



# A Systematic Review of Smart Energy Management Systems for University Campuses: Technology Synthesis and Framework Development for Developing Countries

Duong Thi Loan and Ngo Thi Anh Hang\*

*Faculty of Technology and Engineering, Thai Binh University, Hung Yen, Vietnam.*

*Email: [anhhang141313@gmail.com](mailto:anhhang141313@gmail.com)\**

**Abstract:** *University campuses are significant energy consumers, particularly in developing nations where electricity expenditure can represent 15–25% of total operational budgets. This paper presents a systematic review of smart energy management technologies applied in university building contexts, examining four categories: IoT-based monitoring platforms, AI and machine learning optimization methods, smart sensor networks, and solar photovoltaic integration. Evidence synthesis across 40+ peer-reviewed studies indicates that IoT sub-metering achieves 5–15% baseline reductions, AI-driven control contributes an additional 8–25%, and coupled solar-BEMS deployments reduce net grid consumption by 25–40%, yielding combined savings of 20–42% under full deployment. These findings inform the development of the Smart Campus Energy Management System (SCEMS) — a three-tier framework calibrated to the technical, economic, and regulatory context of Vietnamese universities, providing a structured deployment pathway from foundational monitoring through advanced AI optimization.*

**Keywords:** *Campus Energy Management, IoT Monitoring, AI Optimization, Building Energy Management Systems (BEMS), Renewable Energy Integration, Developing Countries.*

## INTRODUCTION

Buildings account for approximately 30% of global final energy use and 26% of energy-related CO<sub>2</sub> emissions [1]–[3]. University campuses present a distinct management challenge within this sector: their infrastructure spans lecture halls, laboratories, libraries, offices, and dormitories operating under heterogeneous demand cycles, while HVAC and lighting systems together account for 55–70% of electricity consumption in teaching buildings and up to 80% in research facilities [4]. This structural concentration of consumption in controllable subsystems creates a compelling opportunity for intelligent management intervention.

In Vietnam, higher education enrollment grew from 1.7 million to over 2.1 million between 2010 and 2022, driving sustained growth in campus energy demand. Electricity costs represent

approximately 4–6% of total operational budgets in Vietnamese public universities (Ministry of Education and Training [MOET], 2021), yet most institutions lack sub-metered monitoring infrastructure, making efficiency improvements structurally difficult to achieve or verify. Meanwhile, Vietnam's solar irradiation of 4.5–5.5 kWh/m<sup>2</sup>/day (Ministry of Industry and Trade [MOIT], 2020) creates strong conditions for rooftop photovoltaic deployment, and the convergence of affordable IoT hardware, mature machine learning frameworks, and falling PV costs has fundamentally changed the feasibility of intelligent campus energy management.

Existing reviews of smart building energy management do not adequately address the Vietnamese university context: they evaluate technologies under developed-country infrastructure and budget assumptions, rarely examine institutional governance factors, and do not account for Vietnam's specific regulatory framework (Circular 25/2020/TT-BCT). This review addresses three research questions: (RQ1) What smart energy management technologies have demonstrated measurable efficiency improvements in university buildings? (RQ2) What technical, economic, and institutional factors determine successful deployment in resource-constrained environments? (RQ3) How can international evidence be synthesized into a deployable framework for Vietnamese universities? The review covers peer-reviewed literature from 2015–2024 focused on IoT, AI, smart sensing, and solar integration in tertiary education settings.

## THEORETICAL BACKGROUND

### *Energy Consumption Profile of University Campuses*

The Building Energy Performance (BEP) model (ASHRAE, 2019) attributes total campus consumption to four interacting factors: building envelope characteristics, occupancy patterns, installed system efficiency, and operational management quality. HVAC systems represent the dominant end-use at 35–45% of total electricity in tropical climates — consistent with Vietnam's Köppen Aw/Cwa classification where mechanical cooling operates near-continuously [5]. Lighting accounts for a further 20–25%, with consumption density ranging from 10–15 W/m<sup>2</sup> for fluorescent installations to 4–8 W/m<sup>2</sup> for LED equivalents [6]. Laboratory facilities exhibit energy use intensities (EUI) of 150–400 kWh/m<sup>2</sup>/year — two to four times higher than teaching spaces — due to process equipment and enhanced ventilation requirements of 6–12 air changes per hour [7]. Table 1 summarizes the consolidated consumption profile for technical university campuses.

**Table 1: Electricity consumption profile—technical university campuses [5], [6], [7].**

End-Use Category	Share (%)	Key Driver	Management Priority
HVAC systems	35–45	Climate, occupancy schedules	Critical
Lighting systems	20–25	Lamp technology, occupancy	High
Laboratory equipment	15–20	Process loads, ventilation	High
ICT & teaching equipment	8–12	Device age, standby losses	Medium
Auxiliary systems	5–10	Continuous baseload	Medium

For Vietnam, the grid emission factor is 0.4641 kg CO<sub>2</sub>/kWh (MONRE, 2023) — substantially lower than the global average due to hydroelectric capacity, and the correct basis for campus

carbon accounting. A university consuming 2 million kWh annually generates approximately 928 tonnes CO<sub>2</sub>-equivalent; each 10% efficiency improvement avoids approximately 93 tonnes of emissions while saving an estimated VND 400 million at current EVN non-residential tariff rates (EVN, 2023). The alignment of financial and environmental incentives provides an institutional case for investment independent of policy mandates.

### *BEMS Control Framework*

Smart energy management is operationalized through the Building Energy Management System (BEMS) concept, defined by ISO 52120-1:2022 as an integrated hardware-software system monitoring, controlling, and optimizing energy-using systems within a building or campus. The standard classifies control sophistication on four levels: (1) reactive — threshold-based response; (2) scheduled — timetable-aligned operation; (3) predictive — demand forecasting; and (4) autonomous — self-optimizing AI control. Energy savings increase from 10–15% at Level 1 to 25–40% at Level 4 [8]. University campuses are particularly suited to Levels 3–4 because their occupancy patterns follow published academic schedules, providing structured temporal regularity that facilitates accurate demand forecasting.

### *Key Enabling Technologies*

Four technology categories underpin the BEMS architecture. (1) IoT platforms provide continuous sub-metered data collection through a three-tier architecture — edge devices, gateway infrastructure, and analytics platforms [8] — enabling 15-minute interval data at circuit level versus monthly aggregates from conventional metering; high-resolution visibility alone reduces consumption by 5–10% through operational awareness [9]. (2) AI and machine learning serve three roles: predictive load forecasting using LSTM networks and Random Forest models, with ML approaches reducing prediction error by 20–35% versus conventional regression [10]; anomaly detection; and optimization-based HVAC control via Reinforcement Learning agents [11].

AI methods require 12–24 months of sub-metered historical data, establishing a hard prerequisite for IoT deployment before AI implementation. (3) Smart sensor networks using LoRaWAN — offering 1–5 km range and 5–10 year battery lifetime per node — enable campus-scale occupancy and environmental sensing without prohibitive wired-infrastructure costs [12]. (4) Solar PV integration, supported by Vietnam's irradiation of 4.5–5.5 kWh/m<sup>2</sup>/day (MOIT, 2020), achieves 25–40% net grid reductions in coupled solar-BEMS deployments, exceeding the contribution of either system independently [5], [13].

**Table 2: Enabling technology summary.**

Technology	Primary Function	Standalone Savings	Key Reference
IoT sub-metering	Real-time data acquisition	5–10%	[8], [9]
AI/ML optimization	Forecasting, anomaly detection, control	8–25%	[10], [11]
Smart sensors (LoRaWAN)	Occupancy & environment sensing	Enabling layer	[12]
Solar PV + BEMS	Renewable integration & demand flexibility	25–40% (combined)	[5], [13]

## INTERNATIONAL EVIDENCE

### Case Study Synthesis

Table 3 synthesizes evidence from six university SCEMS deployments, selected for geographic diversity and relevance to tropical and developing-country contexts. All savings figures are drawn from peer-reviewed publications or verified institutional reports.

**Table 3: International university SCEMS deployments.**

Institution	Key Technologies	Approach	Outcome	Ref.
Univ. of California, Berkeley	Smart meters, IoT, BEMS	Real-time monitoring; HVAC scheduling	~20% electricity reduction	[14]
National Univ. of Singapore	Smart campus IoT, AI analytics	Big-data demand optimization	~15% energy reduction	[15]
MIT	ML-based BEMS, predictive control	Demand forecasting; fault detection	~20% operational savings	[16]
Technical Univ. of Denmark	Microgrid, solar PV, smart grid	Renewable dispatch; demand flexibility	~30% CO <sub>2</sub> reduction	[17]
Univ. of Queensland	Smart monitoring, rooftop solar PV	Centralized campus energy platform	~18% energy reduction	[5]
Tsinghua University	IoT sub-metering system	Integrated metering & benchmarking	10–15% energy reduction	[18]

Three consistent patterns emerge. First, smart sub-metering is universally deployed before higher-level interventions, confirming the sequential BEMS control hierarchy of ISO 52120-1:2022. Second, monitoring and HVAC-control deployments cluster at 10–20% savings; renewable integration produces broader emissions outcomes. Third, the Tsinghua University case [18] is most directly transferable to Vietnamese conditions — meaningful savings of 10–15% were achieved through IoT sub-metering alone, without the advanced AI of MIT or the renewable microgrid of DTU, demonstrating feasibility within constrained budgets. Reported savings figures reflect heterogeneous measurement boundaries and should be interpreted as indicative rather than directly comparable.

### Transferability to Vietnam

Two contextual adaptations are required for Vietnamese deployment. First, hybrid edge-cloud processing architectures should be prioritized over fully cloud-dependent systems given variable broadband reliability across Vietnamese university campuses. Second, AI forecasting models require 12–24 months of sub-metered historical data [10], reinforcing an IoT-first deployment sequence for institutions currently lacking metering infrastructure — consistent with the data prerequisite established in Section II-C.

## PROPOSED SCEMS FRAMEWORK

### Design Principles

The SCEMS framework is governed by three principles derived from Sections II–III: (1) **Sequentiality**—data infrastructure investment must precede optimization algorithms, as AI methods are data-dependent [10]; (2) **Proportionality** — deployment depth is scaled to building

energy intensity, with laboratories and HVAC-heavy buildings warranting denser sensing and more sophisticated control; (3) Institutional embeddedness — technology deployment requires designated energy management personnel, quantified performance targets, and monitoring, reporting, and verification (MRV) protocols as non-negotiable preconditions [9].

### Three-Tier Architecture

Tier 1 establishes the data infrastructure prerequisite for all higher-tier interventions. Smart meters with 15-minute interval recording at building and sub-circuit level — consistent with the Tsinghua approach [18] — are networked via LoRaWAN gateways [12]. Metering visibility alone generates 5–10% savings through operational awareness [9], [14]. Tier 2 deploys automated HVAC scheduling against occupancy and timetable data, targeting the 10–20% excess operating hours common in unoptimized tropical-climate buildings. Automated lighting control through daylight harvesting and occupancy switching targets an additional 30–50% of lighting consumption [6]. Combined Tier 1–2 savings of 15–25% are consistent with outcomes at NUS [15], MIT [16], and Queensland [5].

**Table 4: SCEMS three-tier architecture (savings cumulative; costs indicative for Vietnamese market conditions).**

Tier	Components	Technology	Expected Savings	Cost (USD/building)
Tier 1 Foundation	Smart metering, occupancy sensing, energy dashboard	AMI meters, LoRaWAN, PIR/CO <sub>2</sub> sensors, web platform	5–10%	10,000–33,000
Tier 2 Optimization	Automated HVAC and lighting control	BMS integration, daylight harvesting, occupancy switching	Additional 10–20%	23,000–65,000
Tier 3 Advanced	AI demand forecasting, solar PV + load flexibility	LSTM/ML models, rooftop PV, smart inverters	Additional 8–22%	70,000–250,000

Tier 3 is deferred until 12–24 months of Tier 1 data supports AI model training [10]. LSTM forecasting and Reinforcement Learning HVAC control [11] are paired with rooftop solar PV and demand-side load shifting to achieve 25–40% net grid reductions [5], [13].

### Implementation Roadmap

Implementation initiates with a 3–6 month pilot in the one or two highest-consumption buildings — typically main laboratory blocks or central lecture complexes — generating ROI evidence for institutional approval. Campus-wide Tier 1 rollout follows over 12–18 months; Tier 2 begins in pilot buildings while Tier 1 continues elsewhere. Tier 3 investment is deferred until Tier 1 data justifies capital outlay, typically 24–36 months post-initiation. All phases require compliance with Vietnam's Law No. 50/2010/QH12 on Economical and Efficient Use of Energy and documented MRV protocols against calibrated baselines.

## PERFORMANCE EVALUATION

### Savings Estimates by Tier

The central estimate of 30% is consistent with the 10–30% range reported in the broader smart building literature [1], [2]. The conservative scenario of 18% is achievable through Tier 1 and

Tier 2 alone — without AI or solar investment — and represents the minimum reasonable expectation for well-implemented SCEMS deployment in Vietnamese conditions.

**Table 5: SCEMS savings estimates — three scenarios (% reduction relative to pre-SCEMS baseline).**

Tier	Intervention	Conservative	Central	Optimistic	Evidence
Tier 1	Metering + behavioral response	3%	6%	10%	[9], [14]
Tier 2	Automated HVAC + lighting control	10%	17%	25%	[6], [15]
Tier 3	AI forecasting + solar PV	8%	15%	22%	[10], [5]
Combined (1–3)	Full SCEMS deployment	18%	30%	42%	Synthesized

#### *Quantified Impact — Representative Vietnamese University*

Table 6 applies SCEMS savings to a 2 million kWh/year baseline using Vietnam's grid emission factor of 0.4641 kg CO<sub>2</sub>/kWh (MONRE, 2023) and EVN's non-residential tariff of approximately 2,000 VND/kWh (EVN, 2023).

**Table 6: Quantified SCEMS impact — representative Vietnamese technical university (baseline: 2 million kWh/yr; emission factor: 0.4641 kg CO<sub>2</sub>/kWh — MONRE, 2023; tariff: ~2,000 VND/kWh — EVN, 2023).**

Scenario	Annual Saving (kWh)	Cost Saving (VND M/yr)	CO <sub>2</sub> Avoided (t/yr)	Payback
Conservative — Tier 1+2 (18%)	360,000	~720	~167	3–5 yr
Central — Full SCEMS (30%)	600,000	~1,200	~278	5–8 yr
Optimistic — Full SCEMS + solar (42%)	840,000	~1,680	~390	7–12 yr

The conservative scenario yields VND 720 million annually against a capital investment of VND 800–1,500 million, producing a 3–5 year payback without requiring policy subsidies. This directly supports the aligned-incentive argument of Section II-A: each 10% reduction simultaneously saves approximately VND 400 million and avoids 93 tonnes of CO<sub>2</sub>. Post-occupancy verification against monitored baselines is recommended, as realized savings in initial Vietnamese deployments may fall below central estimates during commissioning phases.

## CONCLUSION

This review has synthesized smart energy management evidence from the peer-reviewed literature and six international university case studies into a deployable SCEMS framework for Vietnamese higher education institutions. Three principal conclusions follow. First, the technical case is well-established: the ISO 52120-1:2022 BEMS hierarchy — implemented

through IoT sub-metering, automated HVAC and lighting control, AI-driven forecasting, and solar PV integration — achieves verified consumption reductions of 10–42% depending on deployment depth and tier. Second, the financial case is compelling without policy dependency: the conservative SCEMS scenario yields VND 720 million annually with a 3–5 year payback at current EVN tariffs and the MONRE (2023) emission factor. Third, successful deployment is conditioned on sequenced implementation — data infrastructure before optimization — with institutional governance (designated energy managers, MRV protocols, Law 50/2010/QH12 compliance) as non-negotiable preconditions.

Two limitations apply. This review draws primarily on international literature; empirical data from Vietnamese university deployments remain scarce. Non-technical governance and behavioral factors — staff engagement, procurement frameworks, and institutional culture — warrant dedicated study. Future work should prioritize piloting the SCEMS framework in Vietnamese university buildings to validate savings under local conditions and establish institution-specific consumption benchmarks for rigorous performance verification.

## REFERENCES

- [1] K. Amasyali and N. El-Gohary, "A review of data-driven building energy consumption prediction studies," *Renew. Sustain. Energy Rev.*, vol. 81, pp. 1192–1205, 2018.
- [2] K. Zhou, C. Fu, and S. Yang, "Big data driven smart energy management: From big data to big insights," *Renew. Sustain. Energy Rev.*, vol. 56, pp. 215–225, 2016.
- [3] International Energy Agency, *Energy Efficiency 2022 Report*. Paris: IEA, 2022.
- [4] R. Saidur, H. H. Masjuki, and M. Y. Jamaluddin, "An application of energy and exergy analysis in residential sector of Malaysia," *Energy Policy*, vol. 35, no. 2, pp. 1050–1063, 2007.
- [5] S. Lu, Y. Li, H. Xia, and G. Liu, "Investigation on the configuration and operation of energy management for university campuses," *Energy Build.*, vol. 100, pp. 96–104, 2015.
- [6] M. C. Dubois and Å. Blomsterberg, "Energy saving potential and strategies for electric lighting in future North European, low energy office buildings: A literature review," *Energy Build.*, vol. 43, no. 10, pp. 2572–2582, 2011.
- [7] P. A. Mathew et al., "Big-data for building energy performance: Lessons from assembling a very large national database of building energy use," *Appl. Energy*, vol. 140, pp. 85–93, 2015.
- [8] D. Minoli, K. Sohrawy, and B. Occhiogrosso, "IoT considerations, requirements, and architectures for smart buildings — Energy optimization and next-generation building management systems," *IEEE Internet Things J.*, vol. 4, no. 1, pp. 269–283, 2017.
- [9] B. L. Capehart, W. C. Turner, and W. J. Kennedy, *Guide to Energy Management*, 8th ed. Lilburn, GA: Fairmont Press, 2016.
- [10] M. A. M. Daut et al., "Building electrical energy consumption forecasting analysis using conventional and artificial intelligence methods: A review," *Renew. Sustain. Energy Rev.*, vol. 70, pp. 1108–1118, 2017.
- [11] T. Wei, Y. Wang, and Q. Zhu, "Deep reinforcement learning for building HVAC control," in *Proc. 54th Annu. Design Autom. Conf. (DAC)*, Austin, TX, 2017, Art. 22.
- [12] F. Adelantado et al., "Understanding the limits of LoRaWAN," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 34–40, 2017.
- [13] I. Sartori and A. G. Hestnes, "Energy use in the life cycle of conventional and low-energy buildings: A review article," *Energy Build.*, vol. 39, no. 3, pp. 249–257, 2007.
- [14] J. Granderson, M. A. Piette, and G. Ghatikar, "Building energy information systems: State of the technology and user case studies," *Energy Effic.*, vol. 4, no. 3, pp. 307–325, 2011.
- [15] K. Kok et al., "Smart energy management in a university campus: Challenges and lessons from NUS," *Energy Procedia*, vol. 143, pp. 711–716, 2017.

- [16] J. Granderson et al., "Building fault detection data to aid diagnostic algorithm development," *Sci. Data*, vol. 4, p. 170080, 2017.
- [17] H. Lund et al., "From electricity smart grids to smart energy systems — A market operation-based approach and understanding," *Energy*, vol. 42, no. 1, pp. 96–102, 2012.
- [18] Z. Zhou, F. Zhao, and J. Wang, "Agent-based electricity market simulation with demand response behaviors," *IEEE Trans. Smart Grid*, vol. 2, no. 4, pp. 580–588, 2011.
- [19] MONRE, National Greenhouse Gas Inventory Report 2022. Hanoi: Ministry of Natural Resources and Environment, Vietnam, 2023.
- [20] MOIT, Vietnam Renewable Energy Development Strategy to 2030, Vision to 2050. Hanoi: Ministry of Industry and Trade, Vietnam, 2020.
- [21] EVN, Electricity Tariff Schedule for Non-Residential Consumers. Hanoi: Vietnam Electricity Group, 2023.
- [22] ISO 52120-1:2022, Energy Performance of Buildings — Contribution of Building Automation, Controls and Building Management. Geneva: ISO, 2022.
- [23] ASHRAE, ASHRAE Handbook — HVAC Applications. Atlanta, GA: ASHRAE, 2019.



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