



# Optimization of Photovoltaic Integrated Cold Storage Systems Utilizing Aluminum Oxide Nanoparticle-Enhanced Phase Change Materials for Enhancing Supply Chain Management in Refrigeration Vehicle

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**Abstract:** The integration of photovoltaic (PV) systems with cold storage technologies offers a sustainable approach to energy management by harnessing solar energy for enhancing supply chain management. This study investigates the optimization of aluminum oxide (Al<sub>2</sub>O<sub>3</sub>) nanoparticle-enhanced phase change materials (PCMs) within PV-integrated cold storage systems to improve thermal conductivity and energy efficiency. Through the use of genetic algorithms (GA) and particle swarm optimization (PSO), the research identifies the optimal (Al<sub>2</sub>O<sub>3</sub>) nanoparticle concentration to minimize PCM operating temperatures and enhance energy savings. The study evaluates various concentrations, taking into account key operational parameters such as ambient temperature, thermal conductivity, and storage efficiency. Sensitivity analysis was conducted to understand the influence of these factors on system performance, providing insights for more efficient and cost-effective cold storage solutions. The findings highlight the potential of nanoparticle-enhanced PCMs to increase the overall energy efficiency of PV-integrated systems, contributing to advancements in sustainable energy technology.

**Keywords:** Photovoltaic integrated cold storage; supply chain management; Phase change materials; Thermal conductivity optimization; Genetic algorithm; Particle swarm optimization.

## Introduction

The efficient operation of refrigeration units is vital to maintaining the integrity of perishable goods in industries such as food, pharmaceuticals, and agriculture. A robust and sustainable supply chain for refrigeration units plays a crucial role in ensuring product quality, minimizing waste, and reducing costs [1]. The supply chain of refrigeration units involves multiple stages, including production, transportation, and storage. Each stage requires a consistent and reliable temperature-controlled environment to prevent spoilage

and maintain compliance [2]. Integrating PCMs into refrigeration units can significantly improve energy management by stabilizing temperatures during transit and storage. When further enhanced with nanoparticles like aluminum oxide, PCMs demonstrate improved thermal conductivity and heat transfer rates, enabling faster temperature regulation and reducing energy requirements [3]. These advancements not only enhance the operational efficiency of refrigeration systems but also contribute to the broader goal of supply chain optimization by ensuring consistent cooling performance, lowering operational costs, and minimizing the environmental footprint [4].



PV systems have emerged as a cornerstone of renewable energy technologies, transforming sunlight into electricity through the photovoltaic effect [5]. With the global push for sustainable energy solutions, substantial research has been conducted to improve the efficiency and reliability of PV systems. Innovative materials like perovskite solar cells, which provide better efficiency at cheaper prices than conventional silicon-based cells, are examples of recent breakthroughs in this field [6]. The use of energy storage systems, such as batteries and PCMs, has been found to reduce the intermittent nature of solar energy, resulting in a more constant energy source. Predictive analytics and energy management systems are two examples of smart technologies that have been included to further enhance PV performance and improve the use of generated power. A viable method of utilizing solar energy for effective temperature control was through the combination of photovoltaic systems with cold storage technologies [7]. This strategy guarantees energy savings and improves refrigeration operating performance. These systems use refrigeration technology to keep temperatures stable, decreasing spoilage and waste in a variety of sectors, including food, medicines, and agriculture. Recent advances have centered on improving energy efficiency and sustainability in cold storage operations [8]. The use of PCMs has emerged as a viable strategy for better thermal control and decreased energy usage. The integration of intelligent technologies, such Internet of Things (IoT)-based automation and monitoring systems, has made it possible to check temperature and humidity levels in real-time while maintaining safety regulations. PCMs have gained significant attention in recent years due to their unique ability to store and release thermal energy during phase transitions [9]. These materials can absorb excess heat during melting and release it during solidification, making them ideal for a variety of applications, including thermal energy storage, building temperature regulation, and thermal management in electronic devices. The effectiveness of PCMs was highly dependent on their thermal properties, including latent heat capacity, thermal conductivity, and melting/freezing points [10-14]. Recent research has focused on enhancing the performance of PCMs through various approaches, such as incorporating nanoparticles to improve thermal conductivity and developing composite materials to tailor phase change temperatures. The integration of PCMs with renewable energy systems, particularly in conjunction with solar energy technologies, has also emerged as a promising area of investigation [15]. To further enhance the efficiency of cold storage systems, the integration of PCMs has gained significant attention due to their ability to store and release large

amounts of thermal energy during phase transitions. Phase change materials made more thermally conductive by adding nanoparticles, such as metal oxides and carbon-based compounds, which speeds up the rate at which heat was transferred during the melting and solidification processes. This enhancement not only improves the efficiency of energy storage but also reduces the required volume of PCM needed for effective thermal management [16-19]. PCMs play a crucial role in sustainable energy management by enabling efficient thermal energy storage and release, which was essential for optimizing energy usage and reducing environmental impact. Advanced modeling and simulation techniques have a great deal to offer sustainable energy management. Optimize energy systems and boost the effectiveness of renewable energy technologies such as nanofluid-based solutions. This approach facilitates the exploration of physical phenomena that difficult or impossible to replicate in real-world scenarios [20-22]. Economic analysis, when combined with modeling and simulation, allows for a thorough evaluation of the practicality and cost-effectiveness of using cutting-edge thermal fluid technologies in real-world settings. These tools are essential for improving the performance of nanofluids [23 – 25]. PCMs, known for their ability to absorb and release thermal energy during phase transitions, can be combined with PV systems to mitigate the overheating of solar panels, a common issue that reduces PV efficiency. By integrating PCMs into PV module structures, excess heat generated during peak solar radiation can be stored and released when temperatures drop, ensuring optimal operational conditions for the PV cells [26-27]. This thermal regulation enhances both the efficiency and lifespan of PV panels while also offering potential for utilizing excess heat in auxiliary applications, such as space heating or low-temperature industrial processes.

### Genetic Algorithm for Al<sub>2</sub>O<sub>3</sub> Nanoparticle Concentration Optimization

Optimizing the concentration of Al<sub>2</sub>O<sub>3</sub> nanoparticles was the main goal of this research, which would eventually reduce the operating temperature of PCMs. This study looks at discrete values for concentrations of Al<sub>2</sub>O<sub>3</sub> nanoparticles, especially 0% (pure PCM), 1%, 2%, and 3%. In this optimization procedure, the concentration of Al<sub>2</sub>O<sub>3</sub> nanoparticles was considered as the decision variable, and the goal was to find the ideal concentration that produces the best thermal control of the PCM [28]. Genetic algorithm (GA) was used to achieve this goal. The cumulative total of temperature readings over preset time periods was used



to build the objective function [29-33]. Determining the concentration that lowers the system's total temperature throughout the day was the goal of this optimization procedure, which maximizes the system's thermal performance. The genetic variant with the greatest fitness score was determined to be the best option once the GA run was finished. This person was in line with the Al<sub>2</sub>O<sub>3</sub> nanoparticle concentration that reduces the operating temperature over time. The next part presents the GA analysis data and evaluates and compares the thermal performance of each concentration. This comparative research adds to our understanding of how these materials used in real-world applications by illuminating how varied concentrations work best to achieve maximum thermal performance. While Al<sub>2</sub>O<sub>3</sub> nanoparticles significantly enhance thermal conductivity and phase transition stability, alternative materials like SiO<sub>2</sub> and TiO<sub>2</sub> have also been explored for PCM enhancement. SiO<sub>2</sub> nanoparticles provide high thermal stability but lower thermal conductivity enhancement than Al<sub>2</sub>O<sub>3</sub>. TiO<sub>2</sub> nanoparticles demonstrate excellent dispersion but have higher costs. The selection of Al<sub>2</sub>O<sub>3</sub> in this study is justified by its optimal cost-to-performance ratio and superior heat transfer properties.

The concentration of Al<sub>2</sub>O<sub>3</sub> nanoparticles that successfully reduced operating temperatures over time was found by using the GA. The study offered a quantitative framework for evaluating thermal performance by using a fitness function, which made it possible to make meaningful comparisons between various concentrations [34]. The systematic approach demonstrated the efficiency of the GA in improving thermal performance by enabling it to converge toward an ideal solution across several generations. This method' iterative structure not only made the effects of different concentrations clear, but it also reaffirmed the GA's capacity to handle challenging optimization problems in thermal management systems. These results demonstrate the potential of the GA as a reliable instrument for adjusting nanoparticle concentrations, which ultimately lead to improved thermal control in a range of real-world uses.

To improve thermal management systems, PCMs must have the concentration of AlO<sub>2</sub> nanoparticles optimized. The goal of this work was to formulate the challenge of finding the ideal Al<sub>2</sub>O<sub>3</sub> nanoparticle concentration that reduces PCM operating temperature over time. The concentrations that are being examined are 1%, 2%, 3%, and 0% (pure PCM). In this optimization paradigm, the concentration of Al<sub>2</sub>O<sub>3</sub> nanoparticles acts as the decision variable. The main goal, represented by the objective function, was to reduce the cumulative sum of

temperature readings taken during certain time periods. A GA, which repeatedly refines solutions to arrive on the optimal concentration that maximizes thermal performance, used to assess the efficacy of various concentrations.

To ensure accurate and meaningful comparisons among different concentrations of Al<sub>2</sub>O<sub>3</sub> nanoparticles, the temperature data were normalized prior to analysis. Normalization was a critical preprocessing step that transforms raw temperature readings into a standardized scale, thereby facilitating the evaluation of thermal performance across varying conditions. The normalization process utilized the formula:

$$\text{Normalized Temp (i, j)} = \frac{\text{Temp(I, j)} - \text{Min Temp(j)}}{\text{Max Temp(j)} - \text{Min Temp(j)}}$$

This equation, where Temp (*i, j*)

The temperature recorded at time step *i* for concentration *j* was represented by Temp (*i, j*), whilst the minimum and maximum temperatures measured for that particular concentration are indicated by Min Temp (*j*) and Max Temp (*j*) respectively. This algorithm ensured that all temperature measurements were equivalent independent of the absolute temperature values by scaling each value between 0 and 1. This normalization, which focused on relative performance rather than absolute disparities in temperature measurements, not only increased the stability of the ensuing studies but also improved the GA's capacity to determine the ideal concentration. All things considered, this strategy was essential to streamlining the optimization procedure and producing trustworthy outcomes.

The fitness function was an essential element in optimization issues, especially those utilizing GA, since it provides a quantitative assessment of the performance of various solutions. The fitness function was a statistic that evaluates how well a certain solution satisfies the stated goals of the current challenge. The fitness function was developed in the context of maximizing the concentration of Al<sub>2</sub>O<sub>3</sub> nanoparticles for thermal management using the total cumulative temperature data gathered over predetermined time intervals. In order to maximize thermal performance, this function seeks to reduce the system's total temperature. Throughout its iterative process, the GA can efficiently compare and choose the best solutions by giving each concentration a fitness score. Higher fitness values correspond to higher thermal performance, leading the selection of people for reproduction and enabling the algorithm to converge toward an ideal concentration that provides the intended thermal management results. The creation of a suitable fitness function was crucial because it affects the GA's capacity to investigate the solution



space and, in the end, identify the nanoparticle concentration that works best for the given application. Extending the simulations over all time intervals was necessary in order to fully evaluate the effect of  $\text{Al}_2\text{O}_3$  nanoparticle concentrations on operational temperatures. To do this, the normalization and fitness evaluation procedures must be applied methodically to each time step in order to capture the dynamic thermal behavior of the PCMs during the specified duration. A comprehensive dataset was produced by normalizing temperature data for each concentration at each time interval. This enables a reliable investigation of the ways in which concentration fluctuations affect thermal performance over time. After that, it was possible to compute the cumulative fitness values for each concentration, which offers a thorough analysis of how well it works to reduce temperatures during all periods [35]. The results are more reliable thanks to this comprehensive methodology, which also makes it possible to spot trends and patterns in thermal performance. This information can be used to make better judgments on the ideal concentration of  $\text{Al}_3\text{O}_4$  nanoparticles for better thermal management. In the end, expanding the computations to include all time periods guarantees a comprehensive assessment of the thermal dynamics of the system, opening the door for improvements in energy efficiency and thermal control techniques.

An essential part of the GA optimization process was the assessment of fitness ratings. Fitness scores offer a numerical representation of each candidate solution's or person's performance in respect to the specified target function. The study's fitness scores, which represent the thermal performance of various concentrations of  $\text{Al}_3\text{O}_3$  nanoparticles, were computed using the cumulative temperature measurements during predetermined time intervals. The fitness score of each concentration allowed for a straightforward comparison, showing which concentration successfully reduced the total temperature. Better heat control was indicated by higher fitness ratings, which helped determine the ideal concentrations. Understanding the connection between thermal efficiency and nanoparticle concentration was obtained by methodically examining these scores. In addition to helping to determine the optimal concentrations, our analysis advanced our knowledge of the fundamental processes affecting PCM thermal performance. In the end, the thorough study of fitness scores emphasizes the significance of quantitative analysis in the optimization process and shows how effective the GA was at producing improved thermal management solutions.

## Optimization for Optimization of $\text{Al}_2\text{O}_3$ Nanoparticle Concentration

A multitude of applications necessitate the optimization of thermal performance in systems including  $\text{Al}_2\text{O}_3$  nanoparticles. PSO to determine the lowest temperature during a 24-hour period that can be achieved with different concentrations of PCM and  $\text{Al}_2\text{O}_3$  nanoparticles (1%, 2%, and 3%). Through the effective optimization of nanoparticle concentrations, we want to increase the efficiency of thermal management systems by utilizing the PSO algorithm. This lead to better performance in pertinent applications. This method makes it possible to explore the solution space methodically, which makes it easier to find the ideal concentrations that can dramatically lower thermal loads in a range of operational scenarios.

Energy storage, electronics cooling, and thermal regulation in building materials are just a few of the many applications where it was critical to optimize thermal performance in systems using  $\text{Al}_3\text{O}_4$  nanoparticles. Finding the ideal concentration of  $\text{Al}_2\text{O}_3$  nanoparticles to reduce operating temperatures throughout the day was the difficult part. Conventional techniques for determining these ideal concentrations frequently rely on ineffective and time-consuming trial-and-error procedures. The optimization process was made more difficult by variable operating conditions and external influences. PSO, a computational intelligence method renowned for its effectiveness in resolving nonlinear optimization issues, was utilized in this work to address these issues. In order to improve the thermal performance of systems that incorporate  $\text{Al}_3\text{O}_4$  nanoparticles, this research aims to develop a dependable method for determining the concentration that achieves the lowest temperature by methodically evaluating concentrations of 1%, 2%, 3%, and PCM. By using this strategy, we want to offer insights that result in more effective thermal management systems for a range of applications.

Several crucial factors were determined in the use of PSO for the optimization of  $\text{Al}_3\text{O}_3$  nanoparticle concentrations in order to guarantee efficient convergence and top performance. The number of particles in the swarm, the social and cognitive factors, and the particles' maximum velocity are the main characteristics. A predetermined number of particles, each representing a possible solution in the form of a certain concentration of  $\text{Al}_3\text{O}_4$  nanoparticles, made up the swarm. The social coefficient ( $c_2$ ) determines how much the best-known position of the entire swarm influences the particles, whereas the cognitive coefficient (sometimes represented as  $c_1$ ) affects the particle's propensity to investigate its own

## Application of Particle Swarm



best-known position. Exploration and exploitation within the search space were balanced by the calibration of these factors. To avoid overshooting ideal solutions, the maximum velocity parameter was also adjusted to restrict particle mobility. The PSO algorithm was able to explore the solution landscape with more efficiency and accuracy by fine-tuning these parameters, which guaranteed the identification of the ideal concentration of  $\text{Al}_3\text{O}_4$  nanoparticles. The achievement of the intended results in thermal performance optimization was made possible by this methodical approach to parameter selection and modification.

The PSO algorithm's startup phase was a crucial stage that sets the basic parameters for the optimization procedure. In this stage, a swarm of particles was produced, each of which represents a possible solution in the specified search space with respect to the concentration of PCM and  $\text{Al}_2\text{O}_3$  nanoparticles (1%, 2%, and 3%). The beginning locations and velocities of each particle are chosen at random to match the concentration values under evaluation. In order to provide a varied initial population and enable the PSO algorithm to efficiently explore different portions of the solution space, this randomization was necessary. Next, using a predetermined fitness function that evaluates thermal performance, initial fitness values are assigned to the particles depending on how well their associated concentrations can minimize temperature. This initialization helps the algorithm to converge more quickly and also gives particles a starting point from which to modify their placements based on their individual and collective experiences during the optimization process. In the end, a well-done initialization creates the conditions for a fruitful optimization, improving the algorithm's capacity to determine the ideal  $\text{Al}_2\text{O}_3$  nanoparticle concentration that results in the lowest operating temperature.

Fitness evaluation was an essential part of the PSO optimization process in the context of this study. The fitness function was intended to measure the thermal performance of PCM and  $\text{Al}_2\text{O}_3$  nanoparticles at concentrations of 1%, 2%, and 3%. This function allows the thermal efficiency of different setups to be compared by computing the overall temperature during a specified time period. Lower temperature readings equate to greater fitness scores. The fitness value for each concentration was calculated by averaging the temperature data collected over the optimization cycle. In order to improve thermal performance, it was important to minimize operating temperatures, as this inverse connection highlights. The PSO algorithm efficiently direct the search for optimal solutions by methodically assessing each concentration's fitness. This

eventually makes it easier to identify the concentration that produces the most effective thermal management in real-world applications. By doing this thorough evaluation, the project hopes to develop thermal optimization approaches by offering insightful information on how nanoparticle concentration affects thermal behavior [36].

The velocity and position updating techniques in PSO are essential to the algorithm's capacity to efficiently search the solution space. Based on its position in the multidimensional search space and its velocity, which controls its mobility, each particle in the swarm represents a possible solution. Each particle's location was updated using the following formula:

$$\text{Position}(t+1) = \text{Position}(t) + \text{Velocity}(t+1)$$

Particle velocity adjustments are made in real time, taking into account the particle's past velocity, the distance to its individual optimal location, and the distance to the global optimal position determined by the swarm. The updated version was stated as follows:

$$\text{Velocity}(t+1) = w \cdot \text{Velocity}(t) + c_1 \cdot r_1 \cdot (\text{Personal Best} - \text{Position}(t)) + c_2 \cdot r_2 \cdot (\text{Global Best} - \text{Position}(t))$$

The inertia weight, denoted by  $w$ , governs the influence of the preceding velocity. The random values in the range (0, 1) correspond to the cognitive and social coefficients, respectively. Particles simultaneously explore the search space and take use of well-established solutions thanks to this dual updating technique. The interaction between the social and cognitive components of learning as the particles converge towards the ideal solution improves the swarm's overall performance in identifying the ideal concentrations of  $\text{Al}_3\text{O}_4$  nanoparticles that reduce operating temperatures in thermal management applications.

### *Step 6: Iterative Process*

Optimization methods, such as PSO, rely on the iterative process to improve convergence towards optimal solutions. The iterative approach used in this work entails many cycles of assessing potential solutions to determine their thermal performance in minimizing temperature over a predetermined time period. In particular, several concentrations of  $\text{Al}_3\text{O}_3$  nanoparticles (1%, 2%, 3%, and PCM) are evaluated. A population of viable solutions was initialized at the start of each cycle and was then assessed using a fitness function that measures how well lower temperature. The PSO method directs the swarm's particle locations and velocities toward regions of the solution space that exhibit better thermal performance, based on how well these solutions perform. This feedback system refines the concentration values progressively while promoting exploration and exploitation, enabling a thorough search of the



parameter space. PSO's iterative structure not only makes it easier to navigate the challenging optimization environment, but it also makes it easier to identify the ideal concentrations of nanoparticles to improve thermal management in a variety of applications. The iterative method guarantees that the algorithm converges on resilient and efficient solutions to handle the thermal difficulties presented by various operational circumstances by means of repeated assessments and modifications.

### *Step 7: Identification of Optimal Solution*

One of the most important aspects of this work was figuring out the best way to concentrate  $\text{Al}_3\text{O}_4$  nanoparticles in thermal management systems. We conducted a systematic evaluation of the thermal performance in relation to several concentrations (1%, 2%, 3%, and phase change material, PCM) using PSO in order to determine the formulation that yields the lowest operating temperature during the day. PSO was an effective computing technique that simulates the interaction of particles that represent possible solutions, allowing the solution space to be explored. It was inspired by the social behavior of birds. Through a process of iterations, each particle refines its position by considering its own experiences as well as those of its neighbors, eventually convergent toward ideal solutions. By using this technique, we were able to measure the thermal performance of every concentration and improve our comprehension of how these differences affect the overall efficiency of the system. In order to increase thermal performance and provide more realistic thermal management solutions, the PSO analysis findings crucial in identifying the concentration that reduces temperature.

### *Ant Colony*

The following structured method used to optimize the concentration of  $\text{Al}_2\text{O}_3$  nanoparticles using Ant Colony Optimization (ACO). Clearly defining the issue at hand was crucial for adjusting the concentration of  $\text{Al}_3\text{O}_4$  nanoparticles for thermal management applications. Finding the ideal concentration of  $\text{Al}_2\text{O}_3$  nanoparticles to reduce operating temperature over a given time period was the main goal of this study. This entails developing an objective function that assesses the thermal performance of different concentrations in a quantifiable manner. In order to guarantee that the concentrations stay within reasonable and legal bounds, such as 1%, 2%, 3%, or pure PCM, constraints must also be set. The study's goal was to offer an organized method for maximizing the concentrations of nanoparticles, which

ultimately lead to improved thermal efficiency in pertinent applications, by outlining these criteria [37].

Data preparation that guarantees the accuracy and dependability of the optimization process while utilizing Ant Colony Optimization (ACO) to optimize the concentration of  $\text{Al}_3\text{O}_3$  nanoparticles. First, the pertinent temperature data, which include varied time periods and matching temperature readings for various  $\text{Al}_3\text{O}_3$  nanoparticle concentrations, must be gathered. The evaluation of each concentration's thermal performance was based on these data. The temperature data was then normalized so that relevant comparisons between various concentrations made. By standardizing the temperature readings to a similar scale, normalization enables a consistent evaluation of performance measures. This procedure was necessary to make sure that differences in measurement units or ranges do not skew the optimization's findings. Determining the goal function that direct the ACO process was also crucial. In this instance, the goal of the objective function was to reduce the overall operating temperature for every concentration throughout every time interval. Furthermore, limitations on the permissible concentration ranges 1%, 2%, 3%, or pure PCM must be set in order to guarantee that the solutions produced by the ACO algorithm continue to be workable and pertinent. Lastly, the ACO algorithm sets the initial pheromone levels based on first observations or uniformly distributes them over all concentrations, offering a balanced foundation for the optimization procedure. The next phases of the ACO efficiently explore the solution space and determine the ideal concentration of  $\text{Al}_3\text{O}_4$  nanoparticles for improved thermal performance by carefully compiling the data and creating a clear framework.

Ant Colony Optimization (ACO) was used to optimize the concentration of  $\text{Al}_3\text{O}_3$  nanoparticles. The first stage in the procedure was to carefully initialize the parameters that direct the optimization. Important variables are the number of ants, which establishes the search's range, and the maximum number of iterations, which determines the algorithm's maximum execution time. Pheromone evaporation rate was also important since it affects the dynamics of pheromone deposition and degradation. Additionally, a pheromone matrix was created, which shows how desirable any concentration was across the solution space. To guarantee that every option was considered equally at the start of the optimization process, this pheromone matrix can be initially adjusted to uniform values across all concentrations. This fundamental configuration was necessary to provide efficient solution space exploration and exploitation, which in turn enables the ACO



algorithm to determine the ideal concentration for efficiently minimizing operational temperature.

The fitness function was a critical component in assessing the effectiveness of alternative solutions when utilizing Ant Colony Optimization (ACO) to optimize the concentration of Al<sub>3</sub>O<sub>3</sub> nanoparticles. Based on the temperatures measured during certain time intervals, the fitness function was intended to evaluate the thermal performance objectively. In particular, it seeks to reduce the overall working temperature, as this has a direct bearing on how well the concentration of nanoparticles works in thermal management applications. The total temperature for each solution was first determined by adding the recorded temperatures across the specified time periods in order to calculate the fitness of each concentration. The fitness value, which was usually stated as the inverse of the total temperature, was then calculated using this total. Selecting concentrations that result in lower total temperatures was encouraged by higher fitness values, which imply improved thermal performance. Because the fitness function affects the pheromone updating process, it was crucial for directing the ACO algorithm. The method efficiently converges toward ideal concentrations by rewarding pheromone levels linked to solutions that provide greater fitness ratings. Therefore, the fitness function improves the ACO's capacity to explore and utilize the solution space, which in turn produces better thermal performance results, in addition to making it easier to compare different concentrations in a trustworthy manner.

#### *Step 5: Execute ACO Algorithm*

An organized method was used to run the Ant Colony Optimization (ACO) algorithm in order to maximize the concentration of Al<sub>2</sub>O<sub>3</sub> nanoparticles. Firstly, the optimization issue had to be precisely defined. This included the objective function, which had to minimize the overall operating temperature, and the limitations on acceptable concentration levels, which had to be limited to either pure PCM or 1%, 2%, or 3%. Subsequently, the pheromone evaporation rate, the maximum number of iterations, and the number of ants were initialized parameters crucial to the algorithm. In order to provide equal starting pheromone levels for all alternatives, a matrix representing the attractiveness of each concentration was created. After then, each ant built its solution by choosing concentrations in a probabilistic manner according to heuristic information and pheromone levels; a higher concentration of pheromones indicated a better chance of selection. After the solutions were constructed, the established objective function was used to assess each ant's solution's fitness,

which allowed for an evaluation of how well each concentration reduced temperature [38]. The fitness findings were then used to update the pheromone levels, which reinforced the pathways selected by the most productive ants and allowed for pheromone evaporation to promote the search for new solutions. After a certain number of iterations or until convergence was reached a sign that the solutions had stabilized the steps of solution creation, fitness assessment, and pheromone update were repeated. The ant-generated solutions were analyzed to determine the ideal concentration, which was determined to be the concentration that reduced the operating temperature, after the iterations were completed. In order to assess the outputs, a performance study was carried out, which involved contrasting the optimal concentration found using ACO with the findings of alternative optimization techniques, such as GA. The objective of this research was to evaluate the efficacy and efficiency of the ACO strategy in terms of selecting appropriate nanoparticle concentrations to optimize thermal performance.

#### *Step 6: Determine Optimal Concentration*

Ant Colony Optimization (ACO) was used in a systematic manner to find the ideal concentration of Al<sub>3</sub>O<sub>3</sub> nanoparticles. The optimization issue was first formulated precisely, with the goal of decreasing the overall operating temperature within certain limitations, such as valid concentration levels (1%, 2%, 3%, or pure PCM). The number of ants, the maximum number of iterations, and the rate of pheromone evaporation were determined as key parameters for the ACO algorithm. To illustrate the attractiveness of each concentration, an initial pheromone matrix was made, with equal beginning levels allocated to each choice. Each ant balanced exploration and exploitation as the ACO process got underway by choosing concentrations depending on pheromone levels and heuristic information. This way, each ant created a solution in a probabilistic manner. The established objective function was then applied to each solution to determine its efficacy by summing the measured temperatures for each concentration. After this assessment, the pheromone levels were adjusted to take into account the fitness of the solutions, encouraging the exploration of new possibilities by permitting pheromone evaporation while strengthening pheromones on pathways selected by the top-performing ants. The solutions stabilized, signifying that convergence had been obtained, or a certain number of iterations had been reached. After everything was finished, the concentration that performed the best was taken out as the greatest way to reduce operating temperature. After that, the



effectiveness of the ACO approach was examined by contrasting the best concentration found using ACO with the outcomes of other optimization methods, such as GA. With this all-encompassing method, the effectiveness of ACO was shown in navigating the solution space and locating concentrations that improve thermal management solutions.

To demonstrate the Ant Colony Optimization (ACO) process through iterations and derive optimized results for the concentration of  $\text{Al}_2\text{O}_3$  nanoparticles, we can outline a series of iterations along with simplified calculations. The ACO algorithm mimics the foraging behavior of ants and uses pheromone trails to guide the search for optimal solutions. Here's a step-by-step outline of how the ACO process can be applied in this context:

### Initialization

Establishing a foundation for later rounds of the Ant Colony Optimization (ACO) process which attempt to determine the ideal concentration of  $\text{Al}_2\text{O}_3$  nanoparticles was crucial during the initiation phase. First, four different concentrations were chosen to be tested: pure PCM, 1%, 2%, and 3% of  $\text{Al}_2\text{O}_3$ . Reducing the operating temperature associated with each concentration over time was the aim of the ACO. Equal starting pheromone levels, set at 1, were allocated to each concentration in order to streamline the optimization process. Because of the homogeneous distribution of pheromones, the algorithm can examine every possibility objectively and begin the search for the best solution from a neutral starting point. In the search space, four ants in all were released, each of which represented a possible solution that matched one of the concentrations. Ants use a probabilistic model that takes into account their fitness scores and pheromone levels to choose concentrations during the exploration phase. Generally speaking, lower temperatures are associated with greater fitness. Starting with this initialization phase, the iterative procedure creates a methodical way for the ants to go around the solution environment, adjusting pheromones in response to their discoveries. In the context of thermal management systems, this organized technique enables the progressive convergence toward an ideal concentration that minimizes operating temperatures in an efficient manner [39].

### Iteration Process

To determine the ideal concentration of  $\text{Al}_2\text{O}_3$  nanoparticles for reducing operating temperature, the Ant Colony Optimization (ACO) method was methodically carried out across a number of iterations. Four concentrations were first assessed: pure PCM, 1%, 2%, and 3%  $\text{Al}_2\text{O}_3$ . An initial pheromone level of 1.00 was

assigned to each concentration. Four ants investigated the concentrations in the first iteration and made their selections based on pheromone levels and a probability function that took fitness scores into account. Lower temperatures were associated with better fitness.

### Iteration 1

To investigate the different concentrations of pure PCM and  $\text{Al}_2\text{O}_3$  nanoparticles, four ants were deployed in the first iteration of the Ant Colony Optimization (ACO) procedure. The ants were instructed to choose a concentration by considering the pheromone levels linked to each choice and the fitness scores obtained from earlier assessments of thermal performance. At all doses, the starting pheromone levels were evenly set to 1. The following decisions were made by the ants as a result of this exploratory phase: Ant 1 selected the 1%  $\text{Al}_2\text{O}_3$  concentration, which had a fitness score of 0.85; Ant 2 selected the 2%  $\text{Al}_2\text{O}_3$  concentration, which had a fitness score of 0.90; Ant 3 chose the 3%  $\text{Al}_2\text{O}_3$  concentration, which had a fitness score of 0.88; and Ant 4 determined that PCM was the best option, with a fitness score of 0.92 in comparison. The fitness ratings of the chosen concentrations were used to update the pheromone levels after the selection procedure. With a pheromone evaporation rate of 0.1 used in this update, the pheromone levels be dynamically adjusted to represent the performance of each concentration. Following this loop, the new pheromone levels were computed as follows: The level of 1%  $\text{Al}_2\text{O}_3$  was 0.95, the level of 2%  $\text{Al}_2\text{O}_3$  was 0.97, the level of 3%  $\text{Al}_2\text{O}_3$  was 0.96, and the level of PCM was 0.98. The ants' investigation was directed toward the most promising concentrations in the next rounds by these revised pheromone levels, which also set the stage for succeeding iterations.

### Iteration 2

The ants investigated the concentrations of  $\text{Al}_2\text{O}_3$  nanoparticles once more in the second iteration of the Ant Colony Optimization (ACO) procedure, using the revised pheromone levels from the first iteration. Based on the pheromone concentration and the fitness ratings, which indicated the thermal performance of the various alternatives, each ant chose a concentration. In this iteration, the ants picked the following: two ants selected the 2%  $\text{Al}_2\text{O}_3$  concentration with a fitness score of 0.90, one ant selected the PCM with a fitness score of 0.92, and one ant chose the 1%  $\text{Al}_2\text{O}_3$  concentration with a score of 0.85. The pheromone levels were adjusted after the exploration phase according to the fitness ratings obtained in this iteration. The pheromone update was computed with the following formula:  $\tau(i)=(1-\rho)\tau(i)+\Delta\tau(i)$ , where  $\rho$ , which represents the rate of pheromone evaporation, was set at 0.1. The outcome was the



determination of the updated pheromone levels for each concentration: the pheromone level for the 1%  $\text{Al}_3\text{O}_4$  concentration dropped to 0.90, while the level for the 2%  $\text{Al}_3\text{O}_4$  concentration changed to 0.93. The pheromone level of the 3%  $\text{Al}_2\text{O}_3$  concentration stayed at 0.93, whereas the pheromone level of the PCM concentration marginally dropped to 0.96. Prioritizing concentrations with superior thermal performance, as demonstrated by the fitness scores and pheromone levels, allowed the ants to take advantage of this repeated process, which strengthened the algorithm's capacity to fine-tune its search based on earlier ratings. As a result, in later versions, the pheromone trails progressively guided the search toward ideal solutions.

### Iteration 3

The modified pheromone levels from the previous iteration were again used by the ants to inform their concentration selection in the third iteration of the Ant Colony Optimization (ACO) procedure. Every ant assessed the four concentrations using the present pheromone intensities and matching fitness scores: 1%  $\text{Al}_2\text{O}_3$ , 2%  $\text{Al}_2\text{O}_3$ , 3%  $\text{Al}_2\text{O}_3$ , and PCM. The choices that were made were as follows: Ants 1 through 4 selected different options, with Ant 1 choosing 1%  $\text{Al}_2\text{O}_3$  and scoring 0.85, Ant 2 choosing 2%  $\text{Al}_2\text{O}_3$  and scoring 0.90, Ant 3 choosing PCM and scoring 0.92, and Ant 4 choosing 3%  $\text{Al}_2\text{O}_3$  and scoring 0.88. The performance of each concentration was taken into account when updating the pheromone levels after the ants finished making their selections. The revised pheromone levels for 1%, 2%, 3%, and PCM were determined by applying the pheromone update algorithm. The updated values for  $\text{Al}_3$  and  $\text{O}_2$  were 0.90, 0.93, and 0.96, respectively. The ants were able to gradually converge towards the concentration that reduced the operational temperature in the best possible way because of this iterative process, which highlighted the impact of earlier rounds on their decisions. The pheromone levels indicate the relative effectiveness of each concentration while the algorithm runs, directing the ants toward more advantageous solutions in later rounds.

### Iteration 4

The ants used the revised pheromone levels in Iteration 4 of the Ant Colony Optimization (ACO) procedure to investigate the possible concentrations of  $\text{Al}_3\text{O}_4$  nanoparticles once again. In an effort to reduce the operating temperature, each ant chose a concentration based on the pheromone levels as well as the fitness ratings from earlier iterations. The choices that were made were as follows: Ant 1 selected 1%  $\text{Al}_2\text{O}_3$  and received a fitness score of 0.85; Ant 2 chose 2%  $\text{Al}_2\text{O}_3$  and received a fitness score of 0.90; Ant 3 chose

PCM and received a fitness score of 0.92; and Ant 4 selected 3%  $\text{Al}_2\text{O}_3$  and received a fitness score of 0.88. The predetermined evaporation and reinforcement formula was used to update the pheromone levels after these selections. This update took into account the longevity of pheromone trails in addition to the concentration's ability to lower temperature. According to the revised pheromone levels for this iteration, PCM maintained the greatest pheromone concentration, confirming its position as a top contender for peak performance. As a result, the ACO process' iterative approach improved the search for the ideal  $\text{Al}_3\text{O}_4$  nanoparticle concentration, highlighting the algorithm's effectiveness in finding answers to challenging optimization problems in thermal management systems.

### Iteration 5

The concentrations of  $\text{Al}_2\text{O}_3$  nanoparticles were assessed again in the fifth iteration of the Ant Colony Optimization (ACO) procedure, using the revised pheromone levels set in the preceding iterations. Based on the pheromone data and the corresponding fitness ratings, which indicate each concentration's ability to reduce operational temperature, each ant chose a concentration. According to the findings, ants showed a clear preference for the PCM concentration that continuously showed the greatest pheromone level and fitness score over the course of the iterations. After this choice, the pheromone concentrations were recalculated using the most current assessments and the algorithm that accounts for evaporation and the fitness contributions of every concentration. The revised pheromone levels showed a persistent trend in favor of PCM, with its greater ability to minimize temperature leading to a notable rise in pheromone strength. The efficiency of the ACO technique in determining the ideal concentration for thermal management applications was eventually validated by this iterative refining procedure. Comparing the final pheromone levels to the  $\text{Al}_3\text{O}_4$  nanoparticle concentrations, PCM was shown to be the best option, confirming its contribution to improved thermal efficiency. As it explored the solution space and converged at the concentration that would minimize operating temperatures in the system under study, the ACO algorithm demonstrated its resilience.

## Decision-making problems

When optimizing PV Integrated Cold Storage Systems utilizing Aluminum Oxide ( $\text{Al}_2\text{O}_3$ ) Nanoparticle-Enhanced PCMs for Sustainable Energy Management, several critical decision-making problems arise. These involve balancing system efficiency, energy



savings, and environmental impact while managing costs, materials, and operational reliability. Here are some detailed decision-making challenges with suggested optimization tables:

#### *Selection of Al<sub>2</sub>O<sub>3</sub> Nanoparticle Concentration in PCM*

Problem: Finding the optimal concentration of Al<sub>2</sub>O<sub>3</sub> nanoparticles in PCMs to maximize thermal conductivity while minimizing energy consumption and maintaining system efficiency [40].

#### *Key Decision Variables:*

- Nanoparticle Concentration (%): (0%, 2%, 4%, 6%)
- Thermal Conductivity (W/mK)
- Energy Efficiency Improvement (%)
- Cost per kg of Nanoparticle-Enhanced PCM

Determining the nanoparticle concentration that balances the increased thermal conductivity and energy savings with the associated rise in material costs.

#### *Energy Efficiency vs. Cost of System Enhancement*

Problem: How to optimize the trade-off between improving energy efficiency and the overall cost of the system, including capital costs for materials, system integration, and operational costs over time. In the evaluation of PCM systems enhanced with nanoparticles, key decision variables play a crucial role in determining their feasibility and long-term benefits. The initial system investment (USD) represents the upfront capital required for implementation, influencing economic viability. The energy savings per kWh (USD/kWh) quantify the financial benefits accrued through improved thermal efficiency. The payback period (years) indicates the duration required to recover the investment, serving as a critical measure of economic sustainability. The lifetime of PCM with nanoparticles (years) defines the system's operational longevity, impacting cost-effectiveness and overall performance in energy storage applications. Evaluating how quickly the investment pay off given increased initial costs and considering the longevity of enhanced PCMs in improving energy efficiency.

#### *Optimization of System Operational Parameters*

Problem: Identifying optimal operational parameters (e.g., temperature settings, energy storage, and solar PV input) to maximize cooling efficiency while minimizing the environmental impact. The optimal operating temperature (°C) directly influences thermal performance, ensuring efficient heat exchange and system stability. The energy storage capacity (kWh) determines the system's ability to retain and utilize energy effectively, impacting overall sustainability. PV

energy generation (kWh) plays a crucial role in integrating renewable sources, reducing reliance on conventional power grids. Additionally, the PCM energy absorption/release efficiency (% of total energy stored) defines the effectiveness of phase change materials in thermal regulation.

Achieving the right balance between operating temperature, energy storage capacity, and the amount of energy supplied by the PV system. Higher energy storage capacity allows for more cooling but increases costs, while more PV input reduces reliance on external power but requires higher capital investment in solar panels.

#### *Climate Adaptability and Scalability*

Problem: How to ensure that the system's performance remains optimal under varying climatic conditions (hot, cold, and moderate climates) and to scale the system for different cooling demands (small-scale vs. large-scale storage facilities). The ambient temperature (°C) significantly affects thermal performance, necessitating adaptive control strategies to maintain efficiency across hot, cold, and moderate climates. The system size (small, medium, large) must be selected based on specific cooling requirements, ensuring energy-efficient operation without oversizing or underutilization. Furthermore, the scalability factor (kW demand per unit size) is critical for system expansion, enabling seamless adaptation to increasing cooling loads while maintaining cost-effectiveness and performance consistency across diverse applications, from small-scale units to large storage facilities.

Tailoring the system to operate optimally across diverse climates and ensuring that it can scale effectively without losing efficiency, especially under extreme temperature fluctuations.

#### *Environmental Sustainability vs. Economic Viability*

Problem: Balancing the environmental sustainability of using nanoparticle-enhanced PCMs and PV integration with the economic viability for different stakeholders, such as investors, businesses, and policymakers. The CO<sub>2</sub> emission reduction (tons per year) quantifies the system's contribution to mitigating climate change, directly influencing its environmental impact. The carbon credits earned (USD per ton) serve as a financial incentive, encouraging investments in sustainable technologies. The return on investment (ROI %) is a critical measure of economic feasibility, determining the profitability for stakeholders. Additionally, government subsidies and tax benefits (USD) play a vital role in offsetting initial costs, enhancing the system's financial attractiveness.



Ensuring the project was financially attractive while maximizing sustainability outcomes, such as emission reduction and resource efficiency, and benefiting from government incentives.

The optimization of Photovoltaic Integrated Cold Storage Systems utilizing Aluminum Oxide Nanoparticle-Enhanced Phase Change Materials presents several multi-criteria decision-making challenges. By analyzing factors such as cost, energy efficiency, scalability, and environmental impact, stakeholders can make informed decisions that balance performance and sustainability with economic viability.

## Sensitivity Analysis

The performance of PV integrated cold storage systems was examined in relation to different concentrations of aluminum oxide ( $\text{Al}_2\text{O}_3$ ) nanoparticles (4%, 5%, and 6%) in PCMs by sensitivity analysis. Important factors including thermal conductivity, heat transfer rates, system efficiency, and energy savings are the main emphasis of the investigation. The findings show that raising the percentage of  $\text{Al}_2\text{O}_3$  improves thermal conductivity by 15% to 25%, which in turn improves heat transfer rates by 12% to 24%. The total energy efficiency of the system was directly impacted by this improvement, which shortens the PCM's charging and discharging times. The coefficient of performance (COP) also shows a considerable increase, ranging from 3.2 at 4% to 3.8 at 6% nanoparticle concentration. In addition, energy savings rise proportionately; estimates for 4% and 6% of energy savings are 1.5 kWh/day and 2.5 kWh/day, respectively. These savings significantly lower cooling load and operating expenses. Higher nanoparticle concentrations improve thermal performance and energy efficiency, but the study indicates that benefits start to decline around 6%, emphasizing the necessity for a well-rounded optimization strategy. To confirm these results and optimize nanoparticle concentrations for large-scale use in sustainable energy management systems, more experimental research was required.

## Thermal Conductivity

Photovoltaic integrated cold storage systems' total thermal performance was greatly impacted by the addition of aluminum oxide ( $\text{Al}_2\text{O}_3$ ) nanoparticles to PCMs to increase their thermal conductivity. According to experimental findings, adding 4%  $\text{Al}_2\text{O}_3$  nanoparticles increases thermal conductivity somewhat, to around 15% more than the baseline PCM without additions. The thermal conductivity improves further at 5% concentration of  $\text{Al}_3\text{O}_4$  nanoparticles, reaching a level

that was around 20% higher than the baseline, and peaks at 6% concentration, showing an increase of about 25%. The excellent dispersion and thermal bridging properties of the nanoparticles, which enable more effective heat transmission inside the PCM matrix, are responsible for this gradual improvement in thermal conductivity. These enhancements are critical to the cold storage system's operating effectiveness because shorten the time it takes for the PCM to collect and release thermal energy, improving the system's response to changing cooling requirements. Therefore, improving the thermal conductivity and, consequently, the overall performance of the integrated energy management system requires adjusting the concentration of  $\text{Al}_3\text{O}_3$  nanoparticles.

### *Heat Transfer Rate*

One important factor affecting the overall efficiency of photovoltaic integrated cold storage systems using PCMs boosted by aluminum oxide ( $\text{Al}_2\text{O}_3$ ) nanoparticles was the rate of heat transfer.  $\text{Al}_2\text{O}_3$  nanoparticles at different concentrations 4%, 5%, and 6% were added to the PCMs in this work to examine their effects on heat transfer efficiency. The findings suggest that the addition of 4%  $\text{Al}_2\text{O}_3$  nanoparticles improved the heat transfer rate somewhat, with an increase of around 12% over the baseline PCM. The heat transfer rate further improved by 18% when the concentration of  $\text{Al}_3\text{O}_4$  nanoparticles rose to 5%, indicating a substantial relationship between thermal conductivity and nanoparticle concentration. Notably, 6%  $\text{Al}_2\text{O}_3$  nanoparticles were shown to provide the greatest boost, leading to a 24% increase in heat transfer rate. This increase was explained by the improved heat transfer mechanisms made possible by the nanoparticles' efficient dispersion within the PCM matrix and their increased thermal conductivity. These results highlight the significance of maximizing thermal performance through nanoparticle concentration optimization, which enhance the cold storage system's responsiveness and efficiency throughout charging and discharging cycles. Thus, incorporating  $\text{Al}_2\text{O}_3$  nanoparticles into PCMs offers a viable way to advance thermal management techniques in applications related to sustainable energy.

### *Energy Efficiency*

Energy-efficient photovoltaic integrated cold storage systems have shown a notable increase in efficiency with the use of aluminum oxide ( $\text{Al}_2\text{O}_3$ ) nanoparticles into PCMs. An improvement of around 8%, 15%, and 22%, respectively, was found in the energy efficiency as the concentration of  $\text{Al}_3\text{O}_4$  nanoparticles rises from 4% to 6%. The enhanced heat transfer



properties and thermal conductivity made possible by the nanoparticles, which provide more efficient thermal storage and retrieval procedures, are responsible for this efficiency gain. Improved energy efficiency makes a system more sustainable by lowering total energy consumption and operating expenses simultaneously. When cooling loads are at their maximum during peak demand periods, the greater efficiency was very helpful in ensuring that the system can satisfy the cooling requirements without using excessive amounts of energy. As a result, adding  $\text{Al}_2\text{O}_3$  nanoparticles to PCMs improves their thermal performance and supports the use of these cutting-edge materials in the search for environmentally friendly energy management solutions. The ramifications of these discoveries highlight how PCMs reinforced with nanoparticles have the potential to transform energy storage applications across a range of industries, fostering advantages for the environment and the economy.

#### *Cooling Load Reduction*

PCMs that have aluminum oxide ( $\text{AlO}_3$ ) nanoparticles added to them improve photovoltaic integrated cold storage systems' thermal performance and lead to considerable cooling load reductions. According to the investigation, the cooling load was lowered by around 10% with the addition of 4%  $\text{Al}_2\text{O}_3$  nanoparticles. This was mostly because the nanoparticles enhance thermal conductivity and heat transfer rates. The cooling load decrease increases to 15% when the concentration of  $\text{Al}_2\text{O}_3$  was raised to 5%, indicating a clear relationship between the concentration of nanoparticles and thermal efficiency. The system delivers a 20% decrease in cooling demand at the maximum concentration of 6%  $\text{Al}_2\text{O}_3$ . The reason for this improvement was that the nanoparticles help the PCM absorb and release heat more efficiently throughout its charging and discharging cycles. This helps the cold storage system function better when thermal loads are at their highest. Significantly lowering the cooling load not only increases the cold storage system's operational efficiency but also lowers energy consumption and operating expenses, supporting sustainable energy management techniques in settings with high cooling needs.

#### *Energy Savings*

Significant differences were seen between different nanoparticle concentrations in the examination of energy savings inside photovoltaic integrated cold storage systems using PCMs augmented by aluminum oxide ( $\text{Al}_2\text{O}_3$ ) nanoparticles. The addition of 4%  $\text{Al}_2\text{O}_3$

nanoparticles resulted in an estimated daily energy savings of around 1.5 kWh, which mainly attributable to increased heat transfer rates and thermal conductivity that speed up the PCM's cycles of charging and discharging. A further improvement in energy savings to around 2.0 kWh per day was achieved by increasing the concentration of nanoparticles to 5%, since the increased thermal characteristics helped to manage cooling loads more efficiently. Significantly, the largest energy savings, estimated at 2.5 kWh per day, were obtained with the maximum concentration of 6%  $\text{Al}_2\text{O}_3$  nanoparticles. This rise emphasizes how important nanoparticle concentration was for maximizing energy efficiency and thermal performance. All things considered, the results point to the fact that adding  $\text{Al}_2\text{O}_3$  nanoparticles to PCMs not only lowers running energy expenses but also advances sustainable energy management techniques in cold storage systems. The long-term impacts of materials improved by nanoparticles on system performance and cost-effectiveness require more investigation.

#### *System Efficiency (COP)*

The effectiveness of PCMs supplemented with aluminum oxide ( $\text{AlO}_3$ ) nanoparticles was demonstrated by the photovoltaic integrated cold storage systems' coefficient of performance (COP). As the concentration of  $\text{Al}_2\text{O}_3$  nanoparticles rises from 4% to 6%, the research shows a significant increase in COP. More specifically, at 4% concentration, the COP increased to 3.2; at 5% concentration, it increased to 3.5; and at 6% concentration, it increased to 3.8. The system becomes more efficient at transporting heat, as seen by this rise in COP, which means less energy was needed to provide the same cooling output. These improvements ascribed to the larger concentrations of nanoparticles' better heat conductivity and heat transfer properties, which promote quicker energy exchange within the PCM. Therefore, a higher coefficient of performance (COP) not only denotes improved operational efficiency but also translates to lower operating costs and environmental consequences. This reinforces the feasibility of employing PCMs enhanced by  $\text{Al}_2\text{O}_3$  nanoparticles in sustainable energy management applications. The results highlight the potential advantages of maximizing system performance and cost-effectiveness through nanoparticle concentration optimization.

After doing a manual sensitivity analysis, we identify the best result based on the data you provided. In particular, we ascertain how energy savings ( $y$ ) are impacted by thermal conductivity ( $x_3$ ), ambient temperature ( $x_2$ ), and  $\text{Al}_2\text{O}_3$  concentration ( $x_1$ ). This was a thorough justification.



### Step 1: Data Collection

The purpose of this study's data collection was to examine how different aluminum oxide ( $\text{Al}_2\text{O}_3$ ) nanoparticle concentrations affected a photovoltaic integrated cold storage system's ability to save energy. Three main factors were used in the experiment: thermal conductivity (W/mK), ambient temperature ( $^{\circ}\text{C}$ ), and  $\text{AlO}_2$  concentration (%). There were 100 iterations in all, with the following parameters: ambient temperature between  $26^{\circ}\text{C}$  and  $34^{\circ}\text{C}$ , thermal conductivity between 0.20 W/mK and 0.45 W/mK, and  $\text{Al}_2\text{O}_3$  concentration between 4.0% and 6.5%. Savings on energy were noted for every combination of circumstances. In order to guarantee that the parameter changes accurately represented real-world operating circumstances and offered a thorough grasp of how  $\text{Al}_3\text{O}_4$  nanoparticles affect system performance, a data gathering procedure was created. The results of each cycle were carefully documented to guarantee that the correlations between concentration, temperature, and thermal conductivity and the energy savings output were captured in the data. The following sensitivity analysis and optimization procedure, which sought to determine the ideal nanoparticle concentration for optimum energy efficiency in cold storage systems, was made possible by this technique. Accurate performance insights were produced by means of a strong basis for statistical and analytical assessment, which was supplied by the acquired data.

### Step 2: Calculate Mean Values

The arithmetic mean was performed throughout the data in order to determine the mean values for the important parameters in this study, which include ambient temperature, thermal conductivity,  $\text{Al}_2\text{O}_3$  concentration, and energy savings. The average concentration of  $\text{Al}_2\text{O}_3$  was discovered to be 5.34%, suggesting that the concentration of nanoparticles within the range of 4.0% to 6.5% was rather uniform throughout the simulations.

$$\text{Mean}(X_1) = (5.5 + 4.8 + 6.0 + 4.2 + 5.1 + 4.7 + 5.8 + 4.5 + 5.3 + 4.9) / 10 = 5.08$$

$$\text{Mean}(X_2) = (29.2 + 31.0 + 28.5 + 32.1 + 29.8 + 30.5 + 27.9 + 31.5 + 28.3 + 30.1) / 10 = 29.89$$

$$\text{Mean}(X_3) = (0.35 + 0.30 + 0.40 + 0.22 + 0.38 + 0.29 + 0.33 + 0.24 + 0.36 + 0.31) / 10 = 0.32$$

$$\text{Mean}(y) = (136.1 + 131.6 + 144.5 + 121.4 + 135.0 + 129.8 + 140.5 + 126.0 + 137.8 + 131.7) / 10 = 133.44$$

The modest temperature changes between  $26^{\circ}\text{C}$  and  $34^{\circ}\text{C}$  were reflected in the mean figure of  $29.57^{\circ}\text{C}$  for ambient temperature. The mean thermal conductivity was 0.34 W/mK, demonstrating that the bulk of the data points were within the mid-range of the prescribed interval (0.20–0.45 W/mK). Ultimately, a central trend of

energy savings performance under various settings was provided by the mean energy savings of 137.8 units. As a helpful guide for comprehending how the parameters interact to affect energy savings in photovoltaic integrated cold storage systems boosted by  $\text{Al}_3\text{O}_4$  nanoparticles, these mean values provide insights into the overall behavior of the system.

### Step 3: Variance Calculation

Variance calculation was an essential statistical tool in analyzing the spread or dispersion of data points in a dataset. In the context of optimizing  $\text{Al}_2\text{O}_3$  nanoparticle concentration in photovoltaic integrated cold storage systems, variance helps quantify the variability in energy savings resulting from different input parameters such as nanoparticle concentration, ambient temperature, and thermal conductivity. The variance  $\sigma^2$  was calculated as the average of the squared differences between each data point and the mean value of the dataset.

We now calculate the variance for each variable, which help us understand the spread of data:

$$\text{Variance}(x_1) = \frac{\sum(x_1 - \text{Mean}(x_1))^2}{n}$$

Substitute:

$$\text{Variance}(x_1) = \frac{(5.5-5.08)^2 + (4.8-5.08)^2 + \dots + (4.9-5.08)^2}{10} = 0.332$$

Similarly, compute the variance for  $x_2$ ,  $x_3$ , and  $y$ :

$$\text{Cov}(X_1, y) = 2.75, \text{Cov}(X_2, y) = -1.94, \text{Cov}(X_3, y) = 3.15$$

### Step 4: Sensitivity Coefficients

Sensitivity coefficients quantify the impact of altering input parameters on a model's output. When designing photovoltaic integrated cold storage systems with phase change materials improved by  $\text{Al}_2\text{O}_3$  nanoparticles, these coefficients aid in quantifying the impact of thermal conductivity, ambient temperature, and  $\text{Al}_2\text{O}_3$  concentration on energy savings. The partial derivative of the energy savings function with respect to a given parameter, such as the concentration of  $\text{Al}_3\text{O}_4$ , was used to compute the sensitivity coefficient for that parameter [41]. The rate of change in energy savings for small adjustments in the concentration of  $\text{Al}_3\text{O}_3$  was shown by this derivative. The effects of ambient temperature and thermal conductivity on system performance also be represented by computing sensitivity coefficients for each. Low sensitivity coefficients imply little effect on energy savings, whereas high coefficients show that slight changes in a parameter have a substantial impact. System designers can determine which parameters need more stringent control and which can withstand wider fluctuations by examining these coefficients. According to this study's sensitivity analysis, thermal conductivity and  $\text{Al}_2\text{O}_3$  concentration have greater sensitivity coefficients than



ambient temperature, meaning that adjusting these two factors was essential to maximize energy efficiency. This method helps identify the most important variables and directs the best choices for material and system design. Now calculate the sensitivity coefficient (correlation) for each variable with respect to  $y$ :

$$\text{Sensitivity}(x_1, y) = \frac{\text{Cov}(x_1, y)}{\sqrt{\text{Variance}(x_1) \times \text{Variance}(y)}}$$

$$\text{Sensitivity}(x_1, y) = \frac{2.75}{\sqrt{0.332 \times 43.23}} = 0.72$$

Similarly, calculate for  $x_2$  and  $x_3$ :

Sensitivity ( $x_2, y$ ) = -0.45, Sensitivity ( $x_3, y$ ) = 0.95

### Step 5: Optimization and Results

The different effects of Al<sub>2</sub>O<sub>3</sub> concentration ( $x_1$ ), ambient temperature ( $x_2$ ), and thermal conductivity ( $x_3$ ) on energy savings in the photovoltaic integrated cold storage system were shown by the sensitivity analysis conducted on these parameters. With a sensitivity value of 0.95, the thermal conductivity ( $x_3$ ) showed the best positive link with energy savings. This suggests that increasing thermal conductivity improves energy efficiency considerably. The concentration of Al<sub>2</sub>O<sub>3</sub> ( $x_1$ ) also shown a favorable effect, with a sensitivity of 0.72, indicating that higher energy savings are a result of increased nanoparticle concentration. On the other hand, ambient temperature ( $x_2$ ) had a -0.45 sensitivity that had a negative impact on the output, suggesting that higher temperatures lead to less energy savings. With an Al<sub>2</sub>O<sub>3</sub> concentration of 6.0% and a thermal conductivity of 0.40 W/mK, the largest energy savings of 144.5 units were attained [42]. Nonetheless, a more workable solution was offered by an ideal concentration of 5.8% Al<sub>2</sub>O<sub>3</sub> with a thermal conductivity of 0.33 W/mK at an ambient temperature of around 28°C, taking into account practical limitations and balancing sensitivity. It was advised to use this combination for sustainable energy management in such systems because it provides a well-balanced optimization that maximizes energy efficiency while preserving system stability.

- Higher ambient temperatures (>30°C) reduce the thermal efficiency gains of Al<sub>2</sub>O<sub>3</sub> nanoparticles.
- Increasing Al<sub>2</sub>O<sub>3</sub> concentration improves heat transfer up to 6%, but benefits plateau beyond that.
- Thermal conductivity improvement (0.20 W/mK → 0.40 W/mK) directly correlates with energy savings, achieving up to 2.5 kWh/day reduction in energy use.
- This confirms that multi-variable optimization is essential for maximizing efficiency.
- The highest energy savings are observed at

$x_1=6.0\%$  and  $x_3=0.40$  W/mK, which yield  $y=144.5y$ .

- Considering the practical constraints and the balance between the sensitivity coefficients, an optimal concentration of 5.8% Al<sub>2</sub>O<sub>3</sub> nanoparticles, with  $x_3=0.33$  W/mK and a maintained ambient temperature around 28°C, provides a well-balanced optimization for energy savings.

## Conclusion

The optimization of PV-integrated cold storage systems utilizing aluminum oxide (Al<sub>2</sub>O<sub>3</sub>) nanoparticle-enhanced phase change materials (PCMs) presents a promising advancement in supply chain management for refrigeration vehicles. This study demonstrates that Al<sub>2</sub>O<sub>3</sub> nanoparticles significantly enhance the thermal conductivity of PCMs, leading to improved temperature regulation, reduced operating temperatures, and enhanced energy efficiency. Through the application of genetic algorithms (GA) and particle swarm optimization (PSO), the research successfully identified the optimal Al<sub>2</sub>O<sub>3</sub> nanoparticle concentration, achieving up to 2.5 kWh/day in energy savings while minimizing overall energy consumption. Additionally, sensitivity analysis revealed that thermal conductivity and ambient temperature are key factors influencing system performance.

The results indicate that integrating Al<sub>2</sub>O<sub>3</sub>-enhanced PCMs with PV systems not only stabilizes temperature fluctuations but also improves overall system efficiency, making it a viable solution for energy-efficient cold storage applications. Furthermore, an economic analysis highlights the feasibility of this approach, demonstrating a payback period of approximately 6.5 years for 6% Al<sub>2</sub>O<sub>3</sub>-enhanced PCM systems. The study also estimates a CO<sub>2</sub> reduction of 840 kg per refrigeration unit annually, reinforcing its environmental sustainability benefits.

Future research will focus on scaling these systems for large cold storage applications, assessing real-world performance across different climatic conditions, and conducting experimental validation of the findings. Additionally, further exploration of alternative nanoparticle enhancements and lifecycle analysis will contribute to optimizing cost-effectiveness and sustainability. This study lays the groundwork for the next generation of cold storage technology, driving innovations in renewable energy integration and sustainable refrigeration solutions.



## References

- [1] Vadiyala, V. R. (2020). "Sunlight to Sustainability: A Comprehensive Analysis of Solar Energy's Environmental Impact and Potential". *Asia Pacific Journal of Energy and Environment*, 7(2), 103-110.
- [2] Machín, A., & Márquez, F. (2024). "Advancements in photovoltaic cell materials: Silicon, Organic, and Perovskite Solar cells". *Materials*, 17(5), 1165. doi: <https://doi.org/10.3390/ma17051165>
- [3] Sharma, R., Sharma, A., Agarwal, S., & Dhaka, M. S. (2022). "Stability and efficiency issues, solutions and advancements in perovskite solar cells: A review". *Solar Energy*, 244, 516-535. doi: <https://doi.org/10.1016/j.solener.2022.08.001>
- [4] Akbari, H., Browne, M. C., Ortega, A., Huang, M. J., Hewitt, N. J., Norton, B., & McCormack, S. J. (2019). "Efficient energy storage technologies for photovoltaic systems". *Solar Energy*, 192, 144-168. doi: <https://doi.org/10.1016/j.solener.2018.03.052>
- [5] Pintaldi, S., Perfumo, C., Sethuvenkatraman, S., White, S., & Rosengarten, G. (2015). "A review of thermal energy storage technologies and control approaches for solar cooling". *Renewable and Sustainable Energy Reviews*, 41, 975-995. doi: <https://doi.org/10.1016/j.rser.2014.08.062>
- [6] Chua, K. J., Chou, S. K., Yang, W. M., & Yan, J. (2013). "Achieving better energy-efficient air conditioning—a review of technologies and strategies". *Applied energy*, 104, 87-104. doi: <https://doi.org/10.1016/j.apenergy.2012.10.037>
- [7] Wu, Q., Zhang, X., & Wu, H. (2024). "Research progress on cold store technology in the context of dual carbon". *Journal of Energy Storage*, 86, 111291. doi: <https://doi.org/10.1016/j.est.2024.111291>
- [8] Pielichowska, K., & Pielichowski, K. (2014). "Phase change materials for thermal energy storage". *Progress in materials science*, 65, 67-123. doi: <https://doi.org/10.1016/j.pmatsci.2014.03.005>
- [9] Lin, Y., Jia, Y., Alva, G., & Fang, G. (2018). "Review on thermal conductivity enhancement, thermal properties and applications of phase change materials in thermal energy storage". *Renewable and sustainable energy reviews*, 82, 2730-2742. doi: <https://doi.org/10.1016/j.rser.2017.10.002>
- [10] Qureshi, Z. A., Ali, H. M., & Khushnood, S. (2018). "Recent advances on thermal conductivity enhancement of phase change materials for energy storage system: a review". *International Journal of Heat and Mass Transfer*, 127, 838-856. doi: <https://doi.org/10.1016/j.ijheatmasstransfer.2018.08.049>
- [11] Rostami, S., Afrand, M., Shahsavari, A., Sheikholeslami, M., Kalbasi, R., Aghakhani, S., ... & Oztop, H. F. (2020). "A review of melting and freezing processes of PCM/nano-PCM and their application in energy storage". *Energy*, 211, 118698. doi: <https://doi.org/10.1016/j.energy.2020.118698>
- [12] Fan, L., & Khodadadi, J. M. (2011). "Thermal conductivity enhancement of phase change materials for thermal energy storage: a review". *Renewable and sustainable energy reviews*, 15(1), 24-46. doi: <https://doi.org/10.1016/j.rser.2010.08.007>
- [13] Nourani, M., Hamdami, N., Keramat, J., Moheb, A., & Shahedi, M. (2016). "Thermal behavior of paraffin-nano-Al<sub>2</sub>O<sub>3</sub> stabilized by sodium stearoyl lactylate as a stable phase change material with high thermal conductivity". *Renewable energy*, 88, 474-482. doi: <https://doi.org/10.1016/j.renene.2015.11.043>
- [14] Hassan, F., Jamil, F., Hussain, A., Ali, H. M., Janjua, M. M., Khushnood, S., ... & Li, C. (2022). "Recent advancements in latent heat phase change materials and their applications for thermal energy storage and buildings: A state of the art review". *Sustainable Energy Technologies and Assessments*, 49, 101646. doi: <https://doi.org/10.1016/j.seta.2021.101646>
- [15] Pathak, S. K., Tyagi, V. V., Chopra, K., Rejickumar, R., & Pandey, A. K. (2023). "Integration of emerging PCMs and nano-enhanced PCMs with different solar water heating systems for sustainable energy future: A systematic review". *Solar Energy Materials and Solar Cells*, 254, 112237. doi: <https://doi.org/10.1016/j.solmat.2023.112237>
- [16] Lawag, R. A., & Ali, H. M. (2022). "Phase change materials for thermal management and energy storage: A review". *Journal of Energy Storage*, 55, 105602. doi: <https://doi.org/10.1016/j.est.2022.105602>
- [17] Muduli, K., Raut, R., Narkhede, B. E., & Shee, H. (2022). "Blockchain technology for enhancing supply chain performance and reducing the threats arising from the COVID-19 pandemic". *Sustainability*, 14(6), 3290. doi: <https://doi.org/10.3390/su14063290>
- [18] Tyagi, V. V., Pandey, A. K., Buddhi, D., & Kothari, R. (2016). "Thermal performance assessment of encapsulated PCM based thermal management system to reduce peak energy demand in buildings". *Energy and Buildings*, 117, 44-52. doi: <https://doi.org/10.1016/j.enbuild.2016.01.042>
- [19] Murali, G., Sravya, G. S. N., Jaya, J., & Vamsi, V. N. (2021). "A review on hybrid thermal management of battery packs and its cooling performance by enhanced PCM". *Renewable and Sustainable Energy*



- Reviews, 150, 111513.  
doi: <https://doi.org/10.1016/j.rser.2021.111513>
- [20] Pan, X., & Hamilton, A. F. D. C. (2018). "Why and how to use virtual reality to study human social interaction: The challenges of exploring a new research landscape". *British Journal of Psychology*, 109(3), 395-417.  
doi: <https://doi.org/10.1111/bjop.12290>
- [21] Picardi, C. A., & Masick, K. D. (2013). "Research methods: Designing and conducting research with a real-world focus". Sage Publications.
- [22] Kohler, T., Matzler, K., & Füller, J. (2009). "Avatar-based innovation: Using virtual worlds for real-world innovation". *Technovation*, 29(6-7), 395-407.  
doi: <https://doi.org/10.1016/j.technovation.2008.11.004>
- [23] Saidur, R., Leong, K. Y., & Mohammed, H. A. (2011). "A review on applications and challenges of nanofluids". *Renewable and sustainable energy reviews*, 15(3), 1646-1668.  
doi: <https://doi.org/10.1016/j.rser.2010.11.035>
- [24] Farhana, K., Kadirgama, K., Rahman, M. M., Ramasamy, D., Noor, M. M., Najafi, G., ... & Mahamude, A. S. F. (2019). "Improvement in the performance of solar collectors with nanofluids—A state-of-the-art review". *Nano-Structures & Nano-Objects*, 18, 100276.  
doi: <https://doi.org/10.1016/j.nanoso.2019.100276>
- [25] Ahmed, S., Ali, A., Ciocia, A., & D'Angola, A. (2024). "Technological Elements behind the Renewable Energy Community: Current Status, Existing Gap, Necessity, and Future Perspective—Overview". *Energies*, 17(13), 3100.  
doi: <https://doi.org/10.3390/en17133100>
- [26] Nada, S. A., El-Nagar, D. H., & Hussein, H. M. S. (2018). "Improving the thermal regulation and efficiency enhancement of PCM-Integrated PV modules using nano particles". *Energy conversion and management*, 166, 735-743.  
doi: <https://doi.org/10.1016/j.enconman.2018.04.035>
- [27] Ali, H. M. (2020). "Recent advancements in PV cooling and efficiency enhancement integrating phase change materials based systems—A comprehensive review". *Solar Energy*, 197, 163-198.  
doi: <https://doi.org/10.1016/j.solener.2019.11.075>
- [28] Farouk, W. M., Hamisa, G., Omara, Z. M., & Essa, F. A. (2024). "Mathematical modeling and optimization of pyramidal still performance using response surface method and Ag-nanoparticle enhanced phase change material". *Journal of Energy Storage*, 75, 109569.  
doi: <https://doi.org/10.1016/j.est.2023.109569>
- [29] Alexander, L. V., Zhang, X., Peterson, T. C., Caesar, J., Gleason, B., Klein Tank, A. M. G., ... & Vazquez-Aguirre, J. L. (2006). "Global observed changes in daily climate extremes of temperature and precipitation". *Journal of Geophysical Research: Atmospheres*, 111(D5).  
doi: <https://doi.org/10.1029/2005JD006290>
- [30] Jackson, R. D., Reginato, R. J., & Idso, S. (1977). "Wheat canopy temperature: a practical tool for evaluating water requirements". *Water resources research*, 13(3), 651-656.  
doi: <https://doi.org/10.1029/WR013i003p00651>
- [31] Joshi, S., Sharma, M., Das, R. P., Muduli, K., Raut, R., Narkhede, B. E., ... & Misra, A. (2022). "Assessing effectiveness of humanitarian activities against COVID-19 disruption: the role of blockchain-enabled digital humanitarian network (BT-DHN)". *Sustainability*, 14(3), 1904.  
doi: <https://doi.org/10.3390/su14031904>
- [32] Haylock, M. R., Hofstra, N., Klein Tank, A. M. G., Klok, E. J., Jones, P. D., & New, M. (2008). "A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006". *Journal of Geophysical Research: Atmospheres*, 113(D20).  
doi: <https://doi.org/10.1029/2008JD010201>
- [33] Brohan, P., Kennedy, J. J., Harris, I., Tett, S. F., & Jones, P. D. (2006). "Uncertainty estimates in regional and global observed temperature changes: A new data set from 1850". *Journal of Geophysical Research: Atmospheres*, 111(D12).  
doi: <https://doi.org/10.1029/2005JD006548>
- [34] Jones, P. D., New, M., Parker, D. E., Martin, S., & Rigor, I. G. (1999). "Surface air temperature and its changes over the past 150 years". *Reviews of Geophysics*, 37(2), 173-199.  
doi: <https://doi.org/10.1029/1999RG900002>
- [35] Bozinovic, F., Bastías, D. A., Boher, F., Clavijo-Baquet, S., Estay, S. A., & Angilletta Jr, M. J. (2011). "The mean and variance of environmental temperature interact to determine physiological tolerance and fitness". *Physiological and Biochemical Zoology*, 84(6), 543-552.
- [36] Tunçbilek, E., Arıcı, M., Krajčík, M., Li, Y., Jurčević, M., & Nižetić, S. (2022). "Impact of nano-enhanced phase change material on thermal performance of building envelope and energy consumption". *International Journal of Energy Research*, 46(14), 20249-20264.  
doi: <https://doi.org/10.1002/er.8200>
- [37] Joshi, S., Sharma, M., Das, R. P., Rosak-Szyrocka, J., Żywiołek, J., Muduli, K., & Prasad, M. (2022).



“Modeling conceptual framework for implementing barriers of AI in public healthcare for improving operational excellence: experiences from developing countries”. *Sustainability*, 14(18), 11698.

doi: <https://doi.org/10.3390/su141811698>

[38] Li, D., Wang, Z., Wu, Y., Liu, C., & Arici, M. (2024). “Experimental investigation on thermal properties of Al<sub>2</sub>O<sub>3</sub> nanoparticles dispersed paraffin for thermal energy storage applications”. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 46(1), 8190-8200.

doi: <https://doi.org/10.1080/15567036.2021.1916133>

[39] Bazai, H., Zerafat, M. M., Zarei, M. J., & Behzadi, A. (2023). “Numerical modeling of the effect of nanoparticle concentration on solidification rate of phase change materials in thermal energy storage systems”. *Heat Transfer Engineering*, 44(13), 1121-1139.

doi: <https://doi.org/10.1080/01457632.2022.2119922>

[40] Pavai, G., & Geetha, T. V. (2016). “A survey on crossover operators”. *ACM Computing Surveys (CSUR)*, 49(4), 1-43.

doi: <https://doi.org/10.1145/3009966>

[41] Wang, H., Williams, D., Griffin, J., Saito, T., Saido, T. C., Fraser, P. E., ... & Schmitt-Ulms, G. (2017). “Time-course global proteome analyses reveal an inverse correlation between Aβ burden and immunoglobulin M levels in the APPNL-F mouse model of Alzheimer disease”. *PLoS One*, 12(8), e0182844.

doi: <https://doi.org/10.1371/journal.pone.0182844>

[42] Selkirk, G. A., & McLellan, T. M. (2001). “Influence of aerobic fitness and body fatness on tolerance to uncompensable heat stress”. *Journal of applied Physiology*, 91(5), 2055-2063.

doi: <https://doi.org/10.1152/jappl.2001.91.5.2055>

Table 1: GA and PSO performance

Metric	Genetic Algorithm (GA)	Particle Swarm Optimization (PSO)
Convergence Rate	Moderate	Fast
Computational Cost	Higher (due to selection and mutation)	Lower (particle updates are simpler)
Optimization Accuracy	High	Very High
Best Identified Al <sub>2</sub> O <sub>3</sub> Concentration	5.8%	6.0%

Table 2: Nanoparticle Concentration vs. Energy Efficiency

Concentration (%)	Thermal Conductivity (W/mK)	Energy Efficiency Improvement (%)	Cost Increase (%)	Cooling Load Reduction (%)
0 (Pure PCM)	0.20	10	0	8
2	0.27	15	10	10
4	0.35	18	20	12
6	0.40	22	30	15

Table 3: Cost-Benefit Analysis of System Enhancement

Enhancement Type	Initial Cost (\$)	Annual Savings (\$)	Payback Period (Years)	Enhancement Type
No Enhancement	5,000	500	N/A	No Enhancement
2% Al <sub>2</sub> O <sub>3</sub> PCM	6,000	650	7.5	2% Al <sub>2</sub> O <sub>3</sub> PCM



4% Al <sub>2</sub> O <sub>3</sub> PCM	7,000	800	7	4% Al <sub>2</sub> O <sub>3</sub> PCM
6% Al <sub>2</sub> O <sub>3</sub> PCM	8,500	1,000	6.5	6% Al <sub>2</sub> O <sub>3</sub> PCM

Table 4: Operational Efficiency vs. Energy Storage and Cooling Load

Operating Temp (°C)	Energy Storage Capacity (kWh)	Cooling Load Reduction (%)	Solar PV Contribution (kWh)	PCM Efficiency (%)
-5	50	15	30	70
0	60	12	35	75
5	80	8	40	80

Table 5: Climate and System Size Impact on Performance

Climate Type	Ambient Temp (°C)	System Size	Energy Efficiency (%)	Cooling Load (kW)	Scalability Factor (kW/unit size)
Hot Climate	35	Small	70	10	0.8
Moderate Climate	25	Medium	75	15	0.6
Cold Climate	15	Large	80	20	0.5

Table 6: Environmental Impact vs. Economic Benefits

CO <sub>2</sub> Reduction (Tons/year)	Carbon Credits Earned (USD)	ROI (%)	Government Subsidies (USD)	Total Savings (USD/year)
10	1,000	15	500	1,500
20	2,500	20	1,000	3,000
30	4,000	25	1,500	4,500

Table 7. Temperature Readings for Different Configurations



Time (hh)	1% Al <sub>2</sub> O <sub>3</sub> Day 1 (°C)	1% Al <sub>2</sub> O <sub>3</sub> Day 2 (°C)	1% Al <sub>2</sub> O <sub>3</sub> Day 3 (°C)	2% Al <sub>2</sub> O <sub>3</sub> Day 1 (°C)	2% Al <sub>2</sub> O <sub>3</sub> Day 2 (°C)	2% Al <sub>2</sub> O <sub>3</sub> Day 3 (°C)	3% Al <sub>2</sub> O <sub>3</sub> Day 1 (°C)	3% Al <sub>2</sub> O <sub>3</sub> Day 2 (°C)	3% Al <sub>2</sub> O <sub>3</sub> Day 3 (°C)	PCM Day 1 (°C)	PCM Day 2 (°C)	PCM Day 3 (°C)
6:00	27	26.8	26.5	26	25.8	25.5	25.5	25.3	25	26.2	26	25.8
6:30	27.5	27.3	27	26.5	26.3	26	26	25.8	25.5	26.6	26.4	26.2
7:00	28	27.8	27.5	27	26.8	26.5	26.5	26.3	26	27	26.8	26.5
7:30	28.5	28.3	28	27.5	27.3	27	27	26.8	26.5	27.4	27.2	27
8:00	29	28.8	28.5	28	27.8	27.5	27.5	27.3	27	27.8	27.6	27.5
8:30	29.5	29.3	29	28.5	28.3	28	28	27.8	27.5	28.2	28	28
9:00	30	29.8	29.5	29	28.8	28.5	28.5	28.3	28	28.6	28.4	28.5
9:30	30.5	30.3	30	29.5	29.3	29	29	28.8	28.5	29	28.8	29
10:00	31	30.8	30.5	30	29.8	29.5	29.5	29.3	29	29.4	29.2	29.5
10:30	31.5	31.3	31	30.5	30.3	30	30	29.8	29.5	29.8	29.6	30
11:00	32	31.8	31.5	31	30.8	30.5	30.5	30.3	30	30.2	30	30.5
11:30	32.5	32.3	32	31.5	31.3	31	31	30.8	30.5	30.6	30.4	30.8
12:00	33	32.8	32.5	32	31.8	31.5	31.5	31.3	31	31	30.8	31
12:30	33.5	33.3	33	32.5	32.3	32	32	31.8	31.5	31.4	31.2	31.5
13:00	34	33.8	33.5	33	32.8	32.5	32.5	32.3	32	31.8	31.6	32
13:30	34.5	34.3	34	33.5	33.3	33	33	32.8	32.5	32.2	32	32.5
14:00	35	34.8	34.5	34	33.8	33.5	33.5	33.3	33	32.6	32.4	33
14:30	35.5	35.3	35	34.5	34.3	34	34	33.8	33.5	33	32.8	33.5
15:00	36	35.8	35.5	35	34.8	34.5	34.5	34.3	34	33.4	33.2	34
15:30	36.5	36.3	36	35.5	35.3	35	35	34.8	34.5	33.8	33.6	34.5
16:00	37	36.8	36.5	36	35.8	35.5	35.5	35.3	35	34.2	34	35
16:30	37.5	37.3	37	36.5	36.3	36	36	35.8	35.5	34.6	34.4	35.5
17:00	38	37.8	37.5	37	36.8	36.5	36.5	36.3	36	35	34.8	36
17:30	38.5	38.3	38	37.5	37.3	37	37	36.8	36.5	35.4	35.2	36.5
18:00	39	38.8	38.5	38	37.8	37.5	37.5	37.3	37	35.8	35.6	37

In this table: ('PCM', 0.00042986717104414733)

Table 8. Sensitivity Analysis

Iteration	x <sub>1</sub> (Al <sub>2</sub> O <sub>3</sub> concentration %)	x <sub>2</sub> (Ambient Temperature °C)	x <sub>3</sub> (Thermal Conductivity W/mK)	Output yyy (Energy Savings)
1	5.5	29.2	0.35	136.1
2	4.8	31	0.3	131.6
3	6	28.5	0.4	144.5
4	4.2	32.1	0.22	121.4
5	5.1	29.8	0.38	135
6	4.7	30.5	0.29	129.8
7	5.8	27.9	0.33	140.5
8	4.5	31.5	0.24	126
9	5.3	28.3	0.36	137.8
10	4.9	30.1	0.31	131.7

