capacity, tariffs, hygiene/comfort requirements, standards) have been defined, the following stages are executed (Figure 1):

Stage 1 - Data collection: Compile occupancy data and any BMS/BEMS trends; gather EV-related inputs; collect DHW system data.

Stage 2 - Processing and scenario building: Transform occupancy logs into hourly/seasonal profiles; estimate planning EV share and map EV counts to urgency classes; derive DHW concurrent-flow and daily energy needs by season. Outputs are demand envelopes and parameter estimates used downstream.

Stage 3 - Requirement characterization: Formalize the service targets and constraints. For EV charging, define peak-day counts and size stations; for DHW, compute the design concurrent flow and quantify restart energy.

Stage 4 - Translation to design, topology, and control: Convert requirements into a charger mix, managed-charging rules, and a DHW plant/distribution configuration. Calculate energy/cost conversions in scenario evaluation and define modular solutions.

Stage 5 - Evaluation and verification: Track KPIs such as share of EV users served and DHW temperature stability, verify sizing against monitored peaks and iterate. Deviations feed back to Stage 2 (data) and Stage 4 (requirements/calibration).

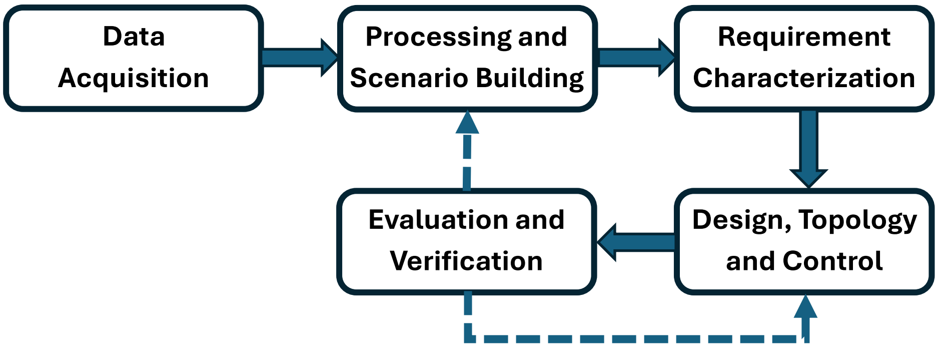

Figure 1. Requirements-Driven Workflow

3.1 Data Collection

Data sources comprise monthly and daily occupancy records by room type, check-in/check-out distributions, and, where available, BMS/BEMS trends of thermal and electrical subsystems. EV-related inputs include traffic snapshots and an on-site survey instrument that elicits the acceptable availability window to a full charge (≤6 h, ≤12 h, ≤36 h). Site constraints such as panel capacity, feeder ratings, and tariff structure are documented to bound charger mix and load-management policies.

For DHW, plant nameplate data, storage volumes, hydraulic topology by floors or wings, and water-quality/temperature requirements are compiled. These data inform both the demand envelopes and the feasible control space.

3.2 Data Processing and Scenario Building

Occupancy logs are transformed to hourly and seasonal profiles and mapped to service demand using observed arrival and activity patterns. For DHW, expected occupied rooms and diversity factors yield concurrent flow and daily energy requirements, differentiated by season to reflect the hotel's operating profile.

As opposed to DHW demand, which can be easily determined based on current consumption data, the prediction of future EV adoption is more challenging. To estimate the future share of EV users over the next decade, a dual-scenario forecasting approach was adopted, defining both lower and upper bounds to reflect a range of plausible adoption trajectories. The lower bound was calculated using Singular Spectrum Analysis (SSA), a time-series technique that identifies long-term trends. Based on national statistics from the past three years, the average annual increase in EV share was found to be approximately 0.7377%, leading to a projected share of 9.7127% in ten years, assuming a steady trend. The upper bound was modeled after Norway's trajectory, where EV market share grew from 2.8% in 2015 to 23.87% in 2023. These levels are comparable to Israel's current baseline. This scenario simulates a high-adoption pathway assuming robust policy support, including tax incentives, toll exemptions, and infrastructure subsidies. By combining these two projections, the study defines a realistic forecast envelope that supports charger mix planning, capacity sizing, and load management policy development.

3.3 Requirement Characterization

EV: The EV-charging requirement is articulated by three peak-day counts:

- X – vehicles that must be served within 6 hours
- Y – within 12 hours
- Z – within 36 hours.

Equations (1-(3) size fast-charging and Level 2 stations from these counts; To make the procedure auditable end-to-end, Equations (4)-(10) specify the upstream forecasting and mapping steps (EV share to counts and urgency classes). The number of fast-charging stations, N_FC, is specified as the ceiling of $\lceil X / 6 \rceil$, under the assumption that one fast-charging post can process six vehicles in six hours:

(1) $N\_FC = \lceil X / 6 \rceil$

Equations (2) and (3) give the number of Level 2 stations, N_L2. If the residual demand for the 36-hour class, $Z - 2Y$, is negative, the capacity installed for the 12-hour class already suffices and $N\_L2 = \lceil Y / 2 \rceil$ per (2). If the residual is non-negative, an additional term $\lceil (Z - 2Y) / 6 \rceil$ is added in (3). In both cases, fast-charging stations from (1) are treated as contingency for unplanned or urgent departures:

(2) $N\_L2 = \lceil Y / 2 \rceil \quad \text{if} \quad Z - 2Y < 0$

(3) $N\_L2 = \lceil Y / 2 \rceil + \lceil (Z - 2Y) / 6 \rceil \quad \text{if} \quad Z - 2Y \geq 0$

Equation (4) records the observed mean annual change in national EV share, ΔS:

(4) $\Delta S = 0.7377\%$

Equation (5) projects a 10-year planning share, S_{10}, by adding ten years of change to today's share, S_0:

(5) $S_{10} = S_0 + 10 \cdot \Delta S = 2.335\% + 10 \times 0.7377\% = 9.7127\%$

Equation (6) maps the planning share to peak-day EVs on site, by multiplying S_{plan} (derived from occupancy and average vehicles per occupied room) with the peak-day vehicle base $N_{veh,peak}$:

(6) $EV_{peak} = S_{plan} \cdot N_{veh,peak}$

Equations (7)–(9) partition that total into urgency classes using survey-derived proportions:

(7) $X = p_6 \cdot EV_{peak}$

(8) $Y = p_{12} \cdot EV_{peak}$

(9) $Z = p_{36} \cdot EV_{peak}$

Equation (10) enforces that the proportions sum to one:

(10) $p_6 + p_{12} + p_{36} = 1$

DHW: Equations (11)-(14) define DHW concurrent-flow and restart-energy relations. Equation 15 defines the downstream conversions used later in costing and seasonal idling. The DHW peak concurrent flow, $Q_{E,max}$, is defined using the whole-building concurrency coefficient K_E, the number of rooms N, per-room design flow Q_i, and within-room concurrency K_v:

(11) $Q_{E,max} = K_E \cdot N \cdot Q_i \cdot K_v$

An empirical linear fit relates the number of rooms in use on the peak day, x, to the maximum design consumption y in the same flow units used for (4):

(12) $y = 0.0502x + 0.8724$

Equations (13) and (14) quantify restart energy for modular DHW operation. The thermal energy $E_{th,restart}$ in (13) reheats a volume V through a temperature rise ΔT, using water's specific heat (4.186 kJ·kg^{-1}·K^{-1}) and the conversion to kWh.

(13) $E_{th,restart} = V\Delta T \times (4.186 / 3600)$

Electrical energy $E_{el,restart}$ divides the restart energy by the heat-pump coefficient of performance, COP:

(14) $E_{el,restart} = E_{th,restart} / COP$

Equation (15) expresses the active storage volume during seasonal idling:

(15) $V_{active} = V_{total} \cdot (1 - f_{idle})$

Finally, Equation (16) converts a total daily energy value to an annual figure, and Equation (17) converts energy to cost using the site tariff:

(16) $E_{year} = E_{day} \cdot 365$

(17) $Cost_{el} = E_{year} \cdot c_{el}$

3.4 Translation to Design, Topology, and Control

For EV charging, the formulas determine minimum post counts by class; electrical capacity and tariff constraints then shape the final mix, with Level 2 prioritized for overnight charging and DC fast-charging reserved for contingencies. Control rules allocate ports by urgency class and enforce demand limits and charging windows through the BEMS.

For DHW, the concurrent-flow target sets the distribution and production capacity, while modular partitioning defines contiguous subsystems (e.g., floor groups) that can be idled in low-season months with controlled restarts. Storage set-points and production schedules are tuned seasonally to reduce standby losses while maintaining temperature stability and hygiene requirements.

3.5 Evaluation Metrics and Costing

Performance is tracked through service quality (share of EV users served within their declared window; DHW temperature stability), energy and cost (including system restart energy), and operational flexibility (fraction of area that can be idled without service loss). Costs include capital, O&M allowances, energy, and restart events, aggregated over a 10-year horizon at a stated discount rate. The same indicators are used for the theoretical scenarios and for the practical hotel case to enable a comparison.

4 Results - Key Findings

This section reports (i) a theoretical application of the workflow to EV-charging and DHW systems using seasonal/weekly scenarios, and (ii) a practical application using partial real-world data from a specific hotel ("Hotel X") and telematics snapshots. It concludes with an expert-based validation of the DHW method.

4.1 Theoretical Application

EV-charging: Using the estimated 10-year national EV share, monthly peak-day EV counts were projected from current peaks after rounding (e.g., in January 2 to 18 EVs; in August from 8 to 69 EVs, etc.). An urgency segmentation was then applied according to three availability windows (≤6 h, ≤12 h, ≤36 h) based on a hypothetical survey profile. Translating these counts with the sizing rules yielded a design emphasizing managed Level 2 charging, with fast DC reserved for short-notice demand: an illustrative configuration of 4 fast-DC stations and 9 Level 2 stations satisfied the seasonal peak envelopes.

DHW: For a stylized 200 room hotel, monthly average occupancies (40–90%) informed the diversity of concurrent draws. In line with the regulatory requirement for hot water storage sized to simultaneous demand, the total storage volume was set to 14.4 m^3. Floor/type analysis identified three adjacent floors (≈33% of system volume) that could be idled in four consecutive low season months (November–February) without service loss. Estimated restart cost for this subsystem was 581.2 ILS (water + labor + reheating). Annualized comparison under a heat-pump scenario indicated electricity use of ~81,505 $kWh \cdot yr^{-1}$ (modular system) vs. ~72,232 $kWh \cdot yr^{-1}$ (non-modular system), corresponding to 52,163 ILS vs. 46,228 ILS in annual electricity cost.

4.2 Practical Application

EV-charging: Given limited telemetry (three June days) and no onsite charger logs, the 10-year planning share was set to 13% (a midrange scenario). Using hotel records (with an occupancy rate of about 90% in August as anchor, and interpolation elsewhere) and EV fractions from telematics (e.g., 3.94% on 15/06/2023), the projected peak-day EV count in June rose from about 19 today to 106 in 10 years (rounded). Because field surveys could not be conducted, demand was assumed to be uniform across the three windows (≤6 h / ≤12 h / ≤36 h), giving 36 / 36 / 36 vehicles, respectively. Applying the sizing rules produced a requirement of ≥6 fast-DC stations and ≤18 Level 2 stations for Hotel X.

DHW: For Hotel X (241 rooms), the storage volume per the same sizing logic was 17 m^3. Monthly occupancy derived from hotel billing and records (Sep 22 – Aug 23) plus the August-as-90% anchor informed a room-type and floor distribution (8 floors; first floor all "Deluxe"). The idling algorithm identified Floors 2–3 as candidates for shutdown in ten months (September–June), representing about 25% of total volume. The restart cost of this subsystem was 552.85 ILS. To estimate annual DHW energy cost, the analysis adopted a sectoral benchmark in which DHW represents ~22% of total hotel electricity (applied to monthly electricity bills). This yielded an annual baseline DHW electricity cost of 427,864 ILS, decreasing to 353,016 ILS under the modular strategy (Floors 2–3 idled outside Jul–Aug). When calculated for a lifetime of 10 years, the modular system was found to be more cost-effective for an installation cost of up to 3.8 M ILS (Figure 2).

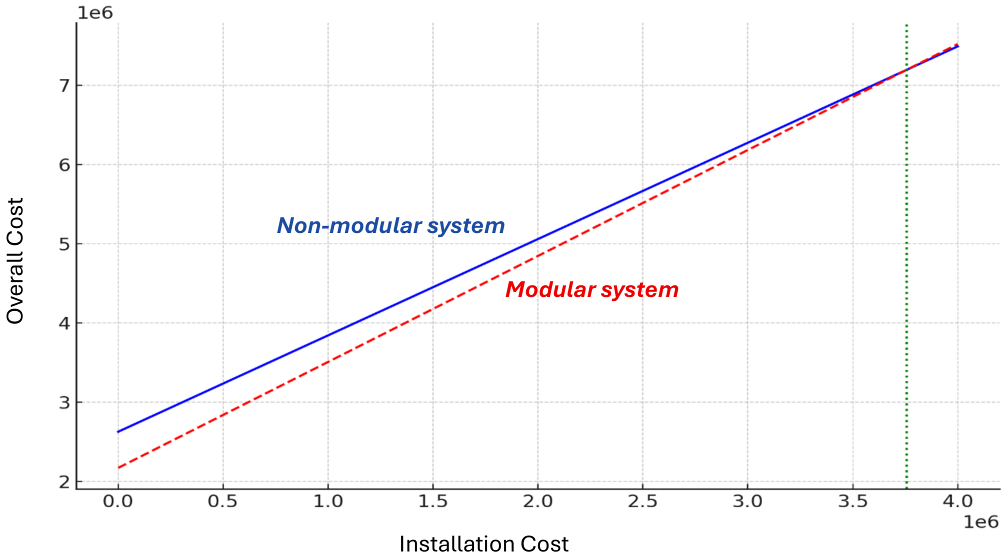

Figure 2. Cost effectiveness of DHW system

4.3 Validation

The DHW method was assessed by three domain experts using a Likert questionnaire covering energy waste detection, consumption reduction potential, demand-pattern analysis, adaptability to variable needs, carbon-footprint reduction, and modular planning. The weighted mean score was 4.07/5. EV-charging was not expert-validated due to reliance on forecasted (rather than observed) demand; dynamic updating is recommended as empirical charger-use data become available.

5 Discussion and Conclusions

The research demonstrates that a requirements-driven workflow can align system provision with actual demand in hotels for EV charging and DHW when design, control, and monitoring are specified as one coherent process. For EV charging, segmenting users by acceptable availability windows (≤6 h/≤12 h/≤36 h) and sizing primarily for Level 2 service, with limited DC fast charging as contingency, reduces queueing risk while respecting electrical capacity constraints. For DHW, defining concurrency explicitly and partitioning the plant and distribution system into separate sub-systems enables seasonal idling and targeted restarts with quantified energy and cost effects.

The paper links requirements characterization to capacity/topology and control in a reproducible sequence. Substantively, it contributes: a segmented service model for hotel EV charging that maps urgency classes to charger counts and managed-charging rules; an occupancy and topology-aware DHW approach that couples diversity-based flow sizing with modular enable/disable strategies and explicit restart accounting; a low-data EV forecasting pathway integrated directly into charger-mix planning; and a modularization lens that treats seasonal idling as a design variable.

Research limitations include the fact that data coverage was limited (single-year occupancy; partial EV telemetry; no onsite charger logs), which restricts statistical confidence and the ability to capture atypical events. Scenario stability is also not guaranteed: changes in regulation, tariffs, technology cost, or travel patterns may alter the relative performance of designs. Finally, implementation challenges such as legacy-system compatibility, added controls, and the need for trained staff may increase CAPEX and O&M and slow adoption.

Future work can focus on dynamic forecasting using real-time occupancy and charger use logs, which could replace static envelopes and refine urgency segmentation. Cross-property studies would test transferability and reveal topology patterns that generalize. AI/IoT integration for anomaly detection, adaptive set-points, and predictive maintenance may increase savings but require careful instrumentation and governance. Long-horizon economics should consider equipment lifetimes, energy price uncertainty, and carbon costs.

To conclude, the proposed data-informed specification of service requirements, paired with modular topologies and BEMS-aligned control, offers a feasible approach to reduce energy use and operating cost in hotels without compromising service.

References

Djunaedy, E., Van den Wymelenberg, K., Acker, B., & Thimmana, H. (2011). Oversizing of HVAC system: Signatures and penalties. *Energy and Buildings*, *43*(2-3), 468-475.

Eisele, M., & Kohler, M. (2023). Modular Electric Drive Platform for Commercial Vehicles. *MTZ worldwide*, *84*(12), 30-35.

European Committee for Standardization. (n.d.). *EN 14511*.

Häkkinen, T., & Belloni, K. (2011). Barriers and drivers for sustainable building. *Building research & information*, *39*(3), 239-255.

Kamis, A., & Abraham, P. S. (2024). Predictive models of electric vehicle adoption in the United States: Charging ahead with renewable energy. *Transportation research interdisciplinary perspectives*, *24*, 101041.

Khan, D. S., Kolarik, J., Hviid, C. A., & Weitzmann, P. (2019, September). Method identifying oversizing of mechanical ventilation systems in office buildings using airflow and electrical power measurements. In *IOP Conference Series: Materials Science and Engineering* (Vol. 609, No. 5, p. 052021). IOP Publishing.

Kumar, G., Goyal, K. K., Batra, N. K., & Mehdi, H. (2025). Optimizing reconfigurable manufacturing system configuration sel ection with multi-objective grey wolf optimization. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, *19*(8), 5567-5582.

Lotfi, M., Almeida, T., Javadi, M. S., Osório, G. J., Monteiro, C., & Catalão, J. P. (2022). Coordinating energy management systems in smart cities with electric vehicles. *Applied Energy*, *307*, 118241.

Park, M., Wang, Z., Li, L., & Wang, X. (2023). Multi-objective building energy system optimization considering EV infrastructure. Applied Energy, 332, 120504.

Pham, M. K. (2023). Using Diffusion Models to Forecast Electric Vehicle Outlook in Finland, Sweden, and Norway.

Stanescu, M., Kajl, S., & Lamarche, L. (2019). Oversizing and HVAC system operation. In E3S Web of Conferences (Vol. 116, p. 00082). EDP Sciences.

Standards Institution of Israel. (n.d.). *SI 5281*.

Zanni, M. A., Soetanto, R., & Ruikar, K. (2017). Towards a BIM-enabled sustainable building design process: roles, responsibilities, and requirements. Architectural engineering and design management, 13(2), 101-129.