

AI-BASED PREDICTIVE ENERGY MANAGEMENT OF INTEGRATED MEP SYSTEMS IN GRID-INTERACTIVE COMMERCIAL BUILDINGS

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Abstract

This study examined an AI-based predictive energy-management framework for integrated mechanical, electrical, and plumbing (MEP) systems in Pakistani commercial buildings. A quantitative, predictive, quasi-experimental design was employed to evaluate short-term energy-demand forecasting, coordinated MEP control, peak-demand management, and grid-interactive energy flexibility. The framework integrated building energy, weather, occupancy, and operational data with machine-learning models and an optimization layer to support predictive rather than reactive energy management. The results indicated that the hybrid AI model achieved strong forecasting performance ($R^2 = .97$; MAPE = 3.91%). AI-managed operation was associated with a 12.34% reduction in electricity consumption, a 14.79% reduction in peak demand, and a substantial increase in load-shifting capacity. Regression results further indicated significant relationships between AI-based predictive management, MEP integration, energy efficiency, forecasting accuracy, and energy flexibility. The study contributes to the Cyber-Physical Systems perspective by linking real-time sensing, AI prediction, optimization, and physical MEP control within a closed-loop framework. The findings highlight the potential of AI-enabled predictive management to improve commercial-building energy efficiency and grid responsiveness in Pakistan.

Introduction

Commercial buildings are increasingly becoming complex energy systems in which mechanical, electrical, and plumbing (MEP) components interact continuously with occupancy, weather, equipment operation, and electricity-grid conditions. Heating, ventilation and air-conditioning (HVAC), lighting, pumps, elevators, ventilation equipment, and other electrical loads can collectively create substantial and highly variable energy demand. Globally, improving building energy efficiency has therefore become an

important component of energy-transition strategies, particularly as electrification, renewable-energy integration, and demand flexibility increase the need for buildings to respond dynamically to grid conditions (International Energy Agency [IEA], 2024).

Conventional building energy management systems generally rely on fixed schedules, predefined control rules, and reactive responses to measured conditions. Although such approaches can reduce unnecessary consumption, they have limited capability to anticipate future loads and

coordinate multiple MEP subsystems simultaneously. Recent advances in artificial intelligence (AI) and machine learning (ML) provide opportunities to transform building management from reactive control toward predictive and adaptive energy optimization. ML-based demand prediction can incorporate historical energy consumption, weather conditions, occupancy patterns, operational schedules, and other variables to forecast short-term building loads and support proactive control decisions (Aliero et al., 2024; Copiaco & Nour, 2024).

The development of grid-interactive efficient buildings has further expanded the role of intelligent energy management. Such buildings are expected not only to minimize their own energy consumption but also to modify demand in response to electricity prices, grid constraints, renewable-energy availability, or demand-response signals. Recent research identifies AI-based forecasting, optimization, interoperability, and automated demand-response coordination as major technological enablers of grid-interactive buildings (Todorean et al., 2025). Deep-learning approaches have similarly demonstrated potential for intelligent demand-response applications by improving load forecasting and supporting adaptive energy scheduling (Boopathy et al., 2024).

An important limitation of existing building-energy research is that individual systems are frequently analyzed separately. HVAC optimization, lighting control, renewable-energy management, and demand-response scheduling may each be optimized independently, whereas actual commercial buildings operate as interconnected MEP systems. Integrated management can potentially identify interactions between cooling loads, occupancy, lighting, ventilation, pumping, and other electrical demands and consequently provide more effective system-level optimization. Recent research on smart-building energy management emphasizes the importance of integrating prediction, optimization, digital technologies, and building-system interoperability rather than relying on

isolated control strategies (Hernández et al., 2024; Mahmood et al., 2024).

The Pakistani context presents a particularly important application area. Pakistan's building sector faces increasing electricity demand, high cooling requirements, energy inefficiencies, and substantial operating costs. The Energy Conservation Building Code 2023 (ECBC-2023) provides an updated framework for improving building energy efficiency through better building design, equipment efficiency, renewable-energy integration, monitoring, and retrofit strategies. However, the implementation of advanced predictive and AI-enabled operational management remains comparatively underdeveloped. Recent research on a Pakistani institutional building demonstrated considerable energy-saving potential through building-envelope and air-conditioning optimization, illustrating the importance of context-specific energy-management interventions under Pakistani climatic and operational conditions (Mustufa et al., 2024).

Existing Pakistani studies have predominantly emphasized building design, energy audits, simulation-based retrofit strategies, BIM-based energy analysis, and individual efficiency measures. For example, BIM-based analysis of a Pakistani academic building demonstrated the potential of integrated building information and energy optimization approaches (Khan et al., 2023). However, these approaches do not fully address real-time predictive control of interconnected MEP systems or their interaction with grid conditions. International research has progressed further toward ML-based load prediction and grid-interactive operation, but many studies have been conducted in climatic, regulatory, and electricity-market environments that differ substantially from Pakistan (Copiaco & Nour, 2024; Todorean et al., 2025).

Accordingly, a research gap exists in developing an AI-based predictive framework specifically designed for integrated MEP energy management in Pakistani commercial buildings. Such a framework could combine historical electricity consumption, weather conditions, occupancy,

operational schedules, equipment status, and grid signals to predict short-term energy demand and determine coordinated operating strategies. The integration of predictive analytics with MEP control could potentially improve energy efficiency while maintaining indoor environmental conditions and enabling demand flexibility.

The present study therefore focuses on the development and evaluation of an AI-based predictive energy-management approach for integrated MEP systems in grid-interactive commercial buildings in Pakistan. The study is intended to contribute to the emerging intersection of artificial intelligence, building energy management, demand response, and smart-grid integration while addressing the contextual requirements of Pakistani commercial buildings. Its findings may provide a technical basis for more intelligent building operation, reduced energy consumption, improved peak-load management, and greater readiness for future grid-interactive energy systems.

Problem Statement

Commercial buildings in Pakistan face increasing pressure to reduce electricity consumption, operating costs, and peak demand while maintaining acceptable indoor environmental conditions. A substantial proportion of building electricity demand is associated with MEP systems, particularly HVAC, lighting, ventilation, pumping, and other electrically driven equipment. Conventional building management practices, however, frequently operate these systems through predetermined schedules, manual intervention, or independent control strategies. Such approaches may fail to respond efficiently to rapid changes in occupancy, weather, equipment demand, and electricity-grid conditions.

The problem becomes more complex in grid-interactive commercial buildings because energy management must address two objectives simultaneously: efficient building operation and flexible interaction with the electricity grid. Grid-interactive buildings can potentially reduce or shift electricity demand during peak periods and

increase consumption when renewable electricity is more available. However, effective demand flexibility requires accurate forecasting and coordinated control of building loads. Recent research identifies AI-based prediction, optimization, interoperability, and automated demand response as important technological requirements for achieving this integration (Boopathy et al., 2024; Todorean et al., 2025).

Despite rapid international development in AI-based building-energy management, important contextual and methodological gaps remain. Existing studies frequently concentrate on individual systems, such as HVAC or lighting, rather than treating MEP infrastructure as an integrated energy system. In addition, predictive models are often evaluated primarily according to forecasting accuracy without sufficiently examining their usefulness for coordinated operational decision-making. A technically accurate energy forecast has limited practical value if it cannot be translated into an optimized control strategy that considers comfort, equipment constraints, peak demand, and grid conditions simultaneously.

The Pakistani research context presents an additional gap. Recent local studies have demonstrated the potential for building-energy optimization through simulation, BIM, building-envelope improvements, and air-conditioning interventions. For example, Mustufa et al. (2024) reported substantial energy-saving potential from optimization and retrofit strategies in an institutional building in Islamabad. However, such research remains largely focused on static or simulation-based energy-efficiency interventions rather than continuous AI-enabled prediction and real-time coordination of integrated MEP systems. Consequently, evidence regarding the applicability of AI-based predictive energy management to Pakistani commercial buildings remains limited. Another important challenge concerns Pakistan's diverse climatic conditions. Commercial buildings in cities such as Karachi, Lahore, Islamabad, Peshawar, and Quetta experience different temperature, humidity, occupancy, and cooling-load profiles. Models developed in other countries

or climates cannot necessarily be transferred directly to Pakistani buildings without calibration and contextual adaptation. Building energy prediction must therefore incorporate local climatic, operational, and behavioral characteristics.

Furthermore, the transition toward grid-interactive buildings requires interoperability between building automation systems, smart meters, distributed energy resources, and grid-management mechanisms. Recent international literature identifies interoperability, data availability, cybersecurity, privacy, and regulatory uncertainty as continuing barriers to large-scale demand-response implementation (Hernández et al., 2024; Todorean et al., 2025). These challenges are particularly relevant to Pakistan, where advanced building automation and demand-response infrastructure remain at an emerging stage.

Therefore, the central research problem is the **lack of a context-specific, integrated, and predictive AI framework capable of forecasting energy demand and coordinating MEP-system operation in Pakistani commercial buildings while accounting for grid-interactive requirements**. Addressing this gap requires moving beyond conventional reactive energy management toward a data-driven approach that can anticipate energy demand, optimize interconnected MEP loads, reduce peak consumption, and enhance building flexibility without compromising operational requirements. The proposed study addresses this problem by investigating how AI-based predictive modeling can be integrated with MEP energy management to support more efficient and grid-responsive commercial-building operation in Pakistan.

Research Questions

1. How accurately can AI models predict short-term energy demand in Pakistani commercial buildings using MEP, weather, occupancy, and operational data?
2. What is the relationship between AI-based predictive management and the energy efficiency of integrated MEP systems?

3. To what extent can AI-based predictive control reduce peak electricity demand in commercial buildings?

4. How effectively can AI-based management coordinate HVAC, lighting, ventilation, pumping, and other MEP loads under grid-interactive conditions?

5. What factors most strongly influence the effectiveness of AI-based predictive energy management in Pakistani commercial buildings?

6. To what extent can AI-based predictive MEP management improve building energy flexibility while maintaining operational and indoor-environmental requirements?

Research Objectives

General Objective

To develop and evaluate an AI-based predictive energy-management framework for optimizing integrated MEP systems in grid-interactive commercial buildings in Pakistan.

Specific Objectives

1. To develop AI-based models for predicting short-term energy demand using MEP, weather, occupancy, and operational variables.
2. To evaluate the predictive accuracy of alternative AI and machine-learning models for commercial-building energy consumption.
3. To examine the effect of AI-based predictive management on the energy efficiency of integrated MEP systems.
4. To assess the potential of predictive MEP management for reducing peak electricity demand.
5. To develop an integrated control strategy for coordinating HVAC, lighting, ventilation, pumping, and other major MEP loads.
6. To evaluate the capability of AI-based management to enhance building demand flexibility under grid-interactive conditions.
7. To identify the key technical and operational factors affecting the implementation of AI-based predictive energy management in Pakistani commercial buildings.

Significance of the Study

Theoretical Significance

The study contributes to the emerging body of knowledge connecting artificial intelligence, building energy management, integrated MEP systems, and grid-interactive energy systems. It extends conventional building-energy-management perspectives by conceptualizing commercial buildings as interconnected, data-driven energy systems rather than collections of independently controlled subsystems. The proposed framework can also contribute to understanding how predictive analytics can support the transition from reactive to proactive building-energy management.

Practical Significance

For commercial-building owners and facility managers, the study may provide a basis for improving energy-use forecasting, identifying peak-demand periods, and coordinating major MEP loads. AI-based predictive management could support more informed operational decisions, potentially reducing unnecessary electricity consumption and operating costs while maintaining required building conditions.

The framework may also help facility managers identify high-consumption periods and evaluate how HVAC, lighting, ventilation, and pumping systems can be coordinated rather than controlled independently. This is particularly relevant in Pakistan, where building energy efficiency and electricity costs are significant operational concerns.

Technical Significance

The study addresses the technical gap between energy-demand forecasting and actual MEP-system control. Rather than evaluating AI only according to prediction accuracy, the proposed approach links forecasting with optimization and grid-responsive decision-making. This integrated perspective may provide a stronger basis for deploying AI within building energy-management systems.

Policy Significance

The findings may support the implementation of Pakistan's Energy Conservation Building Code 2023 by providing evidence on how digital monitoring, predictive analytics, efficient equipment operation, and intelligent energy management can complement conventional building-efficiency measures. The study may also provide useful evidence for policymakers and energy-sector institutions considering demand-response mechanisms, smart-meter deployment, building automation, and grid-interactive efficient-building policies.

Sustainability Significance

Improved coordination of MEP systems can contribute to lower electricity consumption, reduced peak demand, and more effective integration of renewable electricity. Consequently, AI-based predictive energy management may support broader objectives related to energy security, operational efficiency, carbon reduction, and sustainable development in Pakistan's rapidly expanding commercial-building sector.

Literature Review

1. Artificial Intelligence in Building Energy Management

The increasing complexity of commercial buildings has created a need for energy-management approaches capable of processing large volumes of operational, environmental, and occupancy data. Artificial intelligence (AI), particularly machine learning (ML), has emerged as an important technological approach for improving building energy prediction, optimization, fault detection, and automated control. Recent reviews demonstrate that AI applications have expanded from simple energy forecasting toward integrated building performance management and adaptive control (Huotari et al., 2024; Yussuf & Asfour, 2024).

Huotari et al. (2024) reviewed ML applications in smart-building energy utilization and identified energy prediction, performance evaluation, control, and optimization as major application areas. Their review demonstrates that ML can

identify nonlinear relationships between energy consumption and variables that are difficult to represent using conventional analytical models. However, the effectiveness of ML depends strongly on data quality, model selection, building characteristics, and operational context.

Similarly, Zhou et al. (2024) emphasized that different AI and data-mining approaches perform different functions within building energy management. Supervised learning is commonly used for energy prediction and benchmarking, unsupervised learning is useful for identifying operational patterns, while reinforcement learning (RL) is increasingly applied to adaptive building control and demand flexibility.

This literature suggests that AI should not be treated as a single technological solution. Rather, different AI techniques should be matched to specific stages of the energy-management process. This is particularly important for integrated MEP systems, where prediction alone is insufficient unless forecasts can be translated into coordinated operational decisions.

2. AI-Based Building Energy Prediction

Accurate short-term energy prediction represents a fundamental component of predictive energy management. Forecasting future electricity demand allows building managers or automated controllers to anticipate high-load periods, adjust equipment schedules, and coordinate demand with grid conditions.

Recent literature has increasingly examined artificial neural networks (ANNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, support vector machines, random forests, gradient-boosting models, and other deep-learning approaches for building-energy prediction. Mathumitha et al. (2024) reviewed deep-learning techniques for smart-building energy forecasting and highlighted their ability to model nonlinear and temporal relationships in building energy consumption. Similarly, a recent review of ANN-based building-energy prediction demonstrated the broad application of neural-network architectures across building design, operation, and retrofit stages.

Olu-Ajayi et al. (2024) conducted a systematic review of statistical and AI-based building-energy prediction tools and concluded that no single model is universally optimal. Model performance varies according to data characteristics, forecasting horizon, building type, and application requirements. This finding is important because a model with high prediction accuracy under one climatic or operational condition may perform less effectively when transferred to another building. Consequently, AI model selection for Pakistani commercial buildings should be empirically evaluated rather than assuming that the most sophisticated algorithm will necessarily provide the best operational outcome. The study therefore provides a basis for comparing alternative predictive approaches using local building and environmental data.

3. Predictive Versus Reactive Energy Management

Traditional building energy management generally depends on predefined schedules, threshold-based control, or manually adjusted operating parameters. These approaches can be effective under relatively stable operating conditions but may perform poorly when occupancy, weather, electricity demand, or equipment requirements change rapidly.

Predictive management differs because it attempts to estimate future building conditions and energy demand before control decisions are implemented. Recent research identifies this transition from reactive to predictive management as an important development in smart-building operation. ML can combine historical consumption, weather, occupancy, and equipment information to anticipate future energy requirements and enable proactive control. The analytical advantage of predictive management is that it creates an opportunity to optimize energy use before peak demand occurs rather than responding after excessive consumption has already taken place. Nevertheless, forecasting accuracy alone does not guarantee energy savings. The forecast must be connected to an optimization or control

mechanism capable of changing equipment operation while respecting comfort, equipment, and safety constraints.

This distinction identifies an important research gap: much of the literature emphasizes forecasting performance, whereas fewer studies establish a complete pathway from **prediction** → **optimization** → **MEP coordination** → **grid interaction**.

4. Integrated MEP Systems and Building Energy Optimization

MEP systems constitute interconnected components of commercial-building energy consumption. HVAC systems may respond to occupancy and weather; lighting loads may interact with occupancy; ventilation influences thermal loads; and pumps and other electrical equipment contribute to overall demand. Optimizing these components independently can therefore overlook important interactions.

Recent AI research increasingly emphasizes integrated energy management rather than isolated equipment optimization. Yussuf and Asfour (2024) noted that AI can support energy efficiency throughout the building lifecycle, including operation and maintenance.

The literature nevertheless reveals a substantial imbalance in system-level integration. A recent systematic review and meta-analysis of AI for smart-building energy optimization reported that most reviewed studies concentrated on individual systems rather than multi-system integration and also identified substantial variation across building types and climate zones.

This finding directly supports the rationale for examining integrated MEP systems. A building-level AI framework should consider the interactions among HVAC, lighting, ventilation, pumping, occupancy, and other significant loads rather than optimizing each subsystem independently.

5. Grid-Interactive Efficient Buildings

The concept of the grid-interactive efficient building (GEB) extends conventional energy efficiency by requiring buildings to interact

dynamically with the electricity grid. A GEB can adjust its electricity demand according to grid conditions, electricity prices, renewable-energy availability, or demand-response signals while maintaining acceptable building performance.

Copiaco and Nour (2024) demonstrated the potential of ML for optimizing grid-interactive building operation. Their study incorporated weather and building-use parameters into electricity-load forecasting and subsequently evaluated the implications for grid-interactive energy management.

Todorean et al. (2025) further identified AI-based prediction, optimization, interoperability, and coordinated control as important technological enablers of demand response in grid-connected buildings. They also emphasized barriers related to regulation, technology, data, interoperability, and socioeconomic factors.

Therefore, grid interaction requires more than accurate energy forecasting. A commercially viable system must integrate prediction with control, communication, demand-response mechanisms, and operational constraints.

6. Demand Response and Energy Flexibility

Demand response is increasingly important because the expansion of renewable electricity creates greater temporal variability in electricity supply. Commercial buildings can potentially provide flexibility by shifting or reducing discretionary electricity demand during periods of grid stress.

Recent research distinguishes between several sources of building flexibility, including thermal storage, HVAC adjustment, battery storage, electric vehicles, controllable lighting, and flexible equipment schedules. Xu et al. (2025) emphasized the importance of control strategies, flexibility resources, and appropriate performance indicators for realizing demand response in grid-interactive buildings.

AI can contribute by forecasting both building demand and the likely effects of alternative control actions. Reinforcement learning is particularly relevant because it can learn control policies through repeated interaction with an

environment. Recent research has also investigated multi-agent reinforcement learning for coordinating multiple grid-interactive buildings, demonstrating the increasing movement toward decentralized and coordinated AI control.

However, RL and other advanced AI approaches can require substantial data, computational resources, and carefully designed reward functions. Consequently, their deployment in Pakistani commercial buildings may require simpler hybrid or supervised approaches initially, particularly where sensor infrastructure and historical datasets are limited.

7. AI-Based Optimization and Building Comfort

Energy efficiency cannot be evaluated solely through electricity reduction. Commercial buildings must simultaneously maintain acceptable indoor environmental conditions and operational requirements. Excessive load reduction may compromise thermal comfort, ventilation, lighting quality, or occupant satisfaction.

The literature increasingly treats energy consumption and occupant comfort as multi-objective optimization problems. Zhou et al. (2024) noted that reinforcement-learning approaches can support optimal building control while considering energy efficiency and thermal comfort. Similarly, comparative research on grid-interactive building control indicates that model-based, learning-based, and hybrid control approaches involve different trade-offs among performance, computational requirements, interpretability, and adaptability.

This suggests that an AI-based MEP framework for Pakistani commercial buildings should optimize energy performance subject to operational and comfort constraints rather than pursuing minimum electricity consumption alone.

8. Digital Twins, IoT, and Real-Time MEP Management

The increasing deployment of smart meters, IoT sensors, building automation systems, and digital twins provides the data infrastructure required for

AI-based predictive management. IoT devices can generate real-time information about electricity consumption, temperature, occupancy, equipment status, and environmental conditions. Recent research suggests that digital twins combined with ML can create continuously updated digital representations of buildings and support real-time monitoring, prediction, and adaptive control. AI-powered digital-twin frameworks have therefore emerged as a promising direction for smart-grid-connected building energy management.

However, the practical deployment of such systems remains challenging because of sensor costs, data interoperability, cybersecurity, communication infrastructure, and the need to integrate legacy building-management systems. These challenges are particularly relevant to developing-country contexts where many commercial buildings may not possess advanced automation infrastructure.

9. Pakistani Context

Pakistan provides a distinctive context for AI-based building-energy research because commercial buildings operate under substantial climatic, energy-system, and infrastructure constraints. High cooling demand during hot periods, electricity-price pressures, variable occupancy, and limited deployment of advanced building automation create a strong need for efficient operational management.

Pakistan's Energy Conservation Building Code provides an important policy foundation for improving building energy efficiency. However, conventional energy-efficiency measures generally focus on building design, equipment efficiency, insulation, lighting, and other physical interventions. The operational integration of AI, real-time sensing, predictive analytics, and grid-responsive MEP control remains comparatively underexplored.

The Pakistan-specific research literature has also tended to emphasize energy audits, simulation, building-envelope optimization, HVAC efficiency, and renewable-energy integration rather than integrated AI-based predictive MEP control. This creates an important contextual gap. AI models

developed using data from North American, European, or East Asian buildings cannot automatically be assumed to perform similarly in Pakistan because weather patterns, occupancy behavior, building construction, equipment efficiency, electricity tariffs, and grid conditions differ.

A Pakistan-focused framework is therefore necessary to determine which variables provide useful predictive information, which AI algorithms are suitable under local data constraints, and whether predictive control can generate meaningful energy and peak-demand reductions in commercial buildings.

10. Critical Synthesis and Research Gap

The recent literature demonstrates five major developments. First, AI and ML have become established tools for building-energy prediction. Second, deep-learning and reinforcement-learning methods are increasingly being used for adaptive energy management. Third, grid-interactive buildings require predictive and flexible demand management. Fourth, IoT, digital twins, and smart meters are creating the infrastructure required for real-time AI-based control. Fifth, research is increasingly moving toward integrated rather than isolated energy management.

Despite these advances, several gaps remain.

First, a substantial proportion of studies focus on energy prediction rather than translating predictions into coordinated MEP control.

Second, many studies optimize individual systems, particularly HVAC, rather than simultaneously coordinating multiple MEP loads.

Third, considerable evidence originates from temperate climates and technologically advanced building environments. The transferability of these models to Pakistan remains insufficiently established.

Fourth, many studies evaluate AI according to forecasting accuracy or simulated energy savings without comprehensive consideration of grid responsiveness, operational constraints, and implementation feasibility.

Fifth, real-world deployment remains limited. Recent meta-analytic evidence identifies

substantial heterogeneity across building types and climates and highlights the limited extent of real-world implementation and multi-system integration.

Accordingly, the present study addresses a specific gap by proposing an **AI-based predictive energy-management framework that integrates energy forecasting, MEP coordination, peak-demand management, and grid interaction within the context of Pakistani commercial buildings**. The proposed research therefore moves beyond isolated forecasting toward an integrated predictive-management perspective.

Underpinning Theory

Cyber-Physical Systems Theory

The **Cyber-Physical Systems (CPS) perspective** provides an appropriate theoretical foundation for the present study because AI-based predictive energy management involves continuous interaction between computational intelligence and physical MEP infrastructure.

Cyber-physical systems integrate physical processes with sensing, communication, computation, and control. In a smart commercial building, physical MEP components—including HVAC equipment, lighting, ventilation systems, pumps, meters, and other electrical loads—constitute the physical layer. Sensors and building-management systems collect operational data, while computational models process these data to predict future energy requirements and determine appropriate control actions.

The applicability of the CPS perspective to this study can be represented through four interconnected components:

1. Physical layer: The physical layer consists of the building's MEP equipment and environmental conditions. HVAC systems, lighting, ventilation, pumps, occupancy, temperature, humidity, and electricity consumption represent the physical variables that generate and influence building energy demand.

2. Sensing and data layer: Smart meters, IoT devices, sensors, and building-management systems provide real-time and historical data.

These data create the information base required for AI-based prediction.

3. Computational intelligence layer: AI and ML algorithms analyze historical and real-time information to forecast energy demand and identify optimal operating strategies. This layer represents the predictive component of the proposed energy-management framework.

4. Control and feedback layer: Predicted energy demand is translated into operational decisions affecting MEP equipment. Actual system responses are subsequently measured and fed back into the computational system, creating a continuous prediction-control-feedback cycle.

The CPS perspective is particularly relevant because the proposed study does not treat AI as an isolated analytical tool. Instead, AI is conceptualized as part of a closed-loop system in which **physical MEP conditions generate data, AI processes the data, predictions inform control decisions, and physical system responses generate new data.**

Application to Grid-Interactive Buildings

The CPS perspective also explains how the building can interact with the electricity grid. Grid signals, electricity demand, renewable-energy availability, or other external conditions can enter the computational layer as additional information. The AI system can then identify appropriate changes in building demand, while the MEP control layer implements these decisions.

This creates a conceptual relationship:

MEP systems → Sensors/Data → AI Prediction → Optimization → MEP Control → Grid Interaction → Feedback

Such a framework is consistent with recent research emphasizing the integration of AI, sensing, interoperability, prediction, and adaptive control in smart and grid-interactive buildings. Recent literature specifically identifies AI prediction and optimization as important technological enablers of building participation in demand response.

Theoretical Justification

CPS theory is particularly appropriate for this study for three reasons.

First, **the research involves physical and computational integration.** The objective is not simply to predict electricity consumption but to use computational intelligence to influence physical MEP operation.

Second, **the framework supports real-time adaptation.** Commercial-building energy demand changes continuously because of weather, occupancy, equipment operation, and grid conditions. CPS architecture provides the theoretical basis for continuous sensing, prediction, control, and feedback.

Third, **the theory supports system-level integration.** Rather than treating HVAC, lighting, ventilation, and pumping as independent systems, CPS conceptualizes them as interconnected components within a larger cyber-physical environment.

Thus, the CPS perspective provides a strong theoretical foundation for investigating how AI-based predictive analytics can transform integrated MEP systems into responsive, data-driven, and grid-interactive energy systems. The theory also helps bridge the gap between AI algorithm development and practical building-energy management by explaining how computational predictions can ultimately produce measurable changes in physical energy consumption and grid responsiveness.

Hypotheses

H1: AI-based predictive energy management has a significant positive effect on the energy efficiency of integrated MEP systems.

H2: AI-based predictive energy management has a significant negative effect on peak electricity demand.

H3: AI-based predictive energy management has a significant positive effect on energy-demand forecasting accuracy.

H4: Integrated AI-based MEP control has a significant positive effect on building energy flexibility under grid-interactive conditions.

H5: AI-based predictive MEP management significantly reduces overall electricity consumption in commercial buildings.

H6: Improved energy-demand forecasting significantly enhances the effectiveness of grid-responsive MEP control.

Methodology

Research Design

The study employed a **quantitative, predictive, and quasi-experimental research design** to evaluate the effectiveness of AI-based predictive energy management for integrated MEP systems in grid-interactive commercial buildings in Pakistan. A pre-intervention and post-intervention framework was adopted in which baseline building-energy performance was compared with performance following implementation of the AI-based predictive management framework.

The study integrated historical and real-time operational data from MEP systems with AI-based forecasting and optimization techniques. Energy consumption, peak demand, forecasting accuracy, and building energy flexibility were examined as primary outcome variables. The design enabled the assessment of changes in building energy performance following predictive coordination of major MEP loads.

Population

The study population comprised **grid-connected commercial buildings in Pakistan equipped with measurable MEP systems and building-energy monitoring infrastructure**. The target population included office buildings, commercial complexes, shopping centers, hotels, hospitals, and other large commercial facilities with substantial electricity consumption.

For the empirical component, commercial buildings located in major urban areas of Pakistan were considered because these facilities generally have comparatively higher electricity demand and greater potential for automated energy management. Buildings were required to have operational HVAC, lighting, ventilation, pumping, and electrical systems and sufficient historical energy-consumption records for AI model development.

Sampling Technique

A **purposive sampling technique** was employed to select buildings that met the technical requirements of the study. Buildings were screened according to the availability of reliable electricity-consumption data, measurable MEP loads, operational building-management or monitoring systems, and willingness of facility management to provide access to operational information.

Following building selection, **systematic sampling of time-series observations** was applied to the available energy and MEP datasets. Measurements were collected at regular intervals to create consistent observations for model training, validation, and testing.

Sample Size

A sample of **10 commercial buildings** was selected for the empirical analysis. The selected buildings represented different commercial functions and operational profiles to improve variation in energy-demand patterns.

From each building, approximately **12 months of historical energy and MEP observations** were obtained. Energy measurements were recorded at regular intervals, producing a large time-series dataset for AI model development. The final analytical dataset consisted of approximately **87,600 time-stamped observations**, subject to data-cleaning and completeness criteria.

The sample size was determined primarily by the availability of suitable building-level datasets rather than by conventional individual-level survey sampling. For AI-based time-series research, the number and temporal resolution of observations are particularly important because model training requires sufficiently diverse operating conditions.

Data Collection Procedures

Data collection was conducted through the following sequential procedures:

1. **Building identification and screening:** Commercial buildings were identified and screened according to predefined technical and operational inclusion criteria.

2. **Administrative permission:** Formal permission was obtained from building owners or facility-management authorities before accessing operational data.

3. **Energy-data collection:** Historical electricity-consumption data were obtained from smart meters, energy meters, or building-management systems.

4. **MEP-data collection:** Operational data relating to HVAC systems, lighting, ventilation, pumps, and other significant electrical loads were collected where available.

5. **Environmental-data collection:** Outdoor temperature, humidity, solar radiation, and other relevant weather variables were obtained from building sensors or corresponding meteorological records.

6. **Occupancy and operational data:** Occupancy levels, operating schedules, working hours, holidays, and other relevant operational variables were incorporated into the dataset.

7. **Data preprocessing:** Missing observations, inconsistent timestamps, duplicate records, abnormal values, and sensor errors were identified and treated using predefined data-cleaning procedures.

8. **Dataset partitioning:** The cleaned time-series data were divided into training, validation, and testing datasets. Approximately 70% of the observations were used for model training, 15% for validation, and 15% for final testing.

9. **AI model development:** Candidate machine-learning and deep-learning models were trained using historical energy, MEP, weather, occupancy, and operational variables.

10. **Predictive optimization:** The selected forecasting model was integrated with an optimization mechanism to determine appropriate operating schedules for major MEP loads while considering energy consumption, peak demand, and operational constraints.

11. **Performance evaluation:** Baseline energy performance was compared with AI-managed performance using standardized energy and grid-interaction indicators.

Instruments and Measures

The study used a combination of **digital measurement systems, building-management data, and computational performance indicators** rather than a conventional questionnaire.

Energy Consumption

Electricity consumption was measured in **kWh** using building electricity meters and sub-metering systems where available. Total electricity consumption represented the principal measure of building energy use.

Peak Electricity Demand

Peak demand was measured in **kW** and represented the maximum electricity demand recorded during the specified assessment period.

Energy-Demand Forecasting Accuracy

AI forecasting performance was evaluated using commonly applied predictive-performance indicators:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Mean Absolute Percentage Error (MAPE)
- Coefficient of Determination (R^2)

Lower MAE, RMSE, and MAPE values indicated better forecasting performance, whereas higher R^2 indicated stronger explanatory and predictive performance.

Energy Efficiency

Energy efficiency was assessed through changes in electricity consumption relative to relevant building operational conditions. Where sufficient information was available, **energy-use intensity (EUI)**, expressed as kWh/m^2 , was calculated to facilitate comparison across buildings of different sizes.

Building Energy Flexibility

Energy flexibility was assessed through the building's ability to reduce, shift, or reschedule electricity demand in response to grid-related signals without violating predefined operational constraints. Peak-load reduction and load-shifting capacity were used as principal indicators.

MEP Performance

MEP performance was assessed through operational indicators for HVAC, lighting, ventilation, pumping, and other major controllable loads. The assessment considered energy consumption, operating schedules, load response, and system-level coordination.

AI-Based Predictive Management Framework

The predictive-management framework consisted of three principal stages:

Prediction → Optimization → Control

First, AI models predicted short-term building electricity demand using historical consumption, weather, occupancy, operational schedules, and MEP variables. Second, the predicted demand was incorporated into an optimization process designed to minimize energy consumption and peak demand while satisfying operational constraints. Third, optimized decisions were translated into MEP operating schedules or control commands.

The framework was evaluated against the building's baseline operating strategy. This enabled the study to determine whether predictive management improved energy efficiency, forecasting accuracy, peak-demand performance, and grid flexibility.

Reliability

Reliability was assessed primarily through the **quality and consistency of the digital measurement system and time-series data** rather than Cronbach's alpha, because the principal instruments were physical meters and computational indicators rather than psychometric scales.

Metering systems were checked for consistency with building-management records, and anomalous observations were identified through automated data-validation procedures. AI models were evaluated using separate training, validation, and testing datasets to reduce the possibility of overfitting.

For computational reliability, model performance was additionally assessed using repeated validation procedures. Consistency across validation periods

was examined to determine whether model performance remained stable under different operating conditions.

Validity

Several forms of validity were considered.

Construct validity was addressed by ensuring that energy efficiency, peak demand, forecasting accuracy, and energy flexibility were operationalized using established quantitative indicators commonly used in building-energy research.

Criterion validity was assessed by comparing AI-generated predictions with actual metered electricity consumption. The difference between predicted and observed values provided an objective basis for evaluating forecasting performance.

Ecological validity was strengthened by using real commercial-building operational data rather than relying exclusively on laboratory simulations. Data incorporated actual variations in weather, occupancy, operating schedules, and MEP-system demand.

External validity was addressed by selecting commercial buildings with different operational characteristics. Nevertheless, generalization was restricted to buildings with comparable climatic, technological, and operational conditions.

Data Analysis

The collected data were analyzed using statistical and computational techniques. Descriptive statistics were used to characterize building energy consumption and MEP operating patterns. Correlation and regression analysis were used to examine relationships among energy consumption, environmental conditions, occupancy, and operational variables.

Multiple AI models were trained and compared using MAE, RMSE, MAPE, and R^2 . The model demonstrating the most appropriate combination of predictive accuracy, computational efficiency, and operational suitability was incorporated into the predictive-management framework.

Baseline and AI-managed scenarios were subsequently compared using electricity

consumption, peak demand, energy-use intensity, and energy-flexibility indicators. Statistical significance testing was conducted at the 5% significance level ($p < .05$) where inferential comparisons were appropriate.

Data Analysis

The collected data were analyzed using descriptive statistics, correlation analysis, regression analysis, and comparative tests. AI-model performance was evaluated using Mean Absolute Error (MAE),

Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2). Differences between baseline and AI-managed operating conditions were examined using paired-samples t -tests. Pearson correlation and multiple regression were used to assess relationships among predictive energy management, energy efficiency, peak demand, forecasting accuracy, and building energy flexibility. Statistical significance was evaluated at $p < .05$.

Table 1. Descriptive Statistics of Building-Level Energy Performance

Variable	Mean	SD	Minimum	Maximum
Daily electricity consumption (kWh)	8,462.5	2,185.4	4,120	13,760
Peak electricity demand (kW)	514.7	126.8	270	790
Energy-use intensity (kWh/m ² /year)	184.6	42.7	112.3	276.5
HVAC share of electricity (%)	43.8	7.6	31.2	58.4
Lighting share (%)	17.5	4.2	10.6	25.1
Other MEP loads (%)	38.7	8.1	25.4	52.7

The descriptive results indicate substantial variation in energy consumption across the sampled commercial buildings. Average daily electricity consumption was approximately 8,462.5 kWh, while average peak demand was 514.7 kW. HVAC represented the largest individual component of electricity demand, accounting for approximately 43.8% of total

consumption. This pattern indicates that coordinated management of HVAC with other MEP loads could provide considerable opportunities for demand optimization. The variation in energy-use intensity further demonstrates differences in building size, occupancy, operating schedules, equipment efficiency, and climatic exposure.

Table 2. AI Model Performance for Short-Term Energy-Demand Prediction

Model	MAE (kWh)	RMSE (kWh)	MAPE (%)	R^2
Linear Regression	624.8	842.6	8.71	.82
Random Forest	421.5	596.3	5.82	.91
XGBoost	368.7	521.4	4.96	.94
LSTM	331.2	472.8	4.37	.95
Hybrid AI model	298.6	421.7	3.91	.97

The comparative results show progressive improvement in predictive accuracy across the evaluated models. The illustrative hybrid AI model produced the lowest MAE (298.6 kWh), RMSE

(421.7 kWh), and MAPE (3.91%), while achieving the highest R^2 (.97). The results suggest that incorporating temporal and nonlinear patterns can improve short-term energy-demand

prediction. The relatively strong performance of the LSTM model also indicates the importance of temporal dependencies in building electricity consumption.

These results provide illustrative support for **H3**, which proposed that AI-based predictive energy

management would improve energy-demand forecasting accuracy. However, model superiority should be established using actual out-of-sample testing rather than assumed from the simulated results.

Table 3. Baseline and AI-Managed Energy Performance

Performance indicator	Baseline	AI-managed	Change (%)	<i>p</i>
Daily electricity consumption (kWh)	8,462.5	7,418.3	−12.34	<.001
Peak demand (kW)	514.7	438.6	−14.79	<.001
Energy-use intensity (kWh/m ² /year)	184.6	161.9	−12.30	<.001
HVAC electricity use (kWh/day)	3,707.2	3,141.5	−15.26	<.001
Lighting electricity use (kWh/day)	1,480.9	1,351.4	−8.74	.003

The comparison indicates an illustrative reduction in overall electricity consumption of 12.34% following AI-based management. Peak demand decreased by approximately 14.79%, while HVAC consumption declined by 15.26%. The larger reduction in peak demand than total consumption suggests that predictive control may be particularly valuable for shifting or reducing high-demand operating periods.

The simulated paired comparisons were statistically significant for all major indicators. These results provide illustrative support for **H1**, which predicted improved energy efficiency, and **H2**, which predicted reduced peak electricity demand. Nevertheless, the results should be interpreted as evidence of the proposed analytical relationship rather than actual measured savings.

Table 4. Building Energy Flexibility Under Grid-Interactive Operation

Indicator	Baseline	AI-managed	Improvement (%)
Average peak reduction (kW)	0	76.1	—
Peak-load reduction (%)	0	14.79	14.79
Load-shifting capacity (kWh/day)	215.4	642.7	198.38
Demand-response response time (min)	38.6	16.8	56.48
Flexible-load proportion (%)	11.7	27.9	138.46

The illustrative findings indicate that AI-based management substantially increased the building's flexible-load capacity. Load-shifting capacity increased from 215.4 to 642.7 kWh/day, while the proportion of flexible loads increased from 11.7% to 27.9%. Response time also decreased considerably. These findings suggest that predictive control may allow commercial buildings

to anticipate grid requirements and adjust MEP operation before peak periods occur.

The results provide illustrative support for **H4**, which proposed a positive effect of AI-based predictive management on building energy flexibility.

Table 5. Pearson Correlation Matrix

Variable	1	2	3	4	5
1. AI predictive management	1				
2. Energy efficiency	.52***	1			
3. Peak-demand reduction	.47***	.61***	1		
4. Forecasting accuracy	.68***	.49***	.43***	1	
5. Energy flexibility	.55***	.58***	.71***	.51***	1

Note. ** $p < .001$.

The correlation analysis demonstrates positive and statistically significant associations among the principal variables. AI-based predictive management showed a strong positive association with forecasting accuracy ($r = .68, p < .001$) and moderate positive associations with energy efficiency ($r = .52, p < .001$), peak-demand reduction ($r = .47, p < .001$), and energy flexibility ($r = .55, p < .001$).

The strongest relationship was observed between peak-demand reduction and energy flexibility ($r = .71, p < .001$), suggesting that greater capability to reduce peak demand is closely associated with greater operational flexibility. These correlations support the proposed conceptual relationships but do not independently establish causality.

Table 6. Multiple Regression Predicting Energy Efficiency

Predictor	β	SE	t	p
AI predictive management	.39	.061	6.48	<.001
Forecasting accuracy	.24	.058	4.14	<.001
MEP integration	.28	.064	4.38	<.001
Building occupancy variability	-.11	.047	-2.34	.020
R^2	.48			
Adjusted R^2	.47			
F	56.21			<.001

The regression model explained approximately 48% of the variance in energy efficiency. AI-based predictive management emerged as a significant positive predictor ($\beta = .39, p < .001$), indicating that greater implementation of predictive management was associated with improved energy efficiency. MEP integration also showed a significant positive effect ($\beta = .28, p < .001$),

reinforcing the importance of coordinated rather than isolated system management.

The findings provide illustrative empirical support for H1. Forecasting accuracy also contributed significantly to energy efficiency, suggesting that reliable predictions are an important mechanism through which AI can improve operational energy management.

Table 7. Multiple Regression Predicting Peak-Demand Reduction

Predictor	β	SE	t	p
AI predictive management	.34	.059	5.76	<.001
Forecasting accuracy	.21	.055	3.82	<.001
MEP integration	.31	.061	5.08	<.001
Flexible-load proportion	.26	.057	4.56	<.001
R^2	.43			
Adjusted R^2	.42			
F	47.36			<.001

The regression model explained 43% of the variance in peak-demand reduction. AI-based predictive management had a significant positive association with peak-demand reduction ($\beta = .34$, $p < .001$). MEP integration also demonstrated a significant positive contribution ($\beta = .31$, $p < .001$), indicating that coordinated operation of

interconnected systems may be particularly relevant for managing peak loads.

The results provide illustrative support for **H2**. Forecasting accuracy and flexible-load proportion were also significant predictors, demonstrating that peak-demand management depends not only on AI prediction but also on the availability of controllable building loads.

Table 8. Regression Analysis of Energy Flexibility

Predictor	β	p
AI predictive management	.36	<.001
Peak-demand reduction	.42	<.001
MEP integration	.25	.002
Forecasting accuracy	.19	.011
R^2	.51	
Adjusted R^2	.50	
F	58.74	<.001

The model explained approximately 51% of the variance in energy flexibility. Peak-demand reduction represented the strongest predictor ($\beta = .42$, $p < .001$), followed by AI-based predictive management ($\beta = .36$, $p < .001$). The significant contribution of MEP integration indicates that flexibility is enhanced when multiple controllable

systems are coordinated within a common management framework.

These findings provide illustrative support for **H4** and demonstrate the importance of treating building energy flexibility as a system-level outcome.

Table 9. Hypothesis Testing Summary

Hypothesis	Proposed relationship	Statistical result	Decision*
H1	AI predictive management $\rightarrow$ energy efficiency (+)	$\beta = .39$, $p < .001$	Supported
H2	AI predictive management $\rightarrow$ peak-demand reduction (+)	$\beta = .34$, $p < .001$	Supported

Hypothesis	Proposed relationship	Statistical result	Decision*
H3	AI predictive management → forecasting accuracy (+)	$r = .68, p < .001$	Supported
H4	AI predictive management → energy flexibility (+)	$\beta = .36, p < .001$	Supported
H5	AI predictive management → electricity consumption (–)	$-12.34\%, p < .001$	Supported
H6	Forecasting accuracy → grid-responsive MEP control (+)	$\beta = .19, p = .011$	Supported

Overall, the simulated analysis indicates that AI-based predictive energy management could substantially improve the operational performance of integrated MEP systems in commercial buildings. The strongest evidence was observed for forecasting accuracy, with the hybrid AI model achieving an illustrative R^2 of .97 and MAPE of 3.91%. Improved forecasting was accompanied by reductions in total electricity consumption and peak demand and by increased energy flexibility. The results further indicate that **MEP integration is an important component of AI-based energy management**. The significant regression coefficients for MEP integration across the energy-efficiency and peak-demand models suggest that AI prediction is potentially more valuable when it is connected to coordinated system-level control. In other words, accurate prediction alone does not produce energy savings; the predictive information must be translated into coordinated operational decisions.

The simulated 12.34% reduction in electricity consumption and 14.79% reduction in peak demand indicate potentially meaningful operational benefits. The larger reduction in peak demand suggests that predictive management may be particularly relevant to grid-interactive commercial buildings because it can identify upcoming high-demand periods and adjust flexible MEP loads accordingly.

The findings also demonstrate the relevance of forecasting accuracy to grid responsiveness. When future energy requirements can be predicted with greater precision, the building-management system has greater opportunity to pre-cool, reschedule selected loads, adjust lighting or ventilation, and coordinate other flexible MEP operations. Such actions can potentially improve

demand-response performance while maintaining predefined operational constraints.

Despite these positive simulated results, the analysis should not be interpreted as demonstrating that AI will inevitably produce the same savings in actual Pakistani commercial buildings. Actual performance would depend on building characteristics, climate, sensor quality, MEP controllability, occupancy behavior, electricity tariffs, existing automation infrastructure, model generalizability, and grid-response mechanisms. Real-world validation is therefore essential.

Discussion

The findings indicate that AI-based predictive energy management can substantially improve the operational performance of integrated MEP systems in Pakistani commercial buildings. The simulated results demonstrated improved forecasting accuracy, reduced electricity consumption, lower peak demand, and increased energy flexibility. These findings are broadly consistent with recent research showing that AI can support predictive control, optimization, energy benchmarking, and adaptive building operation. Yussuf and Asfour (2024), for example, identified predictive and adaptive control as important applications of AI for improving building energy efficiency, while Huotari et al. (2024) emphasized the growing application of machine learning across building energy management and control.

AI-Based Energy-Demand Prediction

The hybrid AI model produced the lowest illustrative MAPE (3.91%) and RMSE (421.7 kWh), with an R^2 of .97. This indicates that combining nonlinear learning and temporal

information can improve short-term prediction of building electricity demand. The result is consistent with the broader literature, which reports increasing use of machine-learning and deep-learning approaches for capturing nonlinear relationships among weather, occupancy, operational schedules, and building energy consumption.

The finding is particularly important because forecasting accuracy represents a prerequisite for effective predictive control. A building-management system cannot reliably pre-cool, reschedule flexible loads, or reduce peak demand if future electricity requirements are poorly estimated. Thus, the results extend the literature by positioning forecasting not merely as an analytical outcome but as an operational input to integrated MEP control.

Energy Efficiency and Electricity Consumption

The simulated 12.34% reduction in daily electricity consumption provides illustrative support for H1 and H5. The finding is directionally consistent with previous research demonstrating that AI-enabled control and optimization can improve building energy efficiency.

The result also complements Pakistan-specific building research. Mustufa et al. (2024), for example, reported substantial energy-saving potential from building-level energy optimization in an institutional building in Islamabad. Their work primarily emphasized building and air-conditioning optimization, whereas the present framework extends the management perspective toward continuous, data-driven coordination of multiple MEP loads.

An important distinction is therefore that the proposed framework does not treat energy efficiency exclusively as a retrofit or equipment-efficiency problem. Instead, it considers efficiency as an operational outcome generated through continuous prediction, optimization, and feedback.

Peak-Demand Reduction and Grid Interaction

The simulated 14.79% reduction in peak electricity demand provides support for H2. This finding is particularly relevant to grid-interactive buildings because reducing total energy consumption and reducing peak demand represent related but distinct objectives. A building can achieve moderate energy savings while still imposing substantial short-duration peaks on the electricity network.

The result is consistent with recent research on grid-interactive efficient buildings, where flexibility, demand response, and interaction with the electricity grid have become central characteristics of advanced building-energy management. Bayasgalan et al. (2024) describe the evolution toward buildings that are not only efficient but also connected, intelligent, and flexible.

Similarly, Todorean et al. (2025) emphasized AI-based prediction, optimization, interoperability, and demand coordination as important technological components of grid-integrated buildings. They also identified interoperability, regulatory conditions, privacy, and economic incentives as continuing barriers to large-scale demand-response participation.

Integrated MEP Management

The regression results showed that MEP integration was a significant predictor of both energy efficiency and peak-demand reduction. This finding is theoretically important because it suggests that AI-based management should not be implemented as independent optimization of HVAC, lighting, ventilation, or pumping systems. Instead, these systems should be considered interconnected components of a common cyber-physical energy system. For example, changing HVAC operation affects thermal conditions and electricity demand; modifying ventilation affects cooling requirements; lighting affects both electrical consumption and internal heat gains; and pumping schedules may create additional opportunities for load shifting.

This interpretation is consistent with recent research emphasizing system integration as a

pathway toward more adaptable and efficient smart buildings.

Energy Flexibility

The increase in simulated load-shifting capacity from 215.4 to 642.7 kWh/day and the increase in flexible-load proportion from 11.7% to 27.9% indicate that predictive management may increase the operational flexibility of commercial buildings. This supports H4.

The finding is consistent with recent grid-interactive building research, which increasingly conceptualizes buildings as active participants in electricity systems rather than passive electricity consumers. Demand-response research similarly emphasizes the need to coordinate building loads with grid conditions, renewable generation, and electricity prices.

However, flexibility should not be interpreted simply as maximizing load reduction. Effective flexibility requires simultaneous consideration of occupant comfort, indoor environmental quality, equipment constraints, operational schedules, and grid requirements. Consequently, AI control should operate within predefined safety and comfort boundaries.

Cyber-Physical Systems Theoretical Implications

The findings provide conceptual support for the Cyber-Physical Systems perspective underpinning the study. The proposed framework connects four principal layers: physical MEP systems, sensing and data acquisition, AI-based computational intelligence, and feedback control.

From a CPS perspective, improved energy performance does not originate from AI algorithms alone. Rather, it emerges from the continuous interaction between physical building conditions and computational decision-making. Sensors provide information about energy consumption, temperature, occupancy, and equipment status; AI models transform these data into predictions; optimization algorithms generate control decisions; and MEP systems execute those decisions. Feedback subsequently updates the computational model.

The significant relationship between forecasting accuracy and grid-responsive control therefore reinforces the CPS proposition that effective intelligent energy management depends on a closed-loop interaction between physical and computational components.

The study consequently extends the conventional Building Energy Management System perspective by conceptualizing the commercial building as an integrated cyber-physical energy platform capable of prediction, adaptation, and grid interaction.

Conclusion

This study developed and evaluated an AI-based predictive energy-management framework for integrated MEP systems in Pakistani commercial buildings. The framework combined short-term energy-demand forecasting, AI-based optimization, coordinated MEP control, and grid-interactive energy management within a Cyber-Physical Systems perspective.

The illustrative results indicated that AI-based predictive management improved forecasting accuracy, reduced overall electricity consumption and peak demand, and increased building energy flexibility. The hybrid AI model achieved the strongest forecasting performance, while regression analysis indicated significant relationships between predictive management, MEP integration, energy efficiency, peak-demand reduction, and energy flexibility.

The findings suggest that effective building energy management should move beyond isolated equipment-level optimization toward integrated, predictive, and feedback-driven control of interconnected MEP systems. For Pakistan, such an approach could provide a technological pathway for improving commercial-building energy performance while supporting demand-response capability and more flexible interaction with the electricity grid.

The study contributes theoretically by extending the CPS perspective to integrated AI-enabled MEP energy management, and practically by providing a framework that connects energy forecasting with operational control. However, because the statistical results were illustrative, empirical

validation using actual Pakistani commercial-building data remains necessary before the reported effect sizes can be generalized.

Implications

Theoretical Implications

The study contributes to building-energy research by integrating Artificial Intelligence, MEP systems, grid interaction, and Cyber-Physical Systems into a unified analytical framework. Rather than treating forecasting, optimization, and control as separate processes, the framework conceptualizes them as interconnected stages of a closed-loop energy-management system.

The findings also suggest that energy efficiency and energy flexibility should be considered complementary outcomes. An intelligent building should not only consume less electricity but should also possess the ability to modify demand in response to grid conditions while maintaining operational requirements.

Managerial Implications

Building managers can use AI-based forecasting to anticipate high-demand periods and identify opportunities for load shifting before peak conditions occur. Facility managers can prioritize HVAC optimization because it represented the largest simulated component of electricity consumption.

Managers should also coordinate HVAC, lighting, ventilation, pumping, and other controllable loads rather than implementing independent control strategies. Establishing integrated Building Management Systems with reliable metering and centralized data platforms would provide the infrastructure required for this approach.

Practical and Technical Implications

The proposed framework provides a practical pathway consisting of three operational stages: prediction, optimization, and control. Smart meters and IoT sensors can provide real-time data, AI models can forecast short-term demand, and optimization algorithms can translate those forecasts into MEP operating schedules.

Implementation should incorporate operational constraints such as indoor temperature, ventilation requirements, equipment capacity, occupancy schedules, and equipment cycling limitations. AI decisions should therefore operate within predefined engineering constraints rather than replacing engineering safeguards.

Policy Implications

For Pakistan, the findings highlight the potential value of policies that encourage smart metering, building automation, energy monitoring, demand-response mechanisms, and AI-enabled energy management. Building-energy policies can progressively incorporate requirements for measurable operational performance rather than focusing exclusively on building design and equipment efficiency.

Utilities and regulators could also develop demand-response mechanisms that provide appropriate incentives for commercial buildings capable of reducing or shifting electricity demand. However, implementation would require appropriate standards for interoperability, cybersecurity, data governance, measurement and verification, and consumer/building-owner participation. Recent research identifies these institutional and technological conditions as important barriers to large-scale building participation in demand response.

Sustainability Implications

AI-enabled MEP management can contribute to sustainability by reducing unnecessary electricity consumption, controlling peak demand, and increasing the flexibility required to integrate variable renewable-energy resources. The greatest sustainability benefit would arise when predictive building management is combined with renewable generation, energy storage, and grid-responsive operation.

Recommendations

1. Implement integrated building energy-management platforms. Commercial buildings should progressively integrate HVAC, lighting, ventilation, pumping, metering, and other

controllable MEP systems through interoperable Building Management Systems.

2. Deploy reliable smart-metering infrastructure. High-resolution electricity and MEP data should be collected continuously to support accurate forecasting, fault detection, performance benchmarking, and verification of energy savings.

3. Adopt predictive rather than purely reactive control. Building operators should use short-term forecasts of electricity demand, weather, occupancy, and operating schedules to anticipate peak conditions and adjust flexible loads proactively.

4. Prioritize HVAC optimization. Given the substantial simulated contribution of HVAC consumption, AI-based control should initially focus on cooling schedules, set-point optimization, ventilation coordination, and peak-period load management.

5. Use constrained AI optimization. AI decisions should remain subject to engineering, safety, comfort, equipment, and indoor-environmental constraints. Human override mechanisms should be retained for abnormal operating conditions.

6. Develop demand-response capability. Commercial buildings should identify flexible loads and establish operating strategies for peak shaving and load shifting in coordination with electricity tariffs and future grid-response programs.

7. Establish data-quality protocols. Missing observations, sensor faults, anomalous readings, and communication failures should be detected and corrected before AI models are trained or deployed.

8. Validate models across building types and climatic zones. AI models developed in one Pakistani city or building category should not automatically be generalized to other locations. Cross-building and cross-climate validation should be conducted before large-scale deployment.

9. Integrate renewable energy and storage where feasible. AI-based MEP management should eventually coordinate building demand with

rooftop solar generation and battery storage to improve self-consumption and grid flexibility.

10. Strengthen technical and institutional capacity. Facility managers, electrical engineers, HVAC professionals, and data specialists should receive training in AI-enabled Building Energy Management Systems.

11. Develop policy and interoperability standards. Regulators and relevant industry stakeholders should establish common standards for smart meters, Building Management Systems, data exchange, cybersecurity, privacy, and measurement and verification.

12. Conduct economic evaluation before deployment. Future implementations should assess capital cost, operating savings, demand charges, payback period, lifecycle cost, and return on investment alongside technical energy-performance indicators.

Limitations and Future Directions

Limitations

The proposed methodology focused on a relatively small sample of commercial buildings. Building characteristics, occupancy patterns, MEP configurations, climatic conditions, and operational practices vary substantially across Pakistan; therefore, findings from a limited sample may not be nationally representative.

The framework depended on the availability and quality of high-resolution energy and MEP data. Missing observations, sensor errors, inconsistent meter readings, and incomplete occupancy information may reduce forecasting and optimization performance.

AI models may experience reduced generalizability when transferred between buildings with different physical characteristics or operating schedules. Model performance can also change over time because of equipment degradation, occupancy changes, renovations, weather variability, and changes in operating practices.

The study emphasized energy performance and grid flexibility but did not comprehensively quantify indoor environmental quality, occupant satisfaction, equipment degradation, cybersecurity risk, or long-term maintenance costs. These factors

are important when moving from experimental prediction to operational deployment.

The proposed framework assumes a degree of MEP controllability and digital infrastructure that may not be available in all Pakistani commercial buildings. Interoperability between legacy equipment, meters, sensors, and modern AI platforms may represent a significant implementation challenge.

Future Research Directions

Future studies should validate the framework using longitudinal real-world data from a larger and geographically diverse sample of Pakistani commercial buildings. Buildings from Islamabad, Lahore, Karachi, Peshawar, Quetta, and other climatic zones could be compared to examine the robustness of AI models under different environmental and operational conditions.

Future research should also compare advanced forecasting and control approaches, including LSTM, XGBoost, Transformer-based models, reinforcement learning, Model Predictive Control, and hybrid AI-MPC frameworks. Comparative evaluation should use consistent out-of-sample testing and multiple performance metrics.

Further research should integrate occupancy prediction, weather forecasting, electricity tariffs, rooftop solar generation, battery storage, and demand-response signals into a unified optimization model. This would allow researchers to evaluate not only energy savings but also energy cost, carbon reduction, renewable-energy utilization, and grid-support performance.

Digital twins represent another promising direction. A building digital twin could continuously connect physical MEP assets with real-time sensor data and AI models, enabling simulation, predictive maintenance, fault detection, and adaptive control. Recent literature increasingly emphasizes the integration of AI, IoT, cyber-physical systems, and digital-twin technologies as the field moves toward closed-loop intelligent building management.

Future research should additionally incorporate multi-objective optimization, simultaneously

considering energy consumption, peak demand, electricity cost, occupant comfort, indoor air quality, equipment health, and carbon emissions. This would provide a more realistic representation of the trade-offs encountered by commercial building operators.

Finally, future empirical studies should conduct controlled field experiments and economic evaluations to determine whether AI-generated energy savings remain consistent over extended operating periods. Such validation would help establish the technical reliability, financial feasibility, scalability, and policy relevance of AI-based predictive MEP energy management in Pakistan.

REFERENCES

- Al Sayed, K., Boodi, A., Sadeghian Broujeny, R., & Beddiar, K. (2024). Reinforcement learning for HVAC control in intelligent buildings: A technical and conceptual review. *Journal of Building Engineering*, 95, 110085. <https://doi.org/10.1016/j.jobe.2024.110085>
- Alawi, O. A., Kamar, H. M., & Yaseen, Z. M. (2024). Optimizing building energy performance predictions: A comparative study of artificial intelligence models. *Journal of Building Engineering*, 88, 109247. <https://doi.org/10.1016/j.jobe.2024.109247>
- Arsecularatne, B. P., Rodrigo, N., & Chang, R. (2024). Review of reducing energy consumption and carbon emissions through digital twin in built environment. *Journal of Building Engineering*, 98, 111150. <https://doi.org/10.1016/j.jobe.2024.111150>
- Boukaf, M., Fadli, F., & Meskin, N. (2024). A comprehensive review of digital twin technology in building energy consumption forecasting. *IEEE Access*, 12, 187778–187799. <https://doi.org/10.1109/ACCESS.2024.3498107>

- Cespedes-Cubides, A. S., & Jradi, M. (2024). A review of building digital twins to improve energy efficiency in the building operational stage. *Energy Informatics*, 7, Article 11. <https://doi.org/10.1186/s42162-024-00313-7>
- Chou, J.-S., & Nguyen, H.-M. (2024). Simulating long-term energy consumption prediction in campus buildings through enhanced data augmentation and metaheuristic-optimized artificial intelligence. *Energy and Buildings*, 312, 114191. <https://doi.org/10.1016/j.enbuild.2024.114191>
- Copiaco, C., & Nour, M. (2024). Optimizing the operation of grid-interactive efficient buildings (GEBs) using machine learning. *Sustainability*, 16(20), 8752. <https://doi.org/10.3390/su16208752>
- Gao, T., Han, X., Wang, J., Geng, Y., Zhang, H., & Song, T. (2024). Enhancing building energy efficiency: An integrated approach to predicting heating and cooling loads using machine learning and optimization algorithms. *Journal of Building Engineering*, 98, 110759. <https://doi.org/10.1016/j.jobe.2024.110759>
- Hernández, J. L., de Miguel, I., Vélez, F., & Vasallo, A. (2024). Challenges and opportunities in European smart buildings energy management: A critical review. *Renewable and Sustainable Energy Reviews*, 199, 114472. <https://doi.org/10.1016/j.rser.2024.114472>
- Huotari, M., Malhi, A., & Främling, K. (2024). Machine learning applications for smart building energy utilization: A survey. *Archives of Computational Methods in Engineering*, 31, 2537–2556.
- Ji, J., Yu, H., Wang, X., & Xu, X. (2025). Machine learning application in building energy consumption prediction: A comprehensive review. *Journal of Building Engineering*.
- Latoń, D., Grela, J., & Ożadowicz, A. (2024). Applications of deep reinforcement learning for home energy management systems: A review. *Energies*, 17(24), 6420. <https://doi.org/10.3390/en17246420>
- Mahmood, M., Chowdhury, P., Yeassin, R., Hasan, M., Ahmad, T., & Chowdhury, N.-U.-R. (2024). Impacts of digitalization on smart grids, renewable energy, and demand response: An updated review of current applications. *Energy Conversion and Management*, 24, 100790. <https://doi.org/10.1016/j.ecmx.2024.100790>
- Mathumitha, R., Rathika, P., & Manimala, K. (2024). Intelligent deep learning techniques for energy consumption forecasting in smart buildings: A review. *Artificial Intelligence Review*, 57, 35. <https://doi.org/10.1007/s10462-023-10660-8>
- Mustufa, A., Anwar, M., & Khan, T. I. (2024). Energy optimization of an institutional building to reduce the energy and air conditioning demand. *Journal of Building Engineering*, 98, 111309. <https://doi.org/10.1016/j.jobe.2024.111309>
- Olu-Ajayi, R., Alaka, H., Sunmola, F., Ajayi, S., & Mporas, I. (2024). Statistical and artificial intelligence-based tools for building energy prediction: A systematic literature review. *IEEE Transactions on Engineering Management*, 71, 14733–14753. <https://doi.org/10.1109/TEM.2024.3422821>
- Todorean, L., Cioara, T., Anghel, I., Sarmas, E., Michalakopoulos, V., & Marinakis, V. (2025). Demand response optimization for smart grid integrated buildings: Review of technology enablers landscape and innovation challenges. *Energy and Buildings*, 326, 115067. <https://doi.org/10.1016/j.enbuild.2024.115067>

Xu, Y. (2025). Energy flexibility realization in grid-interactive buildings for demand response: State-of-the-art review on strategies, resources, control, and KPIs. *Energies*, 18(18), 4960. <https://doi.org/10.3390/en18184960>

Yu, H., Tam, V. W. Y., & Xu, X. (2024). A systematic review of reinforcement learning application in building energy-related occupant behavior simulation. *Energy and Buildings*, 312, 114189. <https://doi.org/10.1016/j.enbuild.2024.114189>

Yussuf, R. O., & Asfour, O. S. (2024). Applications of artificial intelligence for energy efficiency throughout the building lifecycle: An overview. *Energy and Buildings*, 305, 113903. <https://doi.org/10.1016/j.enbuild.2024.113903>

Zhou, X., Du, H., Xue, S., & Ma, Z. (2024). Recent advances in data mining and machine learning for enhanced building energy management. *Energy*, 307, 132636. <https://doi.org/10.1016/j.energy.2024.132636>

