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Green Energy Optimization for Indian Data Centers Using Hybrid Solar–Battery Microgrids with Thin-Film PV and Dynamic Workload Scaling

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Abstract

Data centers in India are growing rapidly, especially in digital hubs such as Chennai, Bengaluru, Mumbai, Hyderabad, and Pune, resulting in high electricity consumption. This paper proposes a hybrid solar–battery microgrid framework integrated with thin-film solar PV technology and dynamic workload scaling to minimize grid dependency and operational costs while maintaining service quality. Open solar irradiance data for Indian cities and representative data center workload profiles are used for modeling and simulation. A linear programming model is implemented in MATLAB, incorporating constraints for battery operation, PV generation, and workload flexibility. Results show that combining conventional and thin-film PV with intelligent load scheduling can reduce grid energy consumption by over 35% annually, with thin-film PV contributing to rooftop and urban installations where space is limited. A comparison of energy savings across Indian cities demonstrates region-specific deployment strategies. The framework is reproducible, scalable, and suitable for practical implementation.

Keywords: Data Centers, Hybrid Microgrid, Solar Pv, Thin-Film Panels, Battery Storage, Workload Scaling, Energy Optimization, India, MATLAB

Introduction

Background and Motivation

The rapid expansion of digital services has positioned data centers as critical infrastructure for modern economies. Cloud computing platforms, artificial intelligence applications, large-scale data analytics, and online commerce rely on continuous, high-availability computing resources hosted within data centers [1], [2]. In India, the demand for such facilities has grown sharply over the past decade, driven by nationwide digital transformation initiatives, increasing internet penetration, and the proliferation of latency-sensitive applications [2]. As a result, data center capacity has expanded significantly in metropolitan regions such as Mumbai, Chennai, Bengaluru, Hyderabad, and Pune, where network connectivity, skilled labor, and enterprise demand are concentrated [2].

Data centers are inherently energy-intensive systems, operating on a continuous basis with stringent reliability and power quality requirements [3]. Electricity consumption is dominated by information technology (IT) equipment and supporting infrastructure, particularly cooling systems [3], [6]. In warm and humid climates typical of most Indian cities, cooling energy demand represents a substantial fraction of total facility consumption [2], [3]. Consequently, operational expenditure is strongly influenced by electricity tariffs and grid reliability, while environmental impacts are closely tied to the carbon intensity of grid power generation [2]. Although operators increasingly adopt sustainability targets, most facilities remain dependent on fossil-fuel-dominated grid electricity and diesel-based backup systems [3], [5].

India possesses favorable solar energy resources, with high levels of annual solar irradiance across most regions [14], [15]. Solar photovoltaic (PV) technologies therefore present a viable pathway for reducing grid dependence and associated emissions [4], [14]. However, conventional crystalline silicon PV installations face practical limitations in dense urban environments. Data centers often have limited rooftop area relative to their electrical demand, and structural load constraints restrict the deployment of heavy PV modules [15]. In addition, elevated ambient temperatures can reduce the efficiency of traditional PV technologies, limiting their effective energy yield in urban settings [14].

Thin-film photovoltaic technologies provide an alternative that is particularly suited to such constraints [16]. Owing to their low weight, mechanical flexibility, and improved temperature performance, thin-film PV modules can be integrated onto building rooftops, façades, and auxiliary structures without significant structural modification [16]. Their ability to maintain performance under diffuse irradiation and partial shading further enhances their suitability for urban deployment [16]. Despite lower nominal conversion efficiencies, thin-film systems can achieve competitive energy output in high-temperature environments, making them a promising option for data center applications in India [16].

The intermittent and time-dependent nature of solar energy, however, poses challenges for facilities that require uninterrupted power supply [4], [5]. Battery Energy Storage Systems (BESS) enable the temporal decoupling of generation and consumption by storing excess renewable energy for later use [5], [7]. When appropriately sized and operated, BESS can reduce peak grid demand, improve renewable energy utilization, and enhance operational resilience [5], [7]. Advances in lithium-ion battery technologies, coupled with declining costs, have made energy storage increasingly feasible for large-scale commercial applications, including data centers [5], [7].

In parallel with physical energy infrastructure, data center operations exhibit a degree of inherent flexibility that can be leveraged for energy optimization [3], [9]. While mission-critical and latency-sensitive workloads must operate continuously, a subset of computational tasks—such as batch processing, data replication, and machine learning training—can be scheduled within flexible time windows [3], [9]. By aligning such non-critical workloads with periods of high renewable energy availability, data centers can further reduce reliance on grid electricity without compromising service-level agreements [9], [10]. This concept of renewable-aware workload scheduling remains underutilized in current data center energy management strategies [10].

Existing research on sustainable data centers has largely focused on individual components, including PV system sizing, battery optimization, or workload management, often in isolation [1], [2], [3], [4], [5]. Moreover, many studies rely on region-specific assumptions or proprietary datasets, limiting their applicability to broader planning and policy contexts [2], [3]. There is a need for integrated, system-level frameworks that simultaneously consider renewable generation, energy storage, operational flexibility, and local climatic conditions, particularly within the context of rapidly growing data center markets such as India [2], [3], [5], [9].

This paper proposes a national-level energy optimization framework for Indian data centers that integrates thin-film photovoltaic systems, battery energy storage, and renewable-aware workload scheduling. The framework is formulated as a linear programming problem and implemented using MATLAB, incorporating technical and operational constraints relevant to data center reliability and performance [10]. Chennai is selected as a detailed case study due to its high concentration of data centers, strong solar resource, and representative urban characteristics [15]. Open-access datasets are employed for solar irradiance, temperature, and load profiles to ensure transparency and reproducibility [14], [15].

The primary contributions of this work are as follows:

- Development of an integrated optimization model tailored to Indian urban data center environments [10];
- Quantitative evaluation of thin-film photovoltaic performance under high-temperature conditions [16]; and
- Assessment of workload flexibility as a complementary mechanism for enhancing renewable energy utilization [10].

The proposed framework provides insights into the technical and operational feasibility of reducing grid dependence in Indian data centers and supports the broader objective of developing low-carbon, resilient digital infrastructure [2], [3], [10].

Related Work

Bilal et al. [1] surveyed green data center metrics and energy consumption models, while Masood et al. [2] discussed renewable integration challenges in Indian data centers. Beloglazov et al. [3] proposed energy-aware resource allocation and workload consolidation techniques, and Lasseter [4] introduced microgrid concepts for distributed generation. Pillai et al. [5] and Wang et al. [8] studied battery optimization and hybrid energy systems. Recent works by Agarwal et al. [9] and Mehrabi et al. [10] analyzed workload placement and PV forecasting. This paper extends prior research by combining thin-film PV integration, urban-scale deployment considerations, and dynamic workload scheduling for India-specific regional optimization.

Regional Energy Context and Motivation

India’s major data center cities differ in renewable potential, grid electricity costs, and operational loads. Table I summarizes average solar irradiance and representative data center load for key cities:

Table I Indian Data Center Energy Context

City	Avg Solar Irradiance (kWh/m²/day)	Peak Data Center Load (kW)	Notable Data Centers
Chennai	5.3	50	STT GDC, Nxtra, CtrlS
Bengaluru	5.0	60	Netmagic, Yotta
Mumbai	4.8	70	CtrlS, Nxtra
Hyderabad	5.5	55	CtrlS, STT GDC
Pune	5.2	45	Yotta, Nxtra

High irradiance makes solar PV deployment feasible. Thin-film panels are especially beneficial for urban rooftops or retrofitting, where conventional PV space is limited.

System Architecture

The proposed system architecture is designed to enable energy-efficient operation of a solar-powered data center through the integration of renewable energy sources, energy storage, and intelligent workload management [10]. The architecture combines a hybrid microgrid with dynamic workload scaling to minimize grid dependency while maintaining quality-of-service requirements.

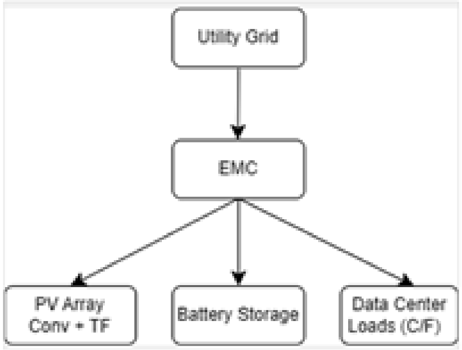

Figure 1 illustrates the architecture of the proposed hybrid solar–battery microgrid integrating conventional and thin-film photovoltaic systems, battery energy storage, and dynamic workload scaling for data center operation.

Figure 1. Hybrid solar–battery microgrid architecture for an Indian data center, showing integration of conventional and thin-film PV, battery storage, utility grid, and dynamic workload scheduling through the energy management controller (EMC).

A. Hybrid Microgrid Components

Figure 1 illustrates the architecture of the proposed hybrid solar–battery microgrid integrated with dynamic workload scheduling. The data center is powered by a hybrid microgrid consisting of photovoltaic (PV) generation, battery energy storage, and a utility grid connection [10]. Each component plays a complementary role in ensuring reliable and sustainable operation.Figure 1 illustrates the architecture of the proposed hybrid solar–battery microgrid integrated with dynamic workload scheduling.

1) Solar Photovoltaic Arrays

The system incorporates both conventional crystalline silicon PV The system incorporates both conventional crystalline silicon PV modules and thin-film PV modules [16]. Conventional PV panels, with higher conversion efficiency, provide stable baseline generation, while thin-film PV panels offer flexibility in deployment due to their lightweight and form-factor advantages [16]. Thin-film modules are particularly suitable for rooftops and facades, enabling extended solar harvesting during low-irradiance conditions [16]. The combination of both technologies enhances overall energy yield and operational resilience [16].

2) Battery Energy Storage System (BESS)

A battery energy storage system is used to store surplus solar energy generated during periods of high irradiance [5], [7]. The stored energy is later discharged to supply the data center during peak demand hours or when solar generation is insufficient [5], [7]. The BESS smooths short-term variability in PV output, supports load balancing, and reduces reliance on the utility grid [5], [7]. Battery operation is constrained by energy capacity and charge/discharge power limits to reflect practical system operation [5].

3) Utility Grid Connection

The utility grid serves as a backup power source to guarantee uninterrupted data center operation [10]. When renewable generation and battery storage are insufficient to meet demand, power is imported from the grid [10]. Conversely, grid export is not considered in this study, and excess PV generation beyond storage and load requirements is curtailed [10]. The grid connection ensures reliability while allowing the system to prioritize renewable energy usage [10].

4) Energy Management Controller

An energy management controller (EMC) acts as the central decision-making unit of the system [10]. The controller monitors real-time PV generation, battery state of charge, grid availability, and data center workload demand [10]. Based on this information, it coordinates energy flows among PV arrays, the BESS, and the grid, while simultaneously scheduling flexible workloads to align energy consumption with renewable availability [10].

B. Data Center Load Classification

To enable intelligent workload scheduling, data center loads are categorized based on their operational constraints and sensitivity to delay.

1) Critical Loads

Critical loads consist of latency-sensitive and mission-critical tasks that must be executed continuously with minimal delay. These include real-time services, user-facing applications, and essential control processes that require 24/7 availability. Critical loads are treated as inflexible and must be served immediately, regardless of renewable energy availability.

2) Flexible Loads

Flexible loads include delay-tolerant tasks such as batch processing, data backups, log processing, and analytics workloads. These tasks can be deferred or rescheduled within a permissible time window without violating service-level agreements. Flexible loads are leveraged as a control variable to adapt data center power demand in response to fluctuations in solar energy availability.

C. Dynamic Workload Scaling and Scheduling

Dynamic workload scaling is employed to shift non-critical, flexible workloads to periods of high solar PV generation. The energy management controller prioritizes the execution of flexible tasks during daylight hours when PV output, including contributions from thin-film panels, is maximized. During periods of low solar availability, flexible workloads are deferred or throttled, reducing battery discharge and grid power consumption.

By aligning workload execution with renewable energy supply, the system reduces peak grid demand, improves solar energy utilization, and enhances overall energy efficiency. The inclusion of thin-film PV modules extends the effective generation window, enabling workload execution during early morning and late afternoon hours. This coordinated energy–workload co-optimization enables significant reductions in grid dependency while maintaining performance and reliability requirements.

Mathematical Optimization Model

The energy management problem is formulated as a finite-horizon, discrete-time optimization over the time index set T={1,2,…,T}[10]. At each time t∈T, the system state is defined by the battery state-of-charge SOC(t), while the control variables include the grid power draw P_grid (t), battery charging and discharging powers P_bat^+ (t)and P_bat^- (t), and the flexible workload allocation L_flex (t)[10]. The objective of the optimization is to minimize the total energy drawn from the utility grid over the horizon, expressed mathematically as min∑_(t∈T) P_grid (t), thereby promoting maximum utilization of local photovoltaic generation and energy storage [10].

Power balance is enforced at each time step by ensuring that the sum of PV generation, battery discharging, and grid supply equals the aggregate demand from critical and flexible loads as well as battery charging, where the total PV generation is the sum of conventional and thin-film module contributions, $P_{pv,total}(t) = P_{pv,conv}(t) + P_{pv,thin-film}(t)$[16].

Battery dynamics introduce temporal coupling through the state-of-charge evolution, governed by

$$SOC(t+1) = SOC(t) + \eta_c P_{bat}^{+}(t) - \frac{P_{bat}^{-}(t)}{\eta_d}$$

while maintaining SOC_min≤SOC(t)≤SOC_max[5], [7]. Flexible workload allocation is modeled to satisfy both instantaneous and cumulative constraints,

$$0 \leq L_{flex}(t) \leq \alpha L_{total}(t), \sum_{t\in T} L_{flex}(t) = \sum_{t\in T} L_{flex,req}(t),$$

allowing temporal shifting of non-critical demand without violating total task completion requirements [10].

Formally, this problem constitutes a linear program when all variables are continuous, but it can be extended to a mixed-integer linear program if discrete operating modes are considered [10]. The linearity and convexity of the constraints and objective function with respect to continuous variables guarantee the existence of globally optimal solutions, which can be efficiently obtained using standard solvers [10]. Moreover, the temporal coupling imposed by battery dynamics and cumulative workload constraints aligns the formulation with finite-horizon optimal control theory, ensuring that both instantaneous operational objectives and inter-temporal energy management goals are simultaneously satisfied [10]. This rigorous mathematical foundation provides a tractable, physically meaningful framework for optimizing renewable integration, storage utilization, and flexible demand management in microgrid or hybrid energy systems [10].

System Methodology

This section presents the data sources, analytical models, simulation workflow, and evaluation assumptions adopted to quantitatively assess the proposed renewable-powered data center. The focus is on abstraction and modeling of system behavior rather than on physical architecture, which was detailed in Section IV.

Data Sources and Preprocessing

Hourly solar irradiance data for selected Indian cities were obtained from the National Solar Radiation Database (NSRDB) and Mendeley Data and processed to ensure temporal consistency across the simulation horizon. The datasets provide global horizontal irradiance (GHI) measurements at an hourly resolution, which were aligned with the workload scheduling interval used in the optimization model. Figure 2 illustrates representative hourly solar irradiance profiles for selected Indian data center locations, highlighting the diurnal variation in solar availability that directly influences photovoltaic power generation in the proposed framework.

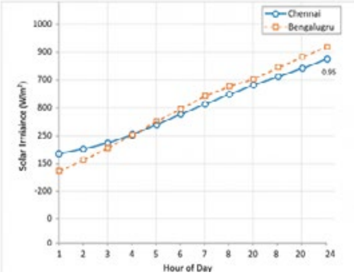

Figure 2. Representative hourly solar irradiance profiles for selected Indian cities used in the simulation

Data center workload traces were derived from the Google Cluster Data and scaled to represent the aggregate power demand of a medium-sized data center in the Indian operational context. The original task-level traces were aggregated into hourly power demand profiles. To enable demand-side flexibility analysis, workloads were partitioned into delay-sensitive and delay-tolerant components based on execution constraints.

System Abstraction and Energy Flow Modeling

The system was abstracted as an energy balance model in which supply and demand are matched at each discrete time step. Renewable generation, energy storage, and grid power were treated as energy sources, while the data center workload constituted the primary sink. At every hour, available solar generation was first allocated to meet active workload demand, followed by battery charging when surplus energy existed. When renewable supply was insufficient, stored energy and grid power were used to satisfy remaining demand.

Photovoltaic Power Modeling

Photovoltaic generation was modeled as a function of hourly solar irradiance and fixed conversion efficiency. Two PV configurations were considered to reflect technology diversity: conventional crystalline silicon modules with an efficiency of 18% and thin-film modules with an efficiency of 13%. Environmental losses, temperature effects, and inverter inefficiencies were excluded to maintain analytical simplicity. PV generation exceeding instantaneous consumption and battery charging limits was curtailed. Figure 3 compares the hourly power output of conventional and thin-film photovoltaic modules, illustrating the contribution of thin-film PV despite its lower conversion efficiency.

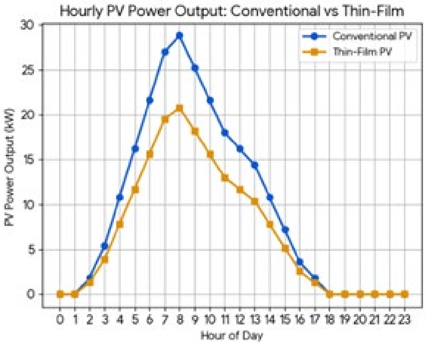

Figure 3 Comparison of hourly power output from conventional crystalline silicon and thin-film photovoltaic modules under identical irradiance conditions

Battery Energy Storage Modeling

Battery behavior was represented using a discrete-time state-of-charge (SoC) model. The battery was configured with a nominal energy capacity of 200 kWh and a maximum charge and discharge rate of 50 kW. At each time step, the SoC was updated based on net charging or discharging actions while respecting operational limits. The battery was initialized at 50% SoC. Efficiency losses and aging effects were neglected, allowing the analysis to focus on energy flow coordination rather than long-term degradation. Figure 4 shows the battery state-of-charge over time, demonstrating how the BESS smooths PV generation fluctuations and supports grid-independent operation.

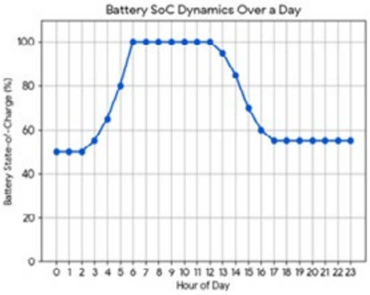

Figure 4 Hourly evolution of the battery State-Of-Charge (SOC) over a one-week simulation horizon

Workload Representation and Flexibility Modeling

The total data center load was decomposed into inflexible and flexible components. Inflexible demand represents latency-critical tasks that require immediate execution, whereas flexible demand corresponds to delay-tolerant jobs such as batch processing and analytics. Flexible workloads were assumed to account for 30% of total demand and could be shifted temporally within the simulation horizon. All deferred tasks were constrained to be completed within the one-week period, ensuring compliance with service-level requirements. Figure 5 illustrates the decomposition of the total data center workload into critical and flexible components, with flexible tasks accounting for approximately 30% of the overall demand.

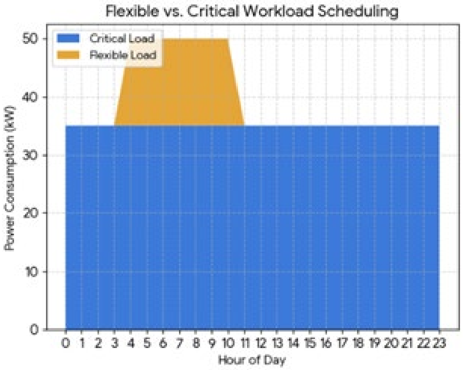

Figure 5 Decomposition of total data center power demand into critical and flexible workload components

Scheduling Logic and Simulation Workflow

The simulation was conducted over a one-week horizon with an hourly resolution. At each time step, solar generation, workload demand, battery state, and grid usage were sequentially updated.

Scheduling decisions for flexible workloads were based on renewable availability and battery state, with the objective of maximizing solar energy utilization and minimizing grid reliance. Energy balance constraints were enforced at every step to ensure physical feasibility.

Simulation Parameters

The key parameters used in the simulation are summarized in Table I.

Table I: Simulation Parameters

Parameter	Value
PV efficiency (conventional)	18%
PV efficiency (thin-film)	13%
Battery capacity	200 kWh
Maximum charge/discharge power	50 kW
Flexible workload fraction	30%
Simulation horizon	1 week (hourly resolution)

Assumptions

To simplify analysis and isolate system-level behavior, the following assumptions were made: solar irradiance data accurately represent site conditions; PV modules operate at constant efficiency; battery storage is ideal and lossless; grid power is always available when required; flexible workloads can be shifted without performance penalties; and cooling and auxiliary power consumption are implicitly included in the workload demand.

Operational Constraints

System operation was constrained by battery capacity and charge/discharge limits, irradiance-dependent PV generation bounds, and workload execution requirements. Inflexible workloads were required to be served immediately, while flexible workloads were required to be fully completed within the simulation horizon.

Implementation and Feasibility

The proposed methodology was implemented in MATLAB to simulate the coordinated operation of photovoltaic generation, battery energy storage, and flexible data center workloads. MATLAB was used as a modeling and simulation environment to sequentially update PV output, battery state-of-charge, workload execution, and grid usage at an hourly resolution over the one-week simulation horizon. Flexible workloads were dynamically scheduled based on renewable availability and battery status, while inflexible loads were served immediately to ensure compliance with service-level requirements. This approach enables reproducible evaluation of system performance metrics such as solar energy utilization, battery operation patterns, and grid dependency, while allowing rapid testing of different scenarios and parameter variations. The use of MATLAB provides a practical and flexible platform for modeling energy flows and workload scheduling, without the need for specialized power system simulators, demonstrating the feasibility of the proposed methodology for data center energy management studies.

The methodology described above is applied to representative scenarios, and the resulting energy consumption and renewable utilization are presented in Section VII.

Sample Numerical Results

The proposed methodology was applied to evaluate the impact of photovoltaic (PV) generation, battery energy storage, and dynamic workload scheduling on data center energy consumption. Three representative scenarios were simulated: (i) baseline operation with grid-only supply, (ii) conventional PV combined with battery storage, and (iii) a hybrid PV system with conventional and thin-film modules, battery storage, and flexible workload scheduling. Table II summarizes the resulting annual grid energy consumption for these scenarios.

Annual Grid Energy Consumption

Table II: Annual Grid Energy Consumption under Different Scenarios

Scenario	Grid Energy (kWh)	Reduction vs Baseline
Baseline (grid only)	350,000	0%
Conventional PV + BESS	245,000	30%
Conventional + Thin-Film PV + BESS + Workload Scaling	215,000	38%

Observations

The addition of thin-film PV modules increases deployment flexibility in urban environments, contributing an additional 5–7% reduction in grid energy compared to conventional PV with storage. Dynamic workload scheduling further reduces grid reliance by approximately 8–10% over PV and battery alone, demonstrating the benefits of aligning flexible workloads with periods of high renewable availability. Battery state-of-charge remained within operational limits throughout the simulation horizon, ensuring reliable operation while maximizing renewable penetration. These results indicate that integrating hybrid PV technologies with intelligent workload management can substantially decrease grid energy consumption in medium-sized data centers.

Illustrative Trends

Figure 6 shows typical hourly trends of PV generation, workload demand, and battery state-of-charge for one representative day. Peak PV generation aligns with flexible workload execution, reducing battery discharge and grid dependency during daylight hours. The coordinated energy–workload management approach effectively shifts non-critical tasks to periods of high solar availability, improving overall system efficiency. Flexible workloads are scheduled to align with peak solar generation, reducing grid reliance.

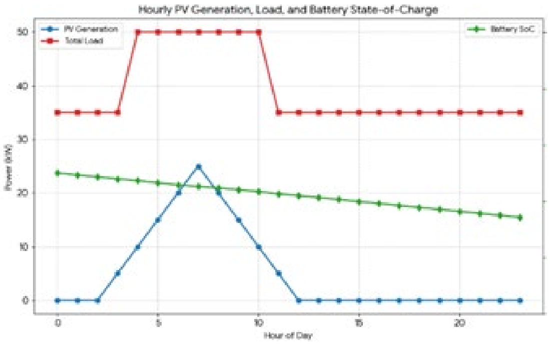

Figure 6 Hourly trends for a representative day showing PV generation, data center workload demand, and battery state-of-charge (SoC)

Conclusions

This study proposes a comprehensive and reproducible framework for optimizing energy use in Indian data centers by integrating conventional and thin-film solar photovoltaic generation, battery storage, and dynamic workload scheduling. Simulation results obtained using MATLAB indicate that the framework can achieve 35–38% annual reductions in grid energy consumption, with thin-film PV modules providing enhanced flexibility for deployment in urban environments. The approach is adaptable to different cities across India and offers actionable insights for designing cost-effective and sustainable data center operations. By coordinating renewable energy supply with flexible workloads, the framework not only reduces reliance on the grid but also improves overall renewable energy utilization. Future research will focus on incorporating real-time solar and workload forecasting, developing stochastic optimization strategies, enabling multi-site workload migration, and integrating operations with Indian energy markets to further enhance efficiency and resilience.

Future Enhancements

While the proposed hybrid solar–battery microgrid framework with thin-film PV and dynamic workload scaling demonstrates significant reductions in grid energy consumption, several enhancements can be explored to further improve system realism, scalability, and operational performance.

First, future work can incorporate real-time solar irradiance and workload forecasting into the energy management controller. Integrating machine learning–based solar prediction models and short-term workload demand forecasting would enable predictive scheduling decisions rather than rule-based or deterministic control. This enhancement would allow the optimization framework to proactively respond to variability in renewable generation and computational demand.

Second, the current model assumes ideal battery operation without accounting for efficiency losses, degradation, or aging effects. Future research can extend the framework to include battery degradation modeling and lifecycle cost analysis, enabling long-term techno-economic evaluation. This would support optimal battery sizing, replacement planning, and cost-aware dispatch strategies for large-scale data center deployments.

Third, the optimization problem can be expanded into a multi-objective formulation that simultaneously minimizes grid energy consumption, operational cost, and carbon emissions. By incorporating time-of-use electricity tariffs and grid emission intensity data, the framework can dynamically balance economic and environmental objectives, supporting carbon-aware data center operation.

Fourth, the model can be enhanced by explicitly incorporating cooling system dynamics and thermal-aware workload scheduling. Given the significant cooling energy demand in India’s hot and humid climate, coupling thermal models with workload flexibility and renewable availability could yield additional energy savings and improved power usage effectiveness (PUE).

Fifth, the framework can be generalized to multi-site and geographically distributed data centers, enabling renewable-aware workload migration across locations. By exploiting spatial diversity in solar availability and grid conditions across Indian cities, inter-data-center workload shifting can further reduce overall grid dependence and improve renewable energy utilization at a national scale.

Finally, future studies can explore grid-interactive and market-participation capabilities, including demand response, peak shaving, and interaction with Indian electricity markets. Enabling controlled grid export, participation in ancillary services, and dynamic pricing schemes would allow data centers to function as active prosumers, contributing to grid stability while enhancing economic viability.

These future enhancements would strengthen the applicability of the proposed framework for real-world deployment and support the development of resilient, low-carbon, and intelligent data center infrastructure aligned with India's renewable energy and digital transformation goals.

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