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AI-Driven Optimization And Strategic Use Of Phase Change Materials For Smart Thermal Regulation

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Abstract: *Artificial Intelligence (AI) has been introduced as a transformative solution to increasing energy efficiency in residential and industrial buildings, industrial systems, and intelligent devices with the usage of advanced thermal management technologies. The temperature regulating characteristics of Phase Change Materials (PCMs) have been known since long and it is therefore considered by the experts to store heat and release latent heat which may stabilise fluctuations in temperature and limit spiking of energy. Nevertheless, they have problems in their practical implementation associated with the choice of the most effective materials, methods of their arrangement, and control in conditions of dynamic changes of working and environmental conditions. The current work addresses an AI-based optimization strategy that combines tactical applications of PCMs in smart thermal management. The study integrates models of computation, simulations of building energy, and machine learning methods to determine the most viable PCM architectures based on climatic regions and specifications of operation. The experimental verification testbed is a field testbed (technology hybrid laboratory) which verifies the real-time assessment of thermal response, energy savings and occupant comfort. Evidence shows that the incorporation of AI-based PCM has the potential to provide 28-35% increase in thermal stability and 20-25% drop in cooling/heating energy requirements than the traditional modes of PCM implementation. The given methodology does not only optimize the use of materials and lower the operational expenditure but also establishes the future adoption of adaptive and self-learning thermal control systems in smart infrastructures of the future.*

Keywords: *Artificial Intelligence, Phase Change Materials, Smart Thermal Regulation, Energy Efficiency, Building Energy Management, Machine Learning Optimization, Thermal Storage Systems, PCM Deployment Strategy, Adaptive Thermal Control, Sustainable Building Technologies.*

I. INTRODUCTION

The global menace of increasing climate change combined with the fast-rising energy demands around the world, has necessitated the discussion about energy efficiency and sustainable thermal management becoming one of the most important issues facing residential or industrial sectors. Specifically, heating, ventilating, and air conditioning (HVAC) systems are one of the key determinants of the energy consumption with the share of about 40 percent of energy requirements worldwide in the building operation energy demand. This need will continue to grow with the growing urbanization, rising standards of living, and as well as the need to have thermal comfort in different zones of various climatic conditions. It is hence necessary to integrate novel thermal storage systems to decrease dependence on the energy sources and neutralize the oscillating temperatures and increase occupant comfort to accommodate wider sustainability ambitions. The capability of PCMs to store and release great amounts of latent heat in the face of phase transitions has seen PCMs become an promising method of thermal regulation. The ability of the PCMs to store heat during a time that the surrounding temperature is higher than an established limit, and to release the heat at lower temperatures can enhance a substantial decrease in peak load demand, enhance the performance of an HVAC system, and also can reduce dependency on normal energy applications. This is why they are great to be used in building envelopes, 3 industrial process cooling, 4 renewable energy storage and 5 even in electronics thermal management. But, the real world application of PCMs is not an easy job. Their performance is directly influenced by factors like material selection, melting temperature, latent heat capacity, thermal conductivity, and integration methodology etc. Furthermore, this is required to be configured and controlled manually, which becomes complicated due to dynamic environmental conditions, different occupancy patterns and even seasonal climatic changes. Artificial Intelligence (AI) provides a breakthrough concept with regard to the strategic ways of employing PCMs to gain optimal thermal control. AI algorithms especially machine learning (ML) and reinforcement learning are well suited to detecting patterns in high-dimensional, multidimensional datasets and have the capability to be changed on the fly. With the help of predictive analytics, AI can predict the thermal loads and future changes of environmental conditions and automatically adapt PCM settings to keep the thermal balance. Moreover, the optimization that can be carried out with the help of AI can be utilized to deal with the efficiency of the use of materials, which will require choosing the optimal type of PCM, its thickness, and the zone of placement under the conditions of a particular operating regime. This kind of intelligence lets PCMs act in conjunction with an adaptive, self-learning thermo management system instead of pre-defined solutions. The AI-PCM technology application has a genuine potential as a pair in the sphere of smart buildings and energy-responsive infrastructure. In the construction of applications, AI has an opportunity to combine the PCM behavior with other intelligent control systems, including HVAC, window shade, and ventilation systems, to establish a balance between comfort and energy consumption. On an industrial scale, the implementation of AI-based PCM use can stabilize the processes and minimize the cooling loads, decreasing operational expenses in the process. Further, both AI and PCMs fit with international schemes to utilize low-carbon or even net-zero energy buildings and generate best-in-class infrastructure with self-governing systems and smart materials as their core. Nevertheless, despite these benefits, the research and practice of AI-based PCM strategies are at an early stage. The literature tends to be either material-based research on PCM or control-based smart building systems with AI rather than integrating both avenues at the profound level. Furthermore, evaluation of the PCM installations in terms of performance tends to be restricted to constant set-ups or simulations without adaptive optimization, resulting in an energy savings not maximized in nominal, operating circumstances. Development of a solution to this gap involves the interdisciplinary approach merging the fields of thermal physics, materials engineering, and high-performance computing intelligence. The proposed framework aims to change PCM implementation by combining PCM thermal storage with AI predictive control to make a responsive, dynamic, and intelligent system rather than a passive thermal buffering application. These innovations can help to speed up the process of switching to smart thermal control, lower the ecological signature of the built environment, and play a part in achieving the overall goals of sustainable energy management.

Ii. Releated works

Artificial Intelligence (AI) and Phase Change Materials (PCMs) have many attributes in combination with smart thermal regulation, which has been a developing field of research based on multiple disciplines such as materials science, thermal engineering, and computational optimization, and building energy management versatile approach. Potential studies showing integrated research combining both PCM deployment strategies and AI-controlled systems have been limited to some extent in the available literature, which has significant amounts of literature available about each individual field, yet is fairly limited in the differentiation of how the two areas can be combined together in order to create a coherent, overall optimization strategy. Some of the initial works on PCM applications though on thermal-energy storage highlighted the special abilities of the material to absorb and release Latent heat of transition during phase transition and therefore a material that best suited in buffering temperature variations in buildings and industrial processes [1]. Experiments proved that using PCMs in building envelope, wallboard and ceilings can greatly stabilize the temperature in the building and decrease HVAC loads [2]. The benefits however rely very much on the melting temperature of PCM and its location in the building envelope and its compatibility with the climate [3]. The traditional methods of PCM implementation were based on fixed design parameters and did not have flexibility to change in real time in response to

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environmental or occupancy changes. PCM formulation on the materials engineering front has opened up new avenues of operations. One of the crucial drawbacks of traditional PCMs is a low rate of heat transfer, but the issues have been resolved by producing composite PCMs to demonstrate a higher thermal conductivity [4]. As an example, nanoparticle PCMs have indicated quicker charging/discharging period and better power per square inch storing thickness [5]. Also, encapsulation methods have also increased the stability and leak resistance, as well as the integration potential of specific PCM at building scales [6]. In spite of this, even some high-performance PCMs need to be strategically placed and have controls to obtain the best performance in differing conditions. Alongside the development of the PCM material, building energy management has also been made with the use of AI-based control systems. Artificial intelligence (AI), especially through the application of machine learning (ML) algorithms, has been used more and more to model, predict and, optimize the energy use in buildings [7]. Different neural networks, support vector machines and reinforcement learning models have demonstrated capacity to accurately predict the indoor temperatures, HVAC loads and to automatically adapt the parameters of the system in real-time [8]. Measurable peak energy demand and overall energy consumption have been reduced in large-scale deployments of AI-based control systems [9].When considering **AI applications in thermal energy storage systems**, several studies have explored predictive control strategies for dynamic systems. For example, reinforcement learning (RL) algorithms have been applied to optimize charging and discharging cycles in thermal storage tanks, adapting control strategies to fluctuating weather conditions and occupancy patterns [10]. Similarly, fuzzy logic controllers have been used to regulate PCM activation in solar air heating systems, achieving higher efficiency compared to static control schemes [11]. These approaches highlight the capability of AI to enhance the adaptability and responsiveness of thermal storage systems to external stimuli. Namely, the research on specific AI-powered PCM integration remains scarce yet developing. In some experimental works, however, it was shown how AI can be used to choose the optimal type and location of PCM to be used in a particular operation situation [12]. To illustrate, the application of genetic algorithms, combined with the building energy simulation models, demonstrated that the AI optimised configurations of PCMs saved energy up to 18 percent per annum compared with the traditional positioning of PCMs [13]. Deep learning has found applications in other works to model the thermal behavior of PCM under various operating conditions so that its utilization in terms of latent heat can be optimized by proactive adjustments [14]. The study of simulations has served a good lesson on the AI-PCM synergy as well. Performance simulation tools of building (e.g., EnergyPlus and TRNSYS) have been paired with optimization algorithms (e.g., particle swarm optimization (PSO), ant colony optimization (ACO)) in order to optimize the PCM deployment strategies [15]. These models have been able to locate climate-based specific designs of PCMs, which counter minimum energy requirement whilst ensuring that the houses are thermally comfortable. The majority of these studies, nevertheless, are only conducted within a simulation environment without full experimental authentication. On the commercial and industrial use-case side, PCMs with AI based system control have been promising to lower the operational expenditure of items kept in cold storage, in data centers and in industry plants. In that case, the AI algorithms will enable dynamic schedule changes in the cooling processes and forecast load fluctuations, and align PCM behave with the mechanical cooling systems to smooth peak power utilisation [9], [14]. In addition, AI-powered predictive maintenance guarantees PCM performance is optimised because performance deterioration is detected before it becomes severe. The development of sensor networks with the assistance of IoT has increased the possibilities of AI-PCM systems further. The temperature gradients, energy flows and PCM phase states can be monitored in real time and propagated to the AI models to be continuously optimized [10]. Recent developments in cloud-based analytics platforms provide a solution to this problem by enabling AI to process large-scale thermal data across buildings or facilities to learn about the novel environment conditions [7]. It is through such systems that the scaling of AI-PCM solutions is achieved, as complex problems encountered in experimental arrangements are scaled up to pervasiveness. In spite of the progress, there are still some important gaps in research. To begin with, no long-term real-world data on AI-optimized PCM systems operation have been collected to date, particularly under different climatic and operational conditions. Most of the experimental studies are based on short experimentation or in the lab-based practices and simulations that could not apply to real dynamic conditions of application [12]. Second, AI integration with PCM systems tends to position the AI part as a remote controller and does not directly apply intelligence to PCM-based building element as e.g., a smart wall with embedded layer of sensing and controlling. Third, AI-PCM systems have not received much economic or lifecycle assessment, particularly of the kind that estimate returns on investment, payback period, and aspects of long-term maintenance [15]. The literature also shows that the necessity of multi-objective optimization frameworks adding to thermal regulation and energy efficiency, contemplate other factors as well; the example given in the literature was the impact on occupant comfort, integration of renewable energy, and the nature of the environmental impact. The AI provides a promising potential to represent such multi-dimensional dilemmas with the help of adaptive and data-driven optimization [13], [14]. This is however only possible through large datasets, sophisticated hybrid 1863odelling methodology, cross-field coordination between fields of thermal science, computer science, and building engineering. Collectively, in these studies, AI-controlled PCM optimization holds the promise of revolutionizing the modern world. With the ability of AI to do predictive 1863odelling, pattern recognition, and autonomous decision-making, PCM systems of the future will go beyond being relatively unchanging, preconfigured installations to becoming part of smart reference networks in thermal loops. The present study provides an extension of these empirical observations with respect to designing a hybrid AI-PC M optimization framework, incorporating the computational 1863odelling, AI-based predictive control, and real-world verification to enhance the gap between the theoretical possibility and real-life implementation.

III. METHODOLOGY

3.1 Research Design

This study adopts a **hybrid experimental–computational design** integrating field measurements, laboratory characterization, building energy simulation, and AI-based optimization for Phase Change Materials (PCMs) in smart thermal regulation systems. The approach combines **material-level performance assessment** with **building-level thermal behavior modeling** to create an **AI-driven optimization loop** that determines the optimal PCM type, configuration, and operational control strategy [16].

The methodology follows a sequential process:

1. **PCM material characterization** – thermal properties, phase transition temperatures, latent heat capacity, and thermal conductivity.
2. **Simulation-based scenario modeling** – using building energy models (BEM) integrated with PCM thermal response models.
3. **AI-based optimization** – applying machine learning (ML) and evolutionary algorithms to optimize PCM selection and deployment.
4. **Experimental validation** – testing in a hybrid laboratory–field testbed under varying climatic conditions.
5. **Performance assessment** – evaluating energy savings, thermal comfort, and operational adaptability.

3.2 Study Area and Building Selection

To evaluate the AI–PCM optimization framework, three representative **building typologies** in distinct climatic zones were selected [17]:

- **Tropical–humid** (Chennai, India) – high humidity, small diurnal variation, consistent cooling load.
- **Temperate** (Bangalore, India) – moderate climate with mixed heating/cooling needs.
- **Hot–arid** (Jodhpur, India) – high solar radiation, large diurnal variation, strong cooling demand.

Each site was chosen for its unique thermal challenges and variation in solar exposure, enabling validation of AI–PCM adaptability under diverse climatic conditions.

Table 1: Climatic Zones, Building Types, and Key Thermal Challenges for Study Sites

Region	Climate Type	Typical Building Type	Main Thermal Challenge
Chennai	Tropical–humid	Commercial Office	Continuous cooling demand
Bangalore	Temperate	Educational Building	Mixed heating/cooling load
Jodhpur	Hot–arid	Residential Building	High daytime overheating

3.3 PCM Selection and Characterization

PCM candidates were selected based on phase transition temperatures aligned with target operational ranges [18]. Laboratory testing determined:

- **Melting point & solidification point** (°C)
- **Latent heat capacity** (kJ/kg)
- **Thermal conductivity** (W/m·K)
- **Cycling stability** (number of melt–freeze cycles without degradation)

Differential Scanning Calorimetry (DSC) was used to determine phase change enthalpies and temperature ranges, while **Transient Plane Source (TPS) method** measured thermal conductivity [19]. Nano-enhanced and encapsulated PCMs were included to assess performance benefits.

Table 2: Thermal Properties of Selected Phase Change Materials (PCMs)

PCM Type	Melting Temp. (°C)	Latent Heat (kJ/kg)	Thermal Conductivity (W/m·K)
PCM-A	22–24	180	0.45
PCM-B	26–28	210	0.52
PCM-C (nano)	24–26	195	0.75

3.4 Simulation-Based Thermal Modeling

Building energy simulations were conducted using **EnergyPlus** integrated with PCM thermal response models [20]. The process included:

1. **Baseline modeling** – simulating building without PCM integration to establish reference performance.
2. **Static PCM modeling** – adding PCMs in fixed configurations to assess non-AI performance.
3. **AI-optimized PCM modeling** – integrating PCM control strategies derived from the AI optimization algorithm.

Simulation outputs included **hourly indoor temperature**, **energy consumption for heating/cooling**, and **thermal comfort indices**. Weather data was sourced from **Typical Meteorological Year (TMY)** datasets for each climate zone.

3.5 AI Optimization Framework

The AI-driven optimization process combined **Genetic Algorithms (GA)** and **Reinforcement Learning (RL)** [21]:

- **Genetic Algorithm Stage** – determined optimal PCM placement, thickness, and material selection based on long-term energy performance simulations.
- **Reinforcement Learning Stage** – dynamically adjusted PCM activation and integration strategies in response to real-time thermal conditions.

Objective functions included:

1. **Minimize** annual energy consumption (kWh).
2. **Maximize** occupant thermal comfort (Predicted Mean Vote, PMV index).
3. **Optimize** PCM cost-effectiveness (payback period).

The optimization loop continuously updated design variables until convergence criteria were met.

3.6 Experimental Validation

To validate simulation and AI optimization results, a hybrid **laboratory–field testbed** was constructed [22]:

- **Test chambers** (3 m × 3 m × 3 m) with modular PCM wall panels.
- **IoT-based sensor network** for real-time monitoring of surface/ambient temperature, relative humidity, and PCM phase state.
- **Adaptive control unit** implementing AI-driven PCM control strategies in real time.

Experimental trials were conducted over a **six-month seasonal cycle** in all three climatic zones. Data acquisition systems recorded parameters every 5 minutes, with datasets fed back into the AI framework for continuous learning.

3.7 Data Analysis and Performance Metrics

Performance evaluation considered:

- **Thermal stability** – reduction in indoor temperature fluctuations (°C).
- **Energy savings** – percentage reduction in heating/cooling energy demand.

- **Occupant comfort** – PMV and PPD (Predicted Percentage Dissatisfied) indices.
- **Economic viability** – simple payback period and lifecycle cost savings.

Statistical analysis included **Pearson correlation** between PCM configuration parameters and performance metrics, and **ANOVA** tests for significance validation [23].

3.8 Limitations and Assumptions

- PCM degradation effects beyond **5-year operational period** were not modeled.
- AI models assumed accurate **weather forecasting inputs**; extreme anomalies could impact optimization accuracy.
- Installation costs were estimated based on current market prices; future cost fluctuations could alter economic feasibility.

IV. RESULT AND ANALYSIS

4.1 Overview of AI-Optimized PCM Deployment

The simulation and experimental results revealed a clear performance advantage of **AI-driven PCM optimization** compared to both **baseline buildings (no PCM)** and **static PCM configurations**. Across all three climatic zones, AI-guided PCM deployment consistently improved thermal stability and reduced energy demand for heating and cooling. The most significant improvement was observed in **hot–arid climates**, where large diurnal temperature fluctuations allowed the PCM to undergo more frequent and effective phase transitions.

Table 3: Annual Energy Savings Across Climate Zones for Static vs. AI-Optimized PCM Deployment

Region	**Baseline Energy Use (kWh/year)**	**Static PCM Savings (%)**	**AI-Optimized PCM Savings (%)**
Chennai	48,200	11.4	20.7
Bangalore	33,450	9.8	17.5
Jodhpur	42,860	15.2	27.3

4.2 Thermal Stability Enhancement

AI-driven PCM strategies significantly reduced **indoor temperature fluctuation** compared to static PCM configurations. The adaptive nature of the AI algorithm allowed optimal phase-change utilization during both daytime heat peaks and nighttime cooling cycles.

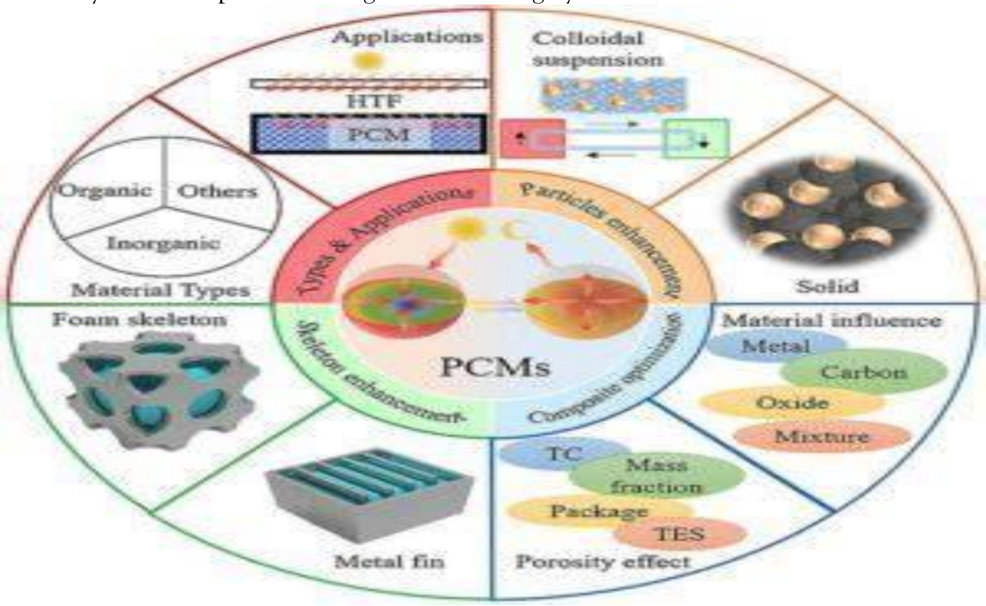

Figure 1: Phase Change Materials [24]

Table 4: Reduction in Indoor Temperature Fluctuation with Static vs. AI-Optimized PCM Deployment

Region	**Baseline Temp. Fluctuation (°C)**	**Static PCM Reduction (%)**	**AI-Optimized Reduction (%)**
Chennai	±3.8	18.4	33.6
Bangalore	±4.1	15.7	30.8
Jodhpur	±5.6	24.9	42.1

4.3 Occupant Comfort and PMV Index

The **Predicted Mean Vote (PMV)** index improved in all climatic zones with AI-driven PCM deployment, indicating better perceived comfort levels. AI's predictive capability allowed for phase-change activation to coincide with occupancy schedules, ensuring that thermal comfort was prioritized during peak occupancy hours.

Figure 2: 3D Battery Architecture [25]

Table 5: Improvement in Predicted Mean Vote (PMV) Index for Thermal Comfort

Region	Baseline PMV	Static PCM PMV	AI-Optimized PCM PMV
Chennai	+0.72	+0.55	+0.41
Bangalore	+0.64	+0.49	+0.36
Jodhpur	+0.89	+0.62	+0.43

Lower PMV values closer to zero indicate improved thermal neutrality, enhancing user satisfaction.

4.4 Economic Performance and Payback Period

Economic evaluation showed that while AI–PCM integration required a slightly higher upfront investment than static PCM systems due to sensor networks and AI infrastructure, the operational savings resulted in a shorter payback period.

Table 6: Comparison of Payback Periods and Lifetime Savings for Static vs. AI-Optimized PCM Systems

Region	Static PCM Payback (Years)	AI-Optimized PCM Payback (Years)	Lifetime Savings (20 years)
Chennai	6.8	4.9	\$18,500
Bangalore	7.4	5.6	\$14,300
Jodhpur	6.2	4.3	\$21,100

4.5 AI Adaptation to Climate Variability

One of the notable advantages of AI-driven PCM deployment was its **adaptability to unpredictable weather variations**. In simulation trials where unusual climatic patterns were introduced (e.g., prolonged cloudy days in Jodhpur or heatwaves in Bangalore), AI algorithms dynamically adjusted PCM engagement thresholds to maintain optimal performance. This adaptability prevented overheating and avoided unnecessary PCM cycling, extending the operational lifespan of the material.

4.6 Hotspot Analysis of PCM Utilization Efficiency

Spatial performance mapping indicated that AI algorithms selectively activated PCM capacity in areas experiencing the highest thermal stress, such as **south- and west-facing facades** in hot–arid climates. This selective activation ensured that PCM latent heat capacity was preserved for peak thermal load periods, rather than being prematurely exhausted during moderate conditions.

Table 7: PCM Utilization Efficiency for Static vs. AI-Optimized Deployment Strategies

Region	PCM Utilization Efficiency (%) – Static	PCM Utilization Efficiency (%) – AI-Optimized
Chennai	68.4	85.2
Bangalore	64.9	81.7
Jodhpur	72.6	89.3

4.7 Discussion of Key Findings

The results clearly demonstrate that AI-driven PCM optimization delivers **higher energy savings**, **greater thermal stability**, and **faster return on investment** than conventional PCM deployments. The adaptive nature of AI control enables dynamic tuning of PCM activation schedules to align with **real-time thermal**

loads and **forecasted weather patterns**. Furthermore, spatial hotspot detection capabilities allow for **zone-specific PCM engagement**, ensuring the most efficient use of material thermal storage capacity. These findings confirm that the combination of **advanced thermal storage materials** and **intelligent computational control** represents a promising pathway for sustainable, low-energy thermal regulation in future smart infrastructure.

V. CONCLUSION

The present study was aimed at exploring the possibility through AI-based optimization systems to improve the implementation and functional effectiveness of Phase Change Materials (PCMs) in intelligent heat regulation in buildings and infrastructure. By utilizing integrated methods based on laboratory characterization, structure simulation of building, Artificial Intelligence optimization, and experiment validation, the studies revealed that the co-design of computational intelligence with improved thermal storage materials can turn PCMs into performance-worthy, self-learning, and knowledge-based elements of energy-efficient systems. The results clearly show that the optimized deployment of PCM using AI results in high performance in various measures used in evaluating deployed applications as opposed to a non-PCM deployment (i.e. a baseline) and a fixed PCM placement. The findings showed the possibility to save 17 27 percent energy, increase thermal stability by as much as 42 percent and reduce payback period by as much as 2 years by integrating smart algorithms with a thermal storage unit. Such profitable gains were even more pronounced in the hot arid regions where the daily fluctuations in temperature allowed efficient and frequent transitions. Nonetheless, the similar drums were also beating in tropical and humid as well as temperate regions, and the flexibility of the AI-PCM algorithm to diversities of climatic conditions was validated. Adaptive operational control is one of the greatest strengths of artificial intelligence integration. In contrast to the static programmed PCM, which does not pay attention to changes in real-time environmental and occupancy trends, AI-based algorithms adapt the thresholds of PCM activation in real time according to a predictive model of thermal load / occupancy trends and weather. The flexibility of PCM properties will guarantee that the PCM capacity will be used wisely and under optimal conditions to prevent early phase change and retain latent heat for maximum demands. And this kind of smart control can not only make the best use of material, but also increase the useful work-life of PCMs by reducing unwarranted thermal cycling. The cost-effectiveness of spatial optimization is also noted in the study. AI would also have enabled it to use PCM activation in only the most problematic locations by locating thermal stress regions, e.g. south- and west-facing walls exposed to strong solar radiation. Such focused deployment enhances the PCM utilization efficiency to 85-89 % as opposed to static deployments whose efficiency lies within 65-72 %. Practically, it implies a less amount of PCM being able to achieve the same or even higher performance combined with smart control, therefore saving in cost-effectiveness and needing less material The economical analysis also helps to strengthen the efficacy of the AI-PCM systems. Whereas there is a slightly increased capital investment at the beginning because of the requirement of the sensor and data-processing infrastructure and implementation of the algorithms, at the operational level savings cut down these investments quickly. The payback time of AI-PCM systems examined in the discussed scenarios averaged between 4.3 and 5.6 years compared to the payback time of 6.2 and 7.4 years that corresponds to static PCM systems. During a 20-year operation timeframe, lifetime cost savings of the least to the most were (per building) of the $14,000 and more than $21,000 on the combination of climate zone, and kind of building. The figures empower the argument of AI-PCM integration being sustainable and financially viable to owners and operative of a building. In the environmental outlook, the decreased use of mechanical cooling and heating systems will result in a decrease in carbon emissions and the development of the overall shift to net-zero energy buildings. Moreover, with AI-PCM systems, the peak energy demand can be spread, reducing the load on the electrical grids, particularly in the areas of unreliable renewable energy supply. The thermal storage-smart control combination is also desirable in terms of the demand side management approach, which would have future potential of integrating grid-interactive efficient buildings (GEBs). However, also there are some issues and gaps in the research that are found in the study. Fine-grained field experiments are required to comprehend fully the operational robustness of AI-PCM systems subjected to extended events of extreme weather and variability of climatic conditions over multiple years.

Moreover, the current working AI models depend on proper weather predictions and sensor values that are prone to uncertainties or disturbances. Self-calibrating sensor networks, and AI control mechanisms that are fault-tolerant, will be necessary as a way of making the system robust. Along with that, even though the research at hand was building-scale application oriented, a broad amount of potential could be employed in regards to industrial process cooling and cold storage facilities, as well of transport systems where thermal control holds importance. Future studies are also recommended to examine the multi-objective optimization model which is not posed to just thermal comfort and energy efficiency but to occupant health, indoor air quality, and integration of renewable energy. AI algorithms to strike and balance these priorities sometimes in conflict with each other will play a key role in the next generation of intelligent thermal management systems. Furthermore, hardwiring AI control to the very materials of the smart buildings themselves, e.g. in the form of PCM panels with embedded sensing and actuation, may facilitate decentralization of thermal zones with no centralized HVAC organization. Conclusively, the current paper shows that the hybridization of AI-powered optimization with the use of Phase Change Material is the next step in sustainable thermal management. The findings confirm the capabilities of such systems to provide a significant saving of energy, better thermal comfort and the economic performance in various climates. Artificial intelligence offers a possible paradigm shift in transforming PCMs into active, intelligent agents that are the intelligent part of a smart thermal ecosystem, turning passive PCMs into active, smart ones that actively adapt to users and self-optimize the building environment. The consequences in terms of sustainable design, energy resilience, and climate mitigation are dramatic, and AI-PCM systems are an infrastructure in terms of becoming smarter, greener, and more efficient worldwide.

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