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Review Article

Latest Advancements in Solar Photovoltaic-Thermoelectric Conversion Technologies: Thermal Energy Storage Using Phase Change Materials, Machine Learning, and 4E Analyses

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In recent times, the significance of renewable energy generation has increased and photovoltaic-thermoelectric (PV-TE) technologies have emerged as a promising solution. However, the incorporation of these technologies still faces difficulties in energy storage and optimization. This review paper addresses these challenges by providing a comprehensive overview of the latest advancements in PV-TE technologies. The paper emphasizes the integration of phase change materials (PCMs) for thermal energy storage, also buttressing the use of encapsulated PCM for thermal storage and efficiency, and the use of hybrid PCM to enhance overall performance. Furthermore, reviews on the use of machine learning techniques for efficient optimization and the integration of thermoelectric modules into tandem perovskite silicon solar cells have been comprehensively analyzed. The advancements in photovoltaic-thermoelectric systems, as reviewed in this article, signify significant progress in attaining sustainable and effective energy production and storage. This review comprehensively addresses the 4Es, underlining their importance. It not only consolidates recent developments but also charts a path for future research in the field of PV-TE technologies, offering precise insights to guide upcoming studies and innovations.

1. Introduction

Many countries throughout the world are looking for alternative energy sources including wind, solar, biomass, and hydropower to either supplement energy security or replace the current conventional methods of generating electricity due to the depletion of fossil fuel reserves and price changes. The ability to do more and significantly reduce costs is a key promise of solar photovoltaic coupled with its advantage of no pollution and silent equipment performance [1–3]. Solar photovoltaics refers to the process of transforming solar radiation into electrical energy through the utilization of semiconductor devices called solar cells [4]. Photovoltaic cells are technologies that use the photovoltaic effect to directly turn sunlight into electricity. They are employed in a wide range of products, from tiny electronic devices to massive power plants, and have emerged as a significant source of renewable energy, decreasing dependence on nonrenewable energy sources and promoting a more sustainable future [1, 3, 5]. Photovoltaic cells are constructed from semiconducting substances, typically silicon, which take in photons from sunlight and release electrons to produce an electrical current [6]. Renewable energy is often produced using PV cells, which are used in solar panels. Over time, their efficiency has gradually increased, with the most recent technology achieving conversion efficiencies of over 20%; however, because of their sensitivity to temperature, shading, dirt, dust accumulation, and aging of the materials, approximately 80% of the incident solar energy is dissipated as heat in silicon solar cells [3, 7, 8]. Therefore, finding effective methods to decrease the excessive heat accumulation in silicon solar cells has become a subject of significant interest. An effective solution to address the issue of photovoltaic overheating is to integrate them in tandem with thermoelectric generators (TEGs) [7, 9].

Thermoelectric materials (TEMs) have the ability to be incorporated into current setups as micropower generators or microcoolers for cooling applications as they can convert heat into electrical energy or vice versa using the Seebeck and Peltier effects [4, 7]. This review explores how thermoelectric modules are being integrated in tandem perovskite silicon solar cells to improve the overall efficiency of the photovoltaic system. Perovskite solar cells have the potential to attain elevated levels of conversion efficiency [10], but they also have a higher tendency to overheat compared to traditional silicon solar cells. By integrating thermoelectric modules, waste heat generated by the perovskite cells can be converted into additional electrical power, effectively increasing the overall energy output of the system. Additionally, by using machine learning (ML) techniques for optimization and integration, the performance of the thermoelectric modules can be further enhanced, making it a promising solution for improving the efficiency and sustainability of photovoltaic technologies as studied by Alghamdi et al. [7]. Additional in-depth optimization research is required to enhance the competitive market position of PV-TE systems; since their efficiency levels have not yet reached parity with nonrenewable energy sources, such as coal-fired power plants utilizing steam, there is still room for improvement in terms of enhancing the conversion efficiencies of renewable energy technologies.

Hence, this review also investigates how machine learning techniques can be utilized as an effective optimization method to enhance the competitive advantage of PV-TE technologies. Figure 1 illustrates the ML architecture employed to derive an optimization function for this purpose. In research by Alghamdi et al. [7], they discovered that the utilization of optimization techniques like the finite element method (FEM) and experimental approaches is often laborious, costly, and frequently inadequate in accurately forecasting the performance of photovoltaic-thermoelectric (PV-TE) systems. They also concluded that ANSYS and COMSOL multiphysics necessitate extremely high computational speeds to carry out complete three-dimensional simulations, highlighting the need to develop additional optimization techniques to address these limitations.

One of the primary challenges in PV-TE systems is the effective management of heat generated by the PV cells. The deployment of phase change materials (PCMs) for thermal energy storage (TES) purposes media has shown promise [11], but there are still issues that require attention, including but not limited to thermal stability, thermal conductivity, and cost, which necessitate further consideration and resolution. Coupled with the fact that there is a need for advanced optimization techniques with the aim of enhancing the efficiency of photovoltaic-thermoelectric (PV-TE) systems as visualized in Figure 2, there is also the need for integration of thermoelectric (TE) modules into tandem perovskite silicon solar cells [12]. These challenges pose a threat to recent advancements in PV-TE technologies which leads to the necessity to review articles in this sphere. Noteworthy progress has been made in the field of PV-TE technologies, which have enabled enhanced and economically viable utilization with improved efficiency of solar energy. While PV cells have long been recognized as a promising source of renewable energy, the technology faces several challenges that limit its competitiveness compared to nonrenewable energy sources [13]. These include issues such as overheating, low conversion efficiency, and cost-effectiveness.

TE modules can convert thermal energy into electrical energy and vice versa by leveraging the Seebeck and Peltier effects. However, integrating TE modules into PV cells is a challenging task that requires careful design and engineering. One area of innovation in this regard is the use of machine learning techniques to optimize the design and parameters of TE modules for efficient integration into PV cells [7]. Another area of innovation in PV-TE technologies is the application of phase change materials (PCMs) for the purpose of storing thermal energy (TES) [11]. PCMs are substances characterized by their ability to undergo a phase transition, wherein they can absorb or release significant quantities of thermal energy. This unique property allows PCMs to store and release substantial amounts of heat during the phase change process which can help to reduce the overheating of PV cells. However, there are still several challenges that need to be addressed to make PCMs a viable solution for TES in PV-TE systems [14]. These include issues such as thermal stability, thermal conductivity, and cost-effectiveness. The recent progress within the realm of hybrid photovoltaic/thermal (PV/T) systems, particularly the incorporation of nanofluids to boost performance, has garnered significant attention. A

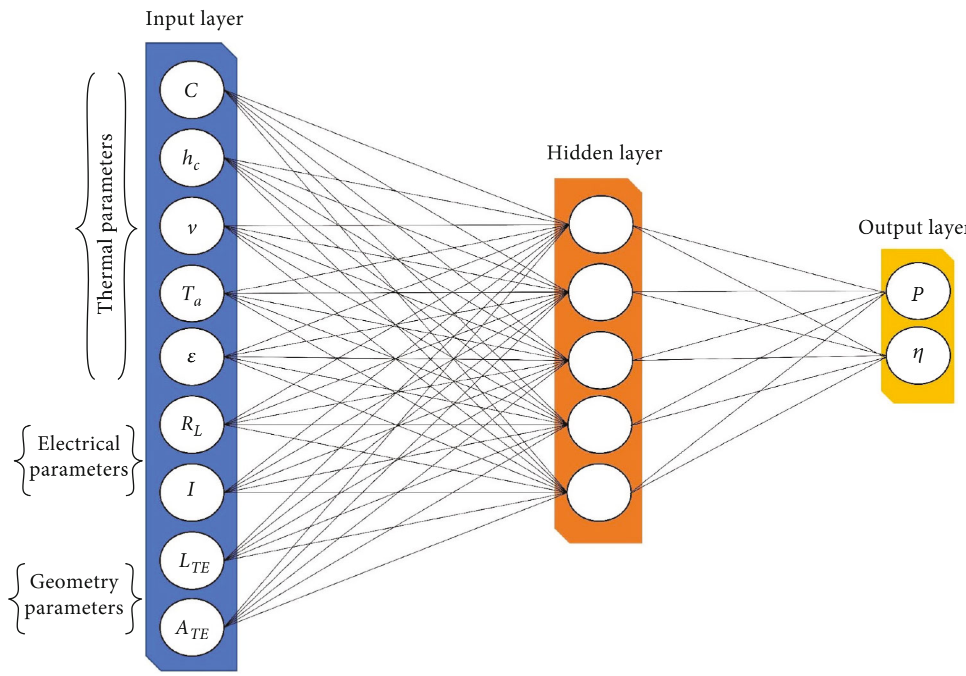


FIGURE 1: ML architecture employed to derive an optimum ANN model [7].

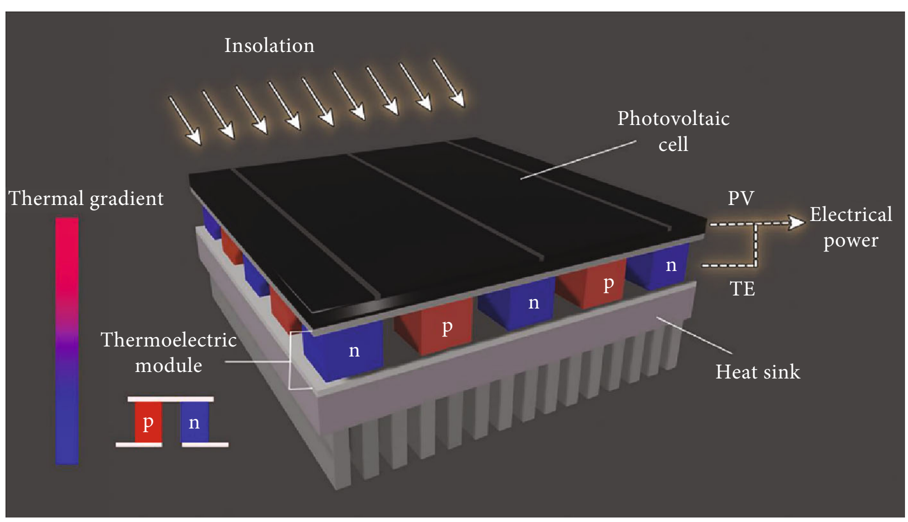


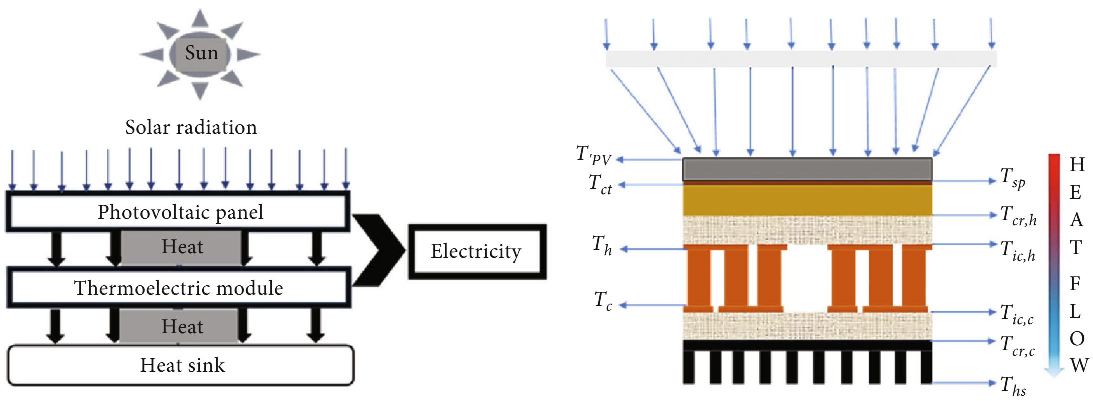
FIGURE 2: PV-TE hybrid system [4].

recent review study by Hossain et al. [15] explores these developments, highlighting improved energy efficiency, heat transfer, and other enhancements achieved through nanofluid integration in PV/T collectors.

It is clear that prior research has not extensively addressed several key aspects related to photovoltaic-thermoelectric systems. To contribute significantly to bridging these research gaps and further advance the field, this comprehensive review paper is aimed at providing valuable insights and addressing the following critical aspects:

(1) *Optimization with Phase Change Materials*. Prior research often overlooks the optimization of PV-TE systems by integrating phase change materials for thermal energy storage and employing advanced numerical methods. This review critically examines the role of PCMs, including their thermal properties, heat transfer characteristics, and phase change behaviors, in enhancing the performance of PV-TE systems compared to standalone PV systems. Furthermore, it explores the utilization of numerical simulations, computational fluid dynamics (CFD), and other modeling techniques to analyze and optimize the thermal behavior of PV-TE systems, considering factors such as heat transfer, fluid dynamics, and temperature distribution

(2) *Economic and Environmental Assessment*. The economic and environmental impacts of PV-TE systems



(a) (b)

FIGURE 3: Schematic of (a) a combined system that integrates both PV and TEG technologies and (b) PV-TEG layers [15].

have been underemphasized in existing studies. This review seeks to fill this research gap by evaluating the economic viability and environmental sustainability of PV-TE systems. It includes an analysis of the cost-effectiveness of PV-TE systems. Additionally, it explores the potential for reducing greenhouse gas emissions and the environmental footprint associated with PV-TE technology deployment

(3) *Machine Learning Techniques and Thermoelectric Integration*. The integration of machine learning techniques for optimizing PV-TE systems remains an underexplored area. This paper delves into the various machine learning algorithms and data-driven approaches applied to PV-TE systems, including supervised learning, unsupervised learning, and deep learning. It assesses their effectiveness in predicting and improving system performance and energy management. Furthermore, it explores the integration of thermoelectric modules into tandem perovskite silicon solar cells, examining the materials, design considerations, and performance enhancements achieved through this integration

(4) *Advancements in PV-TE Technologies*. The continuous evolution of PV-TE technologies holds promise for sustainable energy production. This review provides an in-depth analysis of recent advancements in PV-TE technologies, including innovations in collector designs, materials, and manufacturing processes. It assesses their capabilities in addressing the 4Es (exergy, energy, economics, and environment), considering factors such as energy conversion efficiency, exergy analysis, economic feasibility, and environmental impact

By meticulously focusing on these key areas and providing detailed insights, this review paper is aimed at offering a comprehensive overview of the state of PV-TE systems. It identifies research gaps, challenges, and opportunities, laying the foundation for future research directions. Through our thorough analysis, we aim to significantly contribute to the knowledge base and promote the development of more efficient, sustainable, and economically viable PV-TE systems, addressing the pressing energy and environmental challenges of our time.

In Section 1, we discussed solar photovoltaic technology and the underlying problem of energy efficiency as a standalone device which has been detailed alongside integrating thermoelectric materials to achieve an optimized PV-TE system. Section 2 explains photovoltaic thermoelectric generators. Section 3 details PCM for thermal energy storage and the latest advancements in using PCM to store and release thermal energy in PV-TE systems. Next, Section 4 presents ML techniques for efficient optimization and its challenges furthermore analyzing works by scholars in this niche. Section 5 discusses the integration of thermoelectric modules in tandem perovskite silicon solar cells. Section 6 explains the 4E analysis. Section 7 puts forth an exclusive summary while Section 8 ends the review with a conclusion highlighting avenues for further research and challenges encountered in PV-TEG research.

2. Photovoltaic Thermoelectric Generators (PV-TEG)

Several works have noted that the integration of TEGs and PV systems solar cells in a hybrid format such as in Figure 3 has resulted in improved efficiency in such systems [3, 4, 6–8, 12, 16–19]. Therefore, PV-TE systems are a great option to enhance the efficiency of solar energy-based systems in general. This is because they operate in opposite wavelength ranges and are able to complement each other in terms of utilizing spectral energy. Photovoltaic cells excel in capturing short-wavelength light, such as ultraviolet and visible, efficiently converting it into electricity. In contrast, thermoelectric generators are effective at harnessing longer wavelengths, mainly in the infrared spectrum, where PV cell efficiency diminishes. When combined within a PV-TE system, these technologies create a symbiotic relationship, maximizing spectral energy utilization. This integration enhances overall energy conversion efficiency, making PV-TE systems a compelling choice for improving solar energy-based systems and advancing renewable energy utilization.

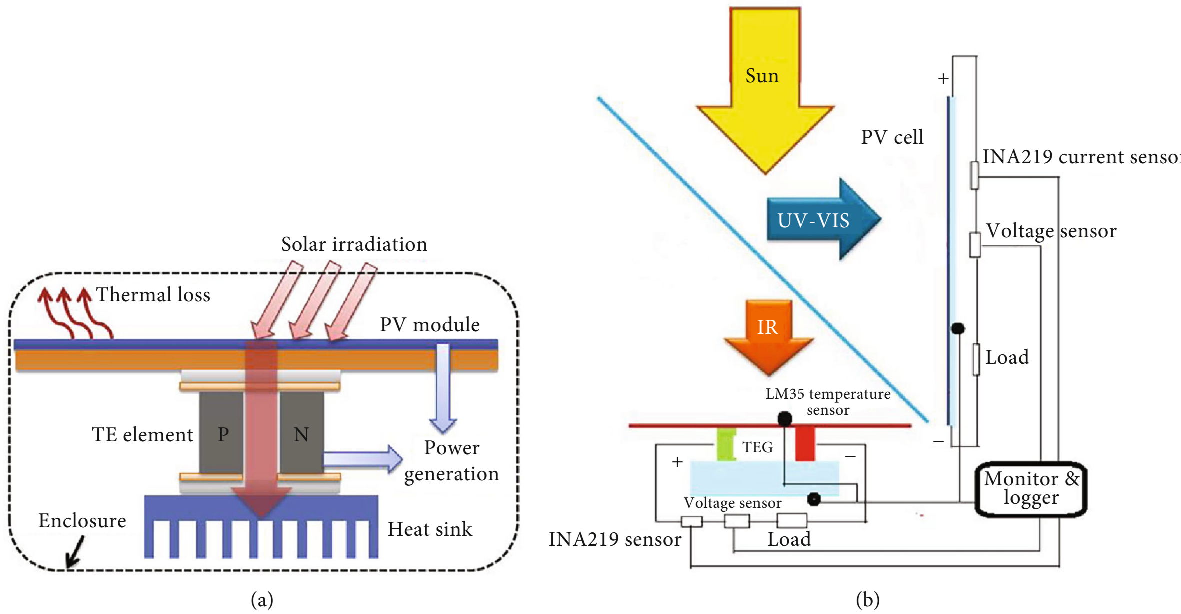


Figure 4: PV-TEG hybrid systems for (a) integrated PV-TEG systems into a single hybrid system and (b) spectrum split system [4].

Combining a PV module and thermoelectric generators allows for a broad spectrum of photons to reach the TEG module, resulting in the production of electricity through the thermoelectric effect. Therefore, this results in an improved conversion efficiency and a decrease in the quantity of thermal energy released by the PV module [20]. Theoretically, there are three methods to achieve PV-TEG hybridization [6]. The first method involves splitting the spectrum into two systems (Figure 4(b)), where one directs a certain wavelength of radiation into the PV cells and the other sends the remaining radiation into the TEG system. In this approach, the solar spectrum is physically split into two distinct systems. One system is designed to selectively direct a certain wavelength range of solar radiation into the PV cells, optimized for photovoltaic conversion. Simultaneously, the other system is configured to direct the remaining portion of the solar spectrum into the TEG system, which excels at harnessing thermal energy in the form of longer-wavelength radiation. This spectrum-splitting method ensures that each component of the hybrid system receives the type of radiation it is most efficient at converting into electricity or thermal energy. The second method integrates both the PV and TEG systems into a single hybrid system [21–33] which involves utilizing thermal paste to establish a link between the segments. By doing so, it allows for the simultaneous operation of both PV and TEG components within a single unit. This integration method is aimed at maximizing the overall energy conversion efficiency of the combined system. The study suggests a third system to connect PV and TEG, which involves making the reverse side of the PV from metal to enable fast heat transfer to the TEG. This allows for a series or parallel electrical connection between the two systems. By adding this metal layer, the PV module can efficiently dissipate excess heat generated during its operation. This enhanced heat transfer capability is crucial for ensuring that the TEG components receive sufficient thermal energy for effective thermoelectric conversion.

The integrated form of the PV-TEG system (Figure 4(a)) configuration offers the advantages of better integration (in terms of space usage) and reduced cost, especially for building applications, despite the fact that both procedures are sound technologies [4]. Some researchers have thus validated the fact that the integration mechanism gives better efficiency [34, 35]. However, Bjørk and Nielsen [21] went further to investigate the theoretical maximum output of dispersed solar photovoltaic and thermoelectric generator systems (PV-TEG). The maximum efficiency limit for photovoltaic systems according to the Shockley-Queisser model and the figure of merit parameter zT for thermoelectric generators served as the foundation for an analytical model that was presented. The researchers discovered that the use of nonconcentrated sunlight, assuming maximum efficiency for the thermoelectric generator (TEG) based on the Carnot efficiency and no temperature impact on the photovoltaic (PV) system, can only increase the efficiency by a maximum increase of 4.5 percentage points in the combined configuration and 1.8 percentage points in the tandem configuration (Figure 5) when compared to a standalone PV system [21].

To assess the performance and viability of photovoltaic-thermoelectric technologies comprehensively, it is crucial to evaluate a range of performance metrics. These metrics provide valuable insights into the efficiency, sustainability, and overall capabilities of PV-TE systems. In Table 1, we present a summary of key performance indicators and metrics associated with integrated PV-TE technologies. These metrics encompass various aspects, including PV-TE efficiency, TE type, and PV type. By examining these metrics collectively, we gain a holistic understanding of the advancements and challenges within the PV-TE integration landscape. Table 1 serves as a valuable resource to navigate the complexities of PV-TE technologies and make informed decisions regarding the performance of integrated PV-TE systems.

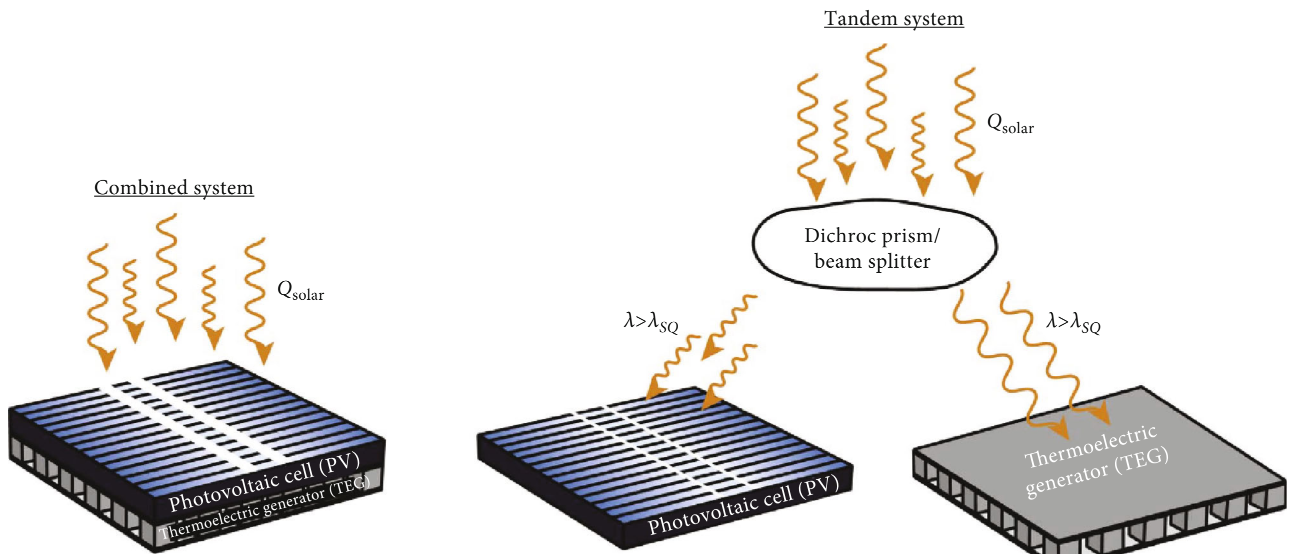


FIGURE 5: Two systems that were analyzed. In the tandem configuration, the incident solar radiation, Q_{solar}, is divided between the PV and TEG at a specific wavelength of λ_{SQ} [21].

TABLE 1: Performance metrics of different integrated PV-TE systems [17].

Ref.	TE system type	PV system type	PV-TE efficiency (%)
Rezania et al. [36]	Bi2Te3	Silicon (Si) solar cell	~16.6
Zhang and Xuan [37]	Bi2Te3 (TEC1-03103)	GaAs	19.10
Soltani et al. [38]	TEC-1206	c-Si	~15.5
Soltani et al. [32]	TEC1-12706	c-Si	~8.25

3. PCM for Thermal Energy Storage

In photovoltaic-thermoelectric generator systems, PCMs are used to regulate the temperature of the system by storing energy, which can improve its overall efficiency [11, 19, 39–41]. PCMs are often used in conjunction with thermoelectric materials to convert waste heat from the PV cells into electricity. In research by Maduabuchi and Mgbemene [42], they performed a numerical study of a solar thermoelectric generator (STEG) integrated with a phase change material (PCM) that exhibits the ability to store and release thermal energy through phase transition. Their objective was to investigate the performance of the STEG-PCM system under different operating conditions and configurations. The researchers formulated a mathematical model for the purpose of the STEG-PCM system, which takes into account the heat transfer mechanisms, thermoelectric conversion, and electrical circuit. They used this model to simulate the system's performance under different parameters such as solar irradiance, PCM melting temperature, and thermoelectric material properties. The results of the simulations show that the STEG-PCM system can significantly improve the efficiency of solar energy conversion by storing and releasing thermal energy. They discovered that the melting temperature of the PCM is a critical parameter that affects the system's performance, with higher melting temperatures resulting in higher energy storage capacity and better performance. They also found out that the material properties of thermoelectric materials play a pivotal role in the system's performance, with higher Seebeck coefficient and lower electrical resistivity leading to higher output power. Overall, the study provided valuable insights regarding the design and optimization of STEG-PCM systems for efficient solar energy conversion, and the numerical model developed in this study can be used as a tool for further research and development in this field. Also, Xiong et al. performed a numerical analysis on the performance of a system with counter-flow type heat exchangers [43]. A two-step thermoelectric energy collection system powered by the residual heat from water in blast furnace slag was designed by them. The performance features of a thermoelectric generator, which used phase change materials as a heat sink to maintain a constant cool side temperature, were assessed through experimentation by Jaworski et al. [44]. They employed an infrared lamp to generate heat and a receptacle containing PCM to absorb heat from a cooler region, thereby maintaining its temperature in their approach. The outcomes of their study validated the feasibility of utilizing phase change materials as a medium for cooling or heating in thermoelectric generators. Wang et al. [45] conducted a theoretical examination on the potential utilization of phase change materials for enhancing the heat transfer characteristic of the hot side of the TEG. The researchers employed vehicle exhaust gas as a heat source, and their findings indicate that the implementation of suitable phase-change materials can notably enhance the TEG's output power and efficiency. Using phase change materials is an appropriate approach for thermal energy storage (TES). The storage capacity of the latest heat storage system (LHSS) can be determined (equation (1)) when a PCM is utilized as the storage medium as calculated by Sharma et al. [46].

$$Q = m\left[\int_{T_i}^{T_m} C_{\mathrm{ps}}\, dT + Bl + \int_{T_m}^{T_f} C_{\mathrm{pi}}\, dT\right], \tag{1}$$

where T_i is the PCM initial temperature, T_m is the melting temperature, C_{ps} is the specific heat capacity in solid state, C_{pi} is the specific heat capacity in liquid state, B is the melt fraction, l is the specific latent heat, and T_f is the final temperature.

3.1. Latent Heat. PCMs exhibit high latent heat, enabling them to retain significant quantities of thermal energy when transitioning from a solid to a liquid state [42]. Out of the various thermal heat storage methods mentioned, latent heat thermal energy storage stands out as a compelling option because of its capacity to offer a high-energy storage density and its unique ability to store heat at a constant temperature that corresponds to the phase-transition temperature of the phase change material. Additionally, they can transition in the following form: solid-solid, solid-gas, liquid-gas, and vice versa. Furthermore, to create a thermal energy storage system that uses latent heat, it is crucial to comprehend three key areas: phase change materials, materials for containers, and heat exchangers [47]. As noted by Pillai and Brinkworth [48], the use of solid-solid phase change materials provides the benefits of requiring fewer rigid containers and offering increased flexibility in design. Figure 6 shows a detailed classification of PCM categorizing the solid-solid phase, solid-liquid, solid-gas, and liquid-gas phase.

To advance the understanding and application of phase change materials (PCMs) in conjunction with thermoelectric generators (TEGs), it is necessary to carefully consider the advantages and drawbacks of the different categories of PCMs as outlined in Table 2.

Studies by Jurinak and Abdel-Khalik [50] and Morrison and Abdel-Khalik [51] assessed the effectiveness of air-powered solar heating systems that utilize units for storing energy through a phase change. Their aim was to study how the thermal performance of an air-based solar heating system is impacted by the melting temperature and latent heat characteristics of the phase change energy storage unit and also create an empirical model for a significant unit of phase change energy storage (PCES). The key finding was that the selection of PCM should be based on its melting point rather than latent heat. Additionally, it was discovered that an air-based system that utilizes sodium sulfate decahydrate as a storage medium necessitates only a quarter of the storage volume of a pebble bed and half the storage volume of a water tank. PCMs possess the capability to absorb and emit thermal energy while maintaining a relatively constant temperature. They possess a heat storage capacity that is 5 to 14 times greater per unit volume than materials such as water, masonry, or rock that store heat based on their temperature [46]. Several researches have shown that a hybrid storage-harvesting energy system that combines phase change materials and thermoelectric generators is an encouraging option.

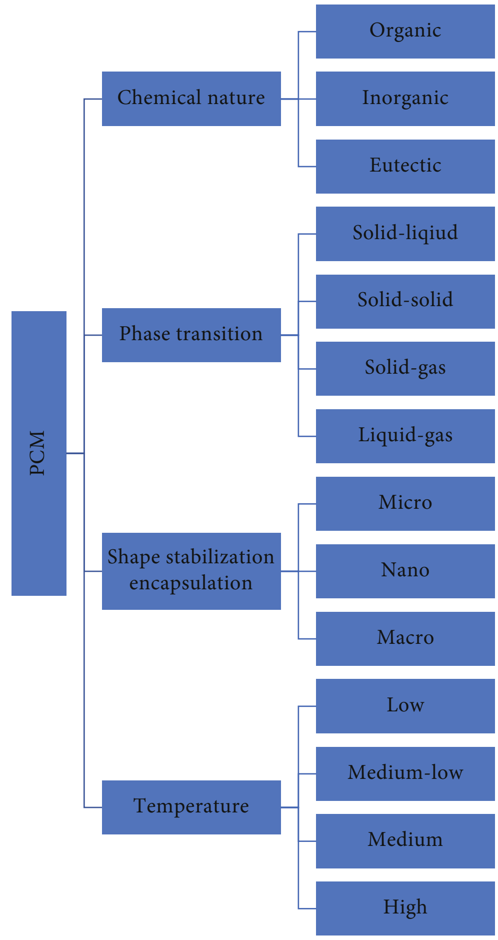


Figure 6: PCM classification [49].

3.2. Recent Advancement in Using PCM to Store and Release Thermal Energy in PV-TE Systems. Phase change materials have shown promising results in storing and releasing thermal energy in PV-TE systems. Recent advancements in this area include the development of new PCMs with higher thermal conductivity, melting temperature, and thermal stability [52–56]. One of the key challenges in using PCM is their low thermal conductivity, which limits the rate of heat transfer [57, 58]. To address this, researchers have explored incorporating high thermal conductivity materials, such as graphene or carbon nanotubes, into the PCM to enhance their heat transfer properties [59–66]. Another area of development is the use of hybrid PCM, which combines two or more PCMs to improve their overall performance [67, 68]. For example, a recent study demonstrated that a hybrid PCM consisting of dextran sulfate sodium (DSS) salt as a polyelectrolyte additive and a salt hydrate component had a higher energy storage capacity which substantially mitigated the phase separation of the salt hydrate [69]. Studies

Table 2: Merits and drawbacks of different PCMs.

Merits	Drawbacks
Organic PCMs	
High energy density: organic PCMs have high energy density, allowing for more energy to be stored in a smaller space compared to traditional thermal storage materials like water.	*Limited temperature range:* organic PCMs typically have a limited temperature range, making them unsuitable for applications that require higher or lower temperatures.
Wide availability: organic PCMs are widely available and can be sourced from renewable resources.	*Flammability:* organic PCMs can be flammable, making them a potential safety hazard.
Good thermal stability: organic phase change materials (PCMs) exhibit favorable thermal stability, enabling them to endure multiple cycles of melting and solidification without undergoing degradation.	*Cost*: some organic PCMs can be expensive compared to traditional thermal storage materials like water.
Inorganic PCMs	
High melting temperature: inorganic PCMs have a high melting temperature, making them suitable for high-temperature applications.	*Limited energy density:* inorganic PCMs have a lower energy density compared to organic PCMs, meaning more space is required to store the same amount of thermal energy.
Good thermal conductivity: inorganic PCMs have good thermal conductivity, allowing for faster heat transfer.	*Limited availability:* inorganic PCMs can be less widely available and more difficult to source compared to organic PCMs.
High heat capacity: inorganic PCMs have a high heat capacity, meaning they can store a large amount of thermal energy.	*Phase separation:* some inorganic PCMs can separate into different phases, which can lead to reduced performance and durability issues over time.
Eutectic PCMs	
Wide temperature range: eutectic PCMs have a wide temperature range, rendering them suitable for a myriad of applications.	*Limited availability:* eutectic PCMs can be less widely available and more difficult to source compared to organic PCMs.
High energy density: eutectic PCMs have a high energy density, allowing for more energy to be stored in a smaller space compared to traditional thermal storage materials like water.	*Limited thermal stability:* eutectic PCMs can have limited thermal stability, meaning they may degrade over time with repeated cycles of melting and solidification.
Good thermal conductivity: eutectic PCMs have good thermal conductivity, allowing for faster heat transfer.	*Cost*: eutectic PCMs can be expensive compared to traditional thermal storage materials like water.

showing the different types of inorganic salt hydrates applied in PCM for thermal regulation [70] have been outlined in Table 3. Although some review articles such as Sikiru et al. [71] reviewed certain recent progressions and the influence of phase change materials on solar energy, there is a need to buttress on future prospect for PV optimization using PCM as covered in this present review.

Researchers are also exploring the use of encapsulated PCM, where the PCM is encapsulated within a shell or capsule to prevent leakage and improve stability. Encapsulation can also allow for the use of higher melting temperature PCMs, which have the potential to store more energy. The normal PCM is a liquid-state PCM with tiny particles. As a result, it results in leakage issues and external environment reactivity [86, 87]. When packaging is disregarded, leakage happens after prolonged usage, and if a casing flaw exists, leakage can happen extremely quickly. Several studies were proposed in order to address these issues with the traditional PCM. A possible approach for addressing the drawbacks of the microencapsulation technique is employed in this thermal storage system. The organic or inorganic materials can enclose PCM droplets smaller than $1000\,\mu$m due to the design of the microencapsulation phase change material (mPCM). Hence, by increasing the PCM's surface-to-volume ratio and covering the liquid PCM surface, it is possible to overcome the drawbacks of the standard PCM, including its diminished thermal conductivity and challenges related to leakage [87–91]. A study by Royo et al. [85] constructed their proposed BIPV-TEG-PCM system (Figure 7), which employs phase change material encapsulated at the microscale (mPCM) to capture lost solar and thermal energy from the building envelope, the best design for manufacturing was determined using numerical analysis. To determine an optimal thermal structure, they investigated various heat fin spacings (Figure 8), the PCM melting temperature, and the TEG layout using computational fluid dynamics (CFD) heat transfer analyses. Table 4 outlines various microencapsulation methods of PCM and their pros and cons [91].

4. Machine Learning Techniques for Efficient Optimization of PV-TE Technologies

4.1. Machine Learning Optimization. Machine learning is a powerful technique used to train computer systems to learn and improve from experience without being explicitly programmed. It finds diverse applications, encompassing

Table 3: Inorganic salt hydrates in PCM for thermal regulation [70].

Reference	Application	System	Salt hydrate
Weinläder et al. [72]	Phase change material for thermal regulation	PCM-façade-panel	S27
Hadjieva et al. [73]		Composite PCM concrete system	$Na_2S_2O_3{\cdot}5H_2O$
Fu et al. [74] and Ye et al. [75]			$CaCl_2{\cdot}6H_2O$
Hasan et al. [76], Hasan et al. [77], Hasan et al. [78, 79], and Nagano et al. [80]		Photovoltaic-phase change material (PV-PCM) system	$CaCl_2{\cdot}6H_2O$
Irsyad et al. [81], Karthick et al. [82], and Oró et al. [83]			$Na_2SO_4{\cdot}10H_2O$
Pichandi et al. [84]			$Na_2CO_3{\cdot}10H_2O$
Pichandi et al. [84]			$MgSO_4{\cdot}7H_2O$
Royo et al. [85]			$Na_2HPO_4{\cdot}12H_2O$

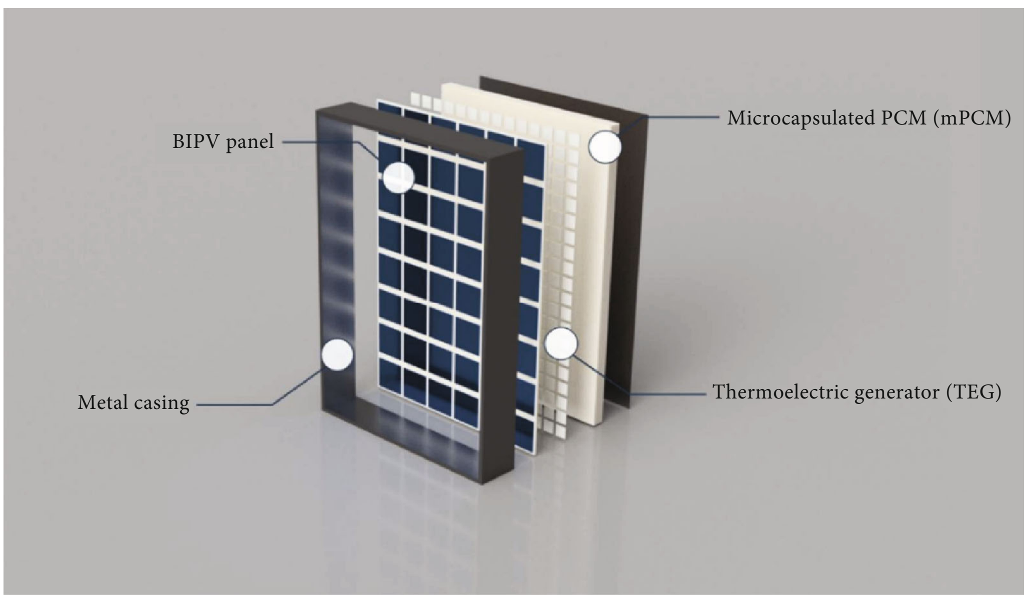
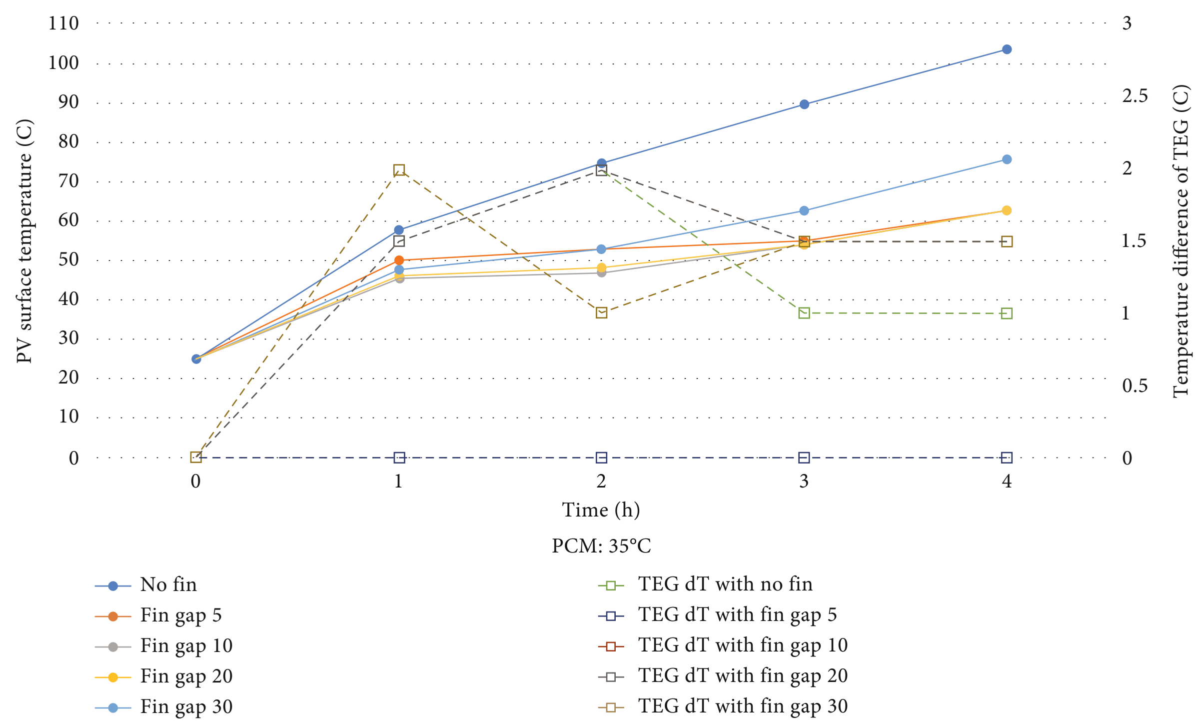


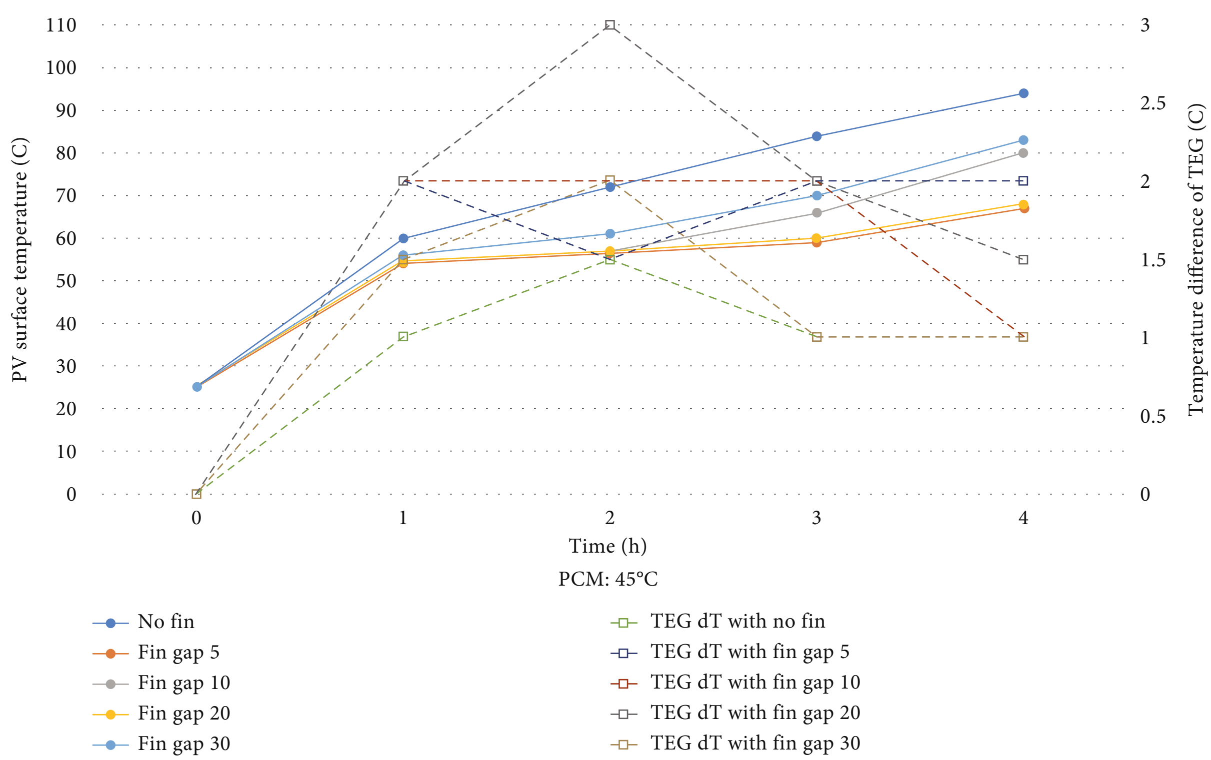
Figure 7: BIPV-TEG-PCM design [87].

optimization purposes, which involves finding the best solution to a problem from a set of possible options. Machine learning for optimization involves using algorithms to automatically find the best solution to a problem, based on data and feedback. This allows the computer system to learn from previous solutions and improve its performance over time. Some popular machine learning algorithms used for optimization include gradient descent, genetic algorithms, and reinforcement learning. By leveraging the power of machine learning for optimization, several novel researches have been conducted and findings published to aid the scientific community [7, 100–105]. There are three primary stages involved in an ML system (Figure 9). The initial step involves gathering in-domain data, which is referred to as the training data. The second stage involves the utilization of specialized methodologies to extract the features, followed by the selection of a learning algorithm in the third step based on mathematical models, which is the model [106, 107]. An analysis is being conducted on the machine learning techniques that are most commonly used.

4.1.1. Supervised Learning. Supervised learning can be used in solar energy studies to predict energy output and optimize system performance [108]. In the context of PV-TEG systems, supervised learning can be applied to train models that can accurately forecast the power generation of the hybrid system, which combines the benefits of both photovoltaic and thermoelectric technologies. This can help optimize the design and operation of the PV-TEG system to achieve maximum energy efficiency. Supervised learning (SL) deals with tasks where both the input and output are known during the initial stage. Some studies have utilized supervised learning for their energy study and optimization [109–122]. In supervised learning, classification and regression tasks correspond to predicting discrete and continuous outputs, respectively. Polynomial regression, linear regression, exponential regression, and Gaussian process regression (GPR) are examples of regression techniques [123, 124]. Support vector machines (SVM) are a popular algorithm that is also used in supervised learning for classification and regression tasks. SVM operate by identifying



(a)



(b)

Figure 8: (a) Surface temperature of PV and the TEG distribution's temperature differential at 35°C fin interval [87]. (b) Surface temperature of PV and the TEG distribution's temperature differential at 45°C fin interval [87].

the optimal hyperplane that effectively segregates data points into distinct classes, thereby maximizing the margin between the classes. They handle both linear and nonlinear data using kernel tricks, making it a versatile algorithm for a variety of supervised learning tasks in energy research [125–128]. The SVM sorts datasets by using two parallel margins [129].

Table 4: Diverse microencapsulation methods of PCMs [91].

Technique	Method	Pros	Cons	Quality (performance)	Shelf life	Reliability
Chemical	Emulsion polymerization [92]	A polymer with a large molecular size	Extracting the polymer from the surfactant to obtain a pure product	Good	Long	Good
	Suspension polymerization [93]	Effective regulation of the reaction's temperature	Only a small number of monomers can dissolve in water	Good	Long	Good
	Interfacial polymerization [94]	Multifunctional, ability to decompose, and mechanical durability	Inadequate mechanical characteristics	Poor	Short	Poor
Physical	Spray drying [95, 96]	Low cost and easy to scale up	Clumping together of particles that are still uncovered	Poor	Short	Poor
Physical-chemical	Sol-gel [97]	An inorganic casing that has a high capacity for conducting heat	Still being investigated	Good	Medium	Good
	Solvent evaporation [98]	Low cost	Combining small-scale production	Poor	Medium	Poor
	Simple coacervation [97]	Versatile and flexible operation	Agglomeration	Poor	Short	Poor
	Complex coacervation [99]	Effective management of the size of the particles	It is challenging to increase the scale of particle agglomeration	Poor	Short	Poor

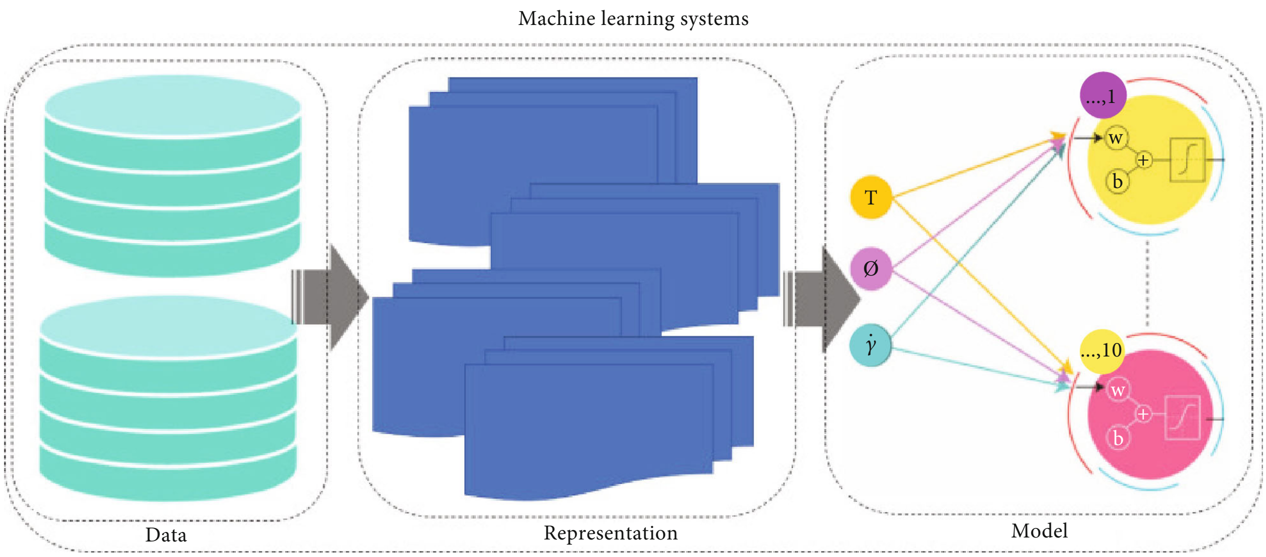


Figure 9: Stages of machine learning systems [107].

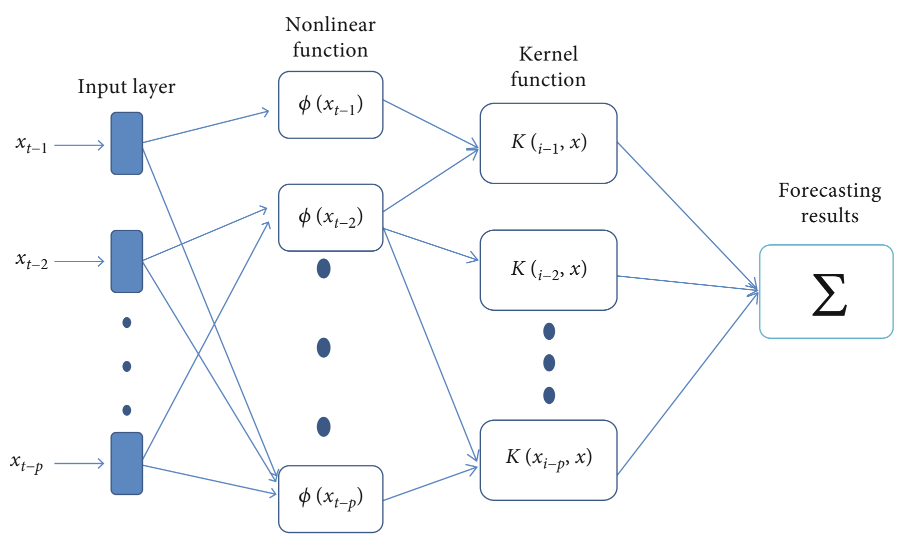


Figure 10: Support vector machine structure [130].

$$W^T + b = 0, \tag{2}$$

$$Y(x) = \frac{1}{N}\sum_{n=i}^{N} w^T k(x_i, x_j) + b, \tag{3}$$

$$W^T(x) + b = 0, \tag{4}$$

$$K(x_i, x_j) = (x_i)^T(x_j). \tag{5}$$

In this context, the weight and deviation vector are denoted as w and b, respectively. Additionally, the sample number and regularization factors are represented by n and λ, respectively. The mapping function is indicated by the symbol φ. Figure 10 shows the structure of SVM.

4.1.2. Deep Learning. Deep learning (DL) belongs to the domain of machine learning (ML) and relies on the application of artificial neural networks (ANNs) [131–134]. ANNs consist of individual units called neurons, each of which takes in multiple inputs, denoted as $x_1, x_2, \ldots, x_m$. These inputs are multiplied by corresponding weights, represented as $w_1, w_2, \ldots, w_m$, and added to a bias term, b, to produce a weighted sum of the inputs. To generate the output y (Figure 11), nonlinear activation functions are utilized.

4.1.3. Unsupervised Learning. Unsupervised learning (USL) is a method of machine learning in which data is analyzed without preexisting labels. The USL approach is commonly used in clustering problems, which can be addressed by various techniques, such as the K-means algorithm, Gaussian mixture model, and mean-shift algorithm. Specifically, the K-means algorithm partitions a given dataset into K clusters, ensuring that data points within each cluster are homogenous. In recent times, numerous researchers have utilized the K-means algorithm to achieve optimal performance in their studies [135, 136].

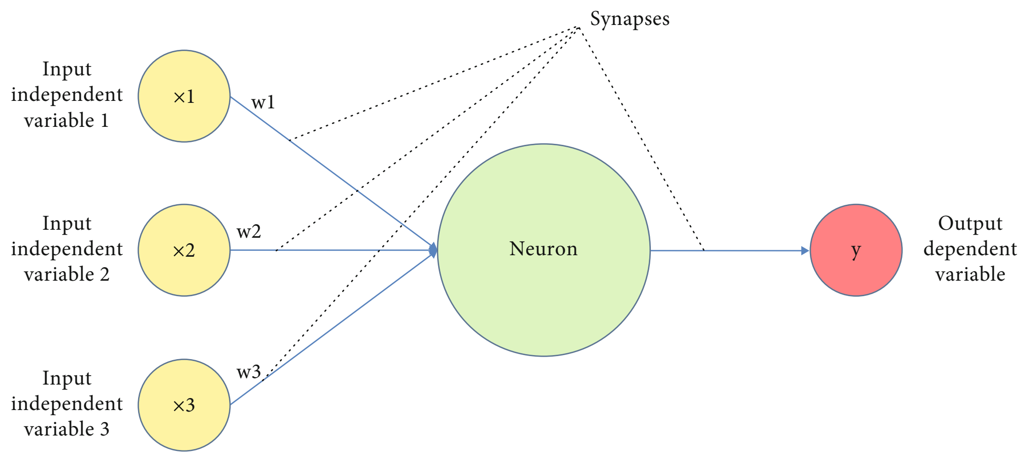


Figure 11: Functionality of a neuron in deep learning.

4.2. Optimization of PV-TE Techniques Using Machine Learning. The optimization of PV-TE techniques using machine learning involves the use of ML algorithms to enhance the efficiency and performance of PV-TE devices. Machine learning techniques such as artificial neural networks, genetic algorithms, and support vector machines are used to model the behavior of PV-TE devices and predict their performance under different conditions. This approach can lead to the development of more efficient and cost-effective PV-TE devices, which can be used to generate clean energy from solar radiation and waste heat. Alghamdi et al. [137] used machine learning to predict the performance of a solar photovoltaic-thermoelectric system comprising various categories of crystalline silicon cells. Their study proposed the use of a deep neural network to accurately predict the performance of a photovoltaic-thermoelectric system, which is designed with three distinct crystalline solar cells, instead of the ineffective numerical methods typically used for analyzing such hybrid systems. The data produced by the numerical solver was then utilized to train an optimized deep neural network with three layers and 20 neurons per layer, resulting in a more efficient method of predicting the hybrid system's performance. The research utilized the Bayesian regularization method and resulted in the deep neural network (DNN) efficiently acquiring knowledge that would typically take a conventional numerical solver 1,600 minutes to generate, completing the task in just 12 minutes and 27 seconds. As a result, the proposed network was found to be 128.51 times faster than the traditional numerical method. Furthermore, on deep neural networks for the optimization of PV systems, Maduabuchi et al. [104] utilized DNN for the purpose of enhancing the thermomechanical performance of segmented TEGs through device geometry optimization. The conventional approach of using numerical methods to enhance the efficacy of segmented thermoelectric generators has proven to require a significant amount of computing time and energy. To ensure the accuracy of the results, they adopted a methodology in which they constructed a numerical model using ANSYS software and incorporated the impact of temperature dependence in the four thermoelectric materials utilized in their study. In their study, the Levenberg-Marquardt algorithm implemented in the deep neural network had a profound impact. The most notable advantage of the proposed method was that it could rapidly and precisely predict device performance within a mere 10 seconds. This was an improvement of 2880 times compared to the conventional numerical optimization method. Furthermore, the optimized device achieved a maximum efficiency of 18%, a significant increase of 78% in contrast to the unoptimized device. The aim of the research was to develop a prediction model for the performance of PV-TE systems using different semiconductor materials through the utilization of optimal surrogate machine learning techniques and to determine the most effective machine learning approach for forecasting the performance [7]. To accomplish this, the study employed multiple surrogate machine learning models and trained them using high-priced finite element generated data. The findings demonstrated that an optimal ML model for this analysis is an ANN structure consisting of two hidden layers, with five neurons in each layer. The study highlights the potential of recurrent neural networks and time delay neural networks for modeling time series data of PV-TE systems in future research. However, the research lacks a comprehensive discussion on the limitations and potential sources of error in using machine learning models to predict PV-TE performance. A study by Maduabuchi [105] describes how a next-generation thermoelectric generator combined with a solar optical concentrating system was optimized through the use of finite elements and Bayesian regularized neural networks. The results indicated that the optimized device produced considerably more power and had higher efficiency compared to the traditional device. Moreover, the Bayesian-regularized neural network (Figure 12) was capable of predicting the device's performance 1,050 times faster than the numerical method with only ten neurons in the hidden layer. However, the article did not address the cost-effectiveness and commercial viability of the proposed device.

In a multiobjective optimization research by Alghamdi et al. [138], they explored the advantages of employing a hybrid concentrated photovoltaic-thermoelectric (CPV-TE) system rather than a standalone CPV. However, finding

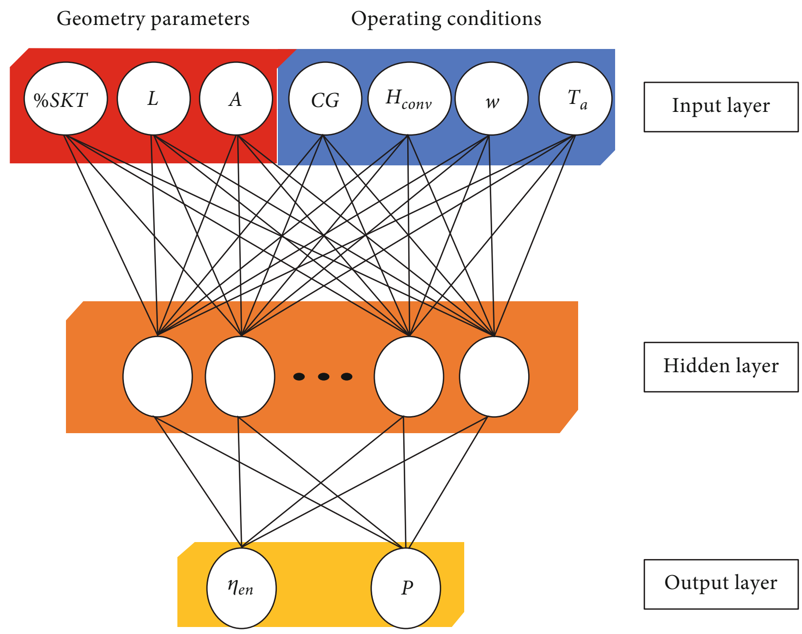


Figure 12: Network architecture of the Bayesian-regularized ANN deployed [105].

the optimal thermoelectric (TE) material can be difficult due to conflicting material properties. To overcome this challenge, the article proposed using a multiobjective optimization genetic algorithm (MOGA) to identify the best TE material for maximum CPV-TE performance. The technique for order performance by similarity to ideal solution (TOPSIS) decision algorithm is then utilized to choose the best performing conditions. The optimization workflow is executed using machine learning algorithms. The outcomes demonstrate that the proposed optimization technique attained an output power of 44.6 W, exergy efficiency of 18.3%, and CO_2 reduction of 0.17 g/day. Among the machine learning algorithms examined, Gaussian process regression exhibited the highest accuracy in learning the performance dataset of CPV-TE (concentrated photovoltaic-thermoelectric) systems.

4.3. Challenges of Conventional Optimization Tools. There are various difficulties in optimizing PV-TE techniques through conventional numerical methods other than using machine learning. These difficulties stem from the nonlinear behavior of PV-TE devices, which is influenced by various nonlinear factors such as illumination intensity and temperature. As conventional numerical tools are meant for linear systems, it can be challenging to model and optimize PV-TE devices due to these nonlinearities [139].

The first challenge is the issue of limited accuracy. Conventional numerical tools, such as finite element analysis and computational fluid dynamics, rely on mathematical models that may not accurately capture all aspects of PV-TE devices. This can lead to inaccurate predictions and suboptimal designs [140]. The second challenge is the lack of scalability. As the complexity of PV-TE devices increases, it becomes increasingly difficult to model and optimize them using conventional numerical tools. This limits the size and scope of optimization studies that can be performed, which may result in suboptimal designs. Furthermore, the third challenge is multiobjective optimization. In many cases, optimizing the performance of PV-TE devices requires balancing multiple objectives, such as maximizing power output while minimizing material and manufacturing costs. Conventional numerical tools are often not well-suited for multiobjective optimization problems, which can lead to suboptimal solutions [138]. And lastly, another challenge is high-dimensional parameter space. The performance of PV-TE devices is influenced by a multitude of parameters, such as material properties [90], device geometry [104, 141], and operating conditions. Optimizing these parameters using conventional numerical tools can be computationally expensive and time-consuming, especially when dealing with a high-dimensional parameter space. Machine learning has helped tremendously in solving issues such as intricate modeling, lengthy computational processes, high energy demands, and even ease of implementation [138, 142–144].

A study by Khan et al. [145] explores the use of a hybrid system that utilizes a revolutionary neural network-based control technique for maximum power point tracking (MPPT) PV-TEG system. The system efficiently utilizes solar energy and improves PV efficiency by mitigating the surface temperature of PV modules. The proposed snake optimizer-based MPPT controller, combined with a multilayer perceptron neural network (MLPNN) and a PID controller, yields consistent, precise, and rapid MPPT even in fluctuating environmental conditions. The research verifies the efficacy of the suggested controller by comparing it to alternative techniques and concludes that the MPPT controller based on the snake optimizer based neural network (SOANN-based) demonstrates superior performance (Figure 13) and provides superior performance regarding efficiency, tracking duration, stability, and fault detection capacity. However, future work can be addressed on the economic feasibility of implementing the proposed system or any potential practical limitations that may arise during real-world implementation.

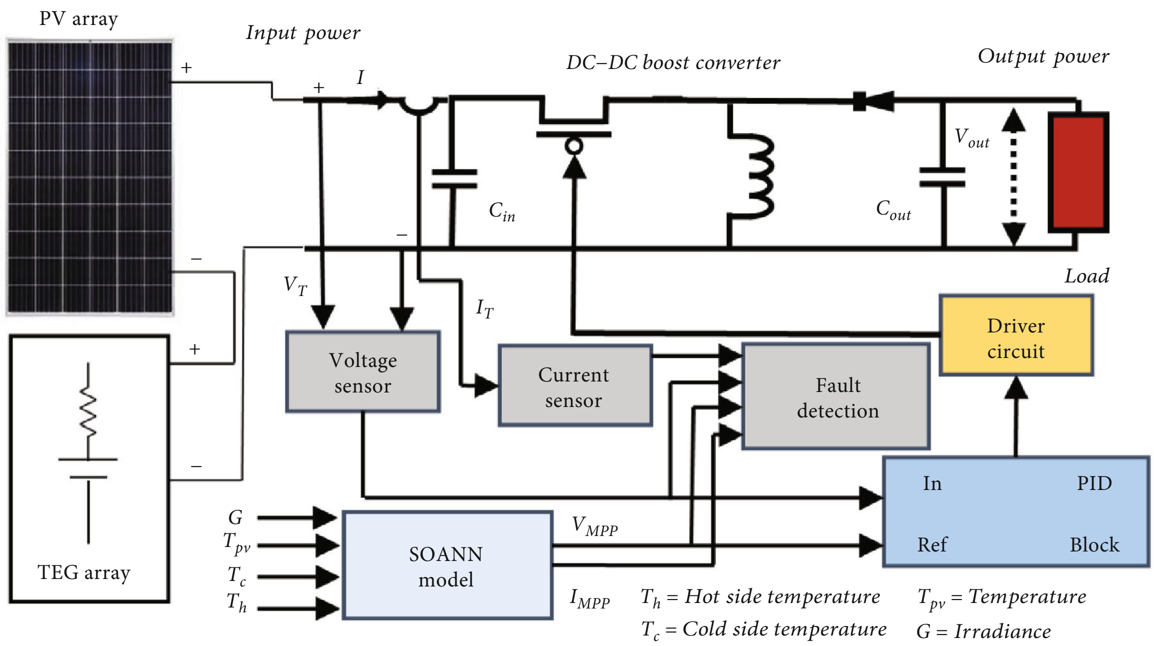


Figure 13: MPPT controller based on snake optimizer based neural network for hybrid photovoltaic-thermoelectric (PV-TEG) system [145].

5. Integration of Thermoelectric Modules into Tandem Perovskite Silicon Solar Cells

Combining thermoelectric modules with tandem perovskite silicon solar cells presents a promising approach to enhance the efficiency of solar energy conversion systems, known as PV-TE (photovoltaic-thermoelectric) applications [12, 146, 147]. Such systems harness both the photovoltaic effect and thermoelectric effect to generate electricity from solar radiation. The photovoltaic effect directly converts light into electricity, whereas the thermoelectric effect converts temperature differences into electrical energy. In a PV-TE system, the thermoelectric module is integrated with the tandem perovskite silicon solar cell to collect the waste heat generated during solar energy conversion. The thermoelectric module then converts this waste heat into additional electrical power, which increases the overall efficiency of the system. One potential challenge in the integration of thermoelectric modules into tandem perovskite silicon solar cells for PV-TE is the need to optimize the thermal management of the system. The thermoelectric module should be designed to efficiently collect the waste heat from the solar cell without overheating the system [148–150]. Selecting appropriate materials for the thermoelectric module that can function effectively under the temperatures and temperature gradients present in the system is another obstacle. Although, bismuth telluride and lead telluride have traditionally been used for thermoelectric modules, new materials and approaches are being explored [151]. Despite the existing difficulties, integrating thermoelectric modules into tandem perovskite silicon solar cells for PV-TE has the potential to significantly enhance the efficiency of solar energy conversion systems, making them more sustainable and cost-effective [12]. Research in this field is ongoing, with a focus on developing optimized designs and materials for PV-TE systems to achieve maximum efficiency.

The investigation of diverse heat transfer media, comprising air, water, and heat pipes, has been undertaken for PV-TE systems. The selection of an optimal heat transfer medium for a specific system design and operational requirements is influenced by multiple factors [152]. For instance, although air is a commonly used medium in PV-TE systems due to its low cost and ease of handling, it possesses a low heat transfer coefficient, potentially causing greater thermal resistance that may compromise the system's efficiency [153, 154]. Conversely, water is another good choice, as it has a higher heat transfer coefficient, but necessitates the use of supplementary components such as pumps and heat exchangers. Table 5 has been included in this review to present a compilation of existing research on PV-TEG systems, specifically focusing on the employed heat transfer medium. This information may serve as a valuable resource for researchers as they navigate potential avenues for future investigation on heat transfer medium.

Heat pipes have exhibited promise, with passive abilities to transfer heat with minimal thermal resistance over extended distances, while accommodating various orientations and high heat fluxes. Ultimately, a comprehensive evaluation is indispensable for identifying the most suitable heat transfer medium for a given PV-TE system.

The figure of merit for a material to generate thermoelectric power is expressed as zT, which is a dimensionless quantity [150].

$$zT = \frac{\sigma \alpha^2 T}{k}. \tag{6}$$

Other than the Seebeck coefficient α, the thermal conductivity k, electrical conductivity σ, and temperature T, are all factors that impact it.

Table 5: PV-TEG systems with their heat transfer medium [155].

Ref	Basic system model	Type of PV panel	TEG module	Auxiliary heat dissipator	Type of study
Mahmoudinezhad et al. [156]	Multijunction solar cell thermoelectric generator	Triple junction cell (GaInP/GaInAs/Ge)	Bismuth telluride	Water	Numerical and experiment
Riahi et al. [157]	CPV-TEG	Monocrystalline	TEC1-12706	Water	Mathematical model/simulation/experiment
Willars-Rodríguez et al. [158]	CPV-TEG	Crystalline silicon	Bismuth telluride	Water	Simulation and experiment
Gopinath and Marimuthu [155]	PV-TEG	Polycrystalline	TEC1-12706	Graphite	Numerical and experiment
Gopinath and Marimuthu [155]	PV-TEG	Polycrystalline	TEC1-12706	Heat sink	Numerical and experiment
Abdo et al. [159]	CPV-TEG	Polycrystalline silicon	Bismuth telluride	Microchannel heat sink	Numerical simulation
Mahmoudinezhad et al. [160]	CPVT combined with the thermoelectric generator	Mono-SI	TEC1-12706	Water	Experiment
Cui et al. [161]	CPV-TEG with PCM	Crystalline Si/CIGS/GaAs	Bismuth telluride	Heat sink	Theoretical model and simulation
Yin et al. [34]	CPV-TEG	3-junction gallium	Bismuth telluride	Water	Experimental optimization
Haiping et al. [162]	LCPVT/TEG system	Double-gazing PV panel	TEG1-242-1.0-1.2-250	Microchannel heat pipe array/water	Experiment
Teffah and Zhang [163]	Hybrid PV-TEG for high concentration	GaInP2/GaAs/Ge	CP-12706/TEG131-2	Heat sink	Simulation and experiment

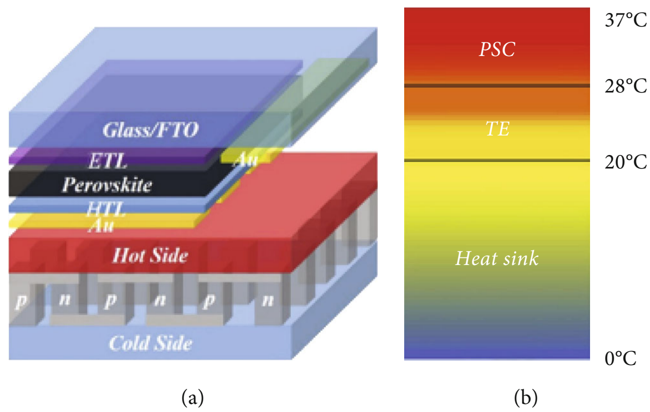


FIGURE 14: (a) Schematic diagram showing the PSC-TE hybrid system created in their study. (b) The simulated variations in heat along the vertical axis of the hybrid PSC-TE system [12].

However, the definition of thermoelectric module or system efficiency for generating electricity can be expressed as follows:

$$\eta = \frac{P}{\dot{Q}_h}. \tag{7}$$

The efficiency η of a thermoelectric device relies on the quantity of electrical energy delivered to a load P and the heat intake on the hot side $\dot{Q}$. There is a maximum limit to this efficiency, which is denoted as $\eta_{\max}$ and expressed by

$$\eta_{\max} = \frac{T_h - T_c}{T_h} \frac{\sqrt{1 + Z\bar{T}} - 1}{\sqrt{1 + Z\bar{T}} + T_c/T_h}. \tag{8}$$

T_h represents the temperature on the hotter side, while T_c represents the temperature on the colder side. It is worth mentioning that the initial segment of equation (8) represents the Carnot efficiency. This is because thermoelectric devices function as heat engines, extracting heat from a high-temperature source and transferring it to a low-temperature source while generating work. The second component of the equation establishes the distance between $\eta_{\max}$ and the Carnot limit.

A study by Zhou et al. [12] proposed a four-terminal configuration hybrid system that combines a perovskite solar cell (PSC) and thermoelectric module to achieve efficient solar energy conversion. The study used simulations and experiments to optimize the bandgap of the PSC and achieved an unprecedented efficiency surpassing 23%; the system demonstrated a notable performance of 18.3% attributed to the perovskite solar cell (PSC), while the remaining efficiency was achieved through heat conversion utilizing the TE module. The research finding (Figure 14) was that the utilization of TE modules presents a promising approach to enhance the utilization of solar radiation through the effective utilization of the low-grade heat generated by perovskite solar cells (PSCs).

The demand for high-efficiency solar cells has been satisfied to a considerable extent by perovskite solar cells (PSCs). The efficiency of PSCs based on lead halide has been rapidly enhanced and the simulated variations in the heat along the vertical axis of the hybrid PSC-TE system [164]. In addition, recent studies have indicated that the introduction of a blend of bromide and iodide into the halide makeup of lead methylammonium perovskites enables the bandgap to be continuously adjusted, making it a desirable characteristic for solar cells with multiple junctions [165]. The two main configurations of tandem devices for solar cells include perovskite-perovskite and perovskite-silicon tandem solar cells [166]. In a study by Kim et al. [167], they developed a bifacial 4-terminal tandem solar cell by combining perovskite and silicon heterojunctions, which achieved an efficiency of 30%. The efficiency of this hybrid bifacial solar cell surpassed the Shockley-Queisser limit of 29.43% for crystalline silicon solar cells. Also, He et al. [165] in their research, attained a tandem heterojunction perovskite/Si solar cell achieved an efficiency of 29.5%, wherein the top and bottom cells of the device generated an open circuit voltage of 1.74 eV. Integrating thermoelectric modules into tandem perovskite silicon solar cells has brought about efficiency in the hybrid system [168]. The standalone PSC, TEG, and the hybrid PSC-TEG system achieved efficiencies of 20.4%, 5.16%, and 20.8%, respectively. Through the optimization of operating parameters, the hybrid device reached a maximum efficiency of 22.9% with an optimal layer thickness of 449.7 nm. The researchers concluded that incorporating the TEG into the PSC helped decrease waste heat emissions and enhance the power and conversion efficiency of the PSC. Additionally, the work by Eke et al. [169] focuses on modeling and analyzing TE devices with a spectrum-splitting tandem perovskite/silicon solar cell to attain improved performance. The research employs a dichroic beam splitter as a solar concentrator to effectively harness the complete solar spectrum. Additionally, a thermoelectric cooler (TEC) is positioned behind the backplate of the tandem solar cell to mitigate overheating and enhance power generation. The impact of altering the halide composition of the perovskite on the performance of the system is also studied, and novel equations are developed for the analysis. The research finds that increasing the bromine composition only improves the system's performance for a specific halide composition and perovskite thickness range. At a split wavelength of 800 nm, the system reached an impressive efficiency of 42%, surpassing the 23.6% efficiency achieved by standalone perovskite/Si solar cells. This study offers valuable insights into the functioning of spectrum-splitting tandem perovskite/silicon solar cells when combined with TE devices.

6. 4E Analysis (Exergy, Energy, Economics, and Environment)

Due to the rising demand for sustainable energy sources and increasing energy needs, photovoltaic-thermoelectric (PV-TE) technologies have gained substantial attention for their potential to simultaneously generate electrical and thermal energy, resulting in improved energy conversion efficiency and reduced environmental impact. As such, PV-TE systems have become a promising area of research and development for meeting the 4Es: energy, environment, exergy, and economics as only a few reviews exist on this. The 4Es significantly contribute to the overall success of a technology. Energy refers to the amount of energy generated and its efficiency, while environment pertains to the environmental impact and sustainability of the technology. Exergy analysis identifies areas for optimization by focusing on the potential for energy efficiency improvement. Meanwhile, economics is concerned with the cost-effectiveness and commercial viability of the technology. In recent years, significant advancements have been made in PV-TE technologies to enhance the 4Es and address the challenges associated with their implementation.

6.1. Exergy Analysis of PV-TE System. Incorporating TEGs into a PV system with the use of PCM/Co3O4 as a working nanofluid resulted in an improvement of 12.28% and 11.6% in electrical and exergy efficiencies, respectively, according to Rajaee et al. [170]. In the context of PV-TE systems, exergy analysis is a crucial approach to evaluate thermodynamic performance and determine potential energy efficiency improvement. Exergy, also known as available energy, quantifies the maximum useful work a system can produce when it reaches thermodynamic equilibrium with the environment [171]. Exergy analysis can help identify exergy losses and efficiency, indicating areas for optimization. In PV-TE systems, exergy analysis can evaluate the efficiency of energy conversion from both PV and thermoelectric generator modules, optimizing the system design for maximum energy conversion efficiency. Exergy analysis can also identify exergy losses in system components, including PV panels, TEG modules, heat transfer media, and heat dissipation systems. Quantifying exergy losses can help identify areas of energy loss and develop strategies to minimize them, thereby improving overall system efficiency and performance. Additionally, exergy analysis can evaluate the effectiveness of advanced materials and technologies used in PV-TE systems, such as high-zT thermoelectric materials and nanofluids as heat transfer media, improving thermoelectric conversion efficiency and reducing exergy losses. Exergy analysis is, therefore, an invaluable tool for promoting the development of more sustainable and efficient PV-TE technologies. A relevant example of the application of exergy analysis in PV-TE systems is seen in the study by Chen et al. [172]. The study illustrates the importance of analyzing temperature distribution and system efficiency to identify opportunities for improvement and optimization, which is a significant application of exergy analysis. Additionally, the study presents empirical data on the impact of various factors, including inlet flow, concentration ratios, and cooling water temperature, on the efficiency and exergy output of the system. The results of their research revealed that the system had an efficient operation with an inlet flow of 0.02-0.06 kg/s, providing significant heat output and cell protection. The exergy output increased with an increasing concentration ratio, but the efficiencies decreased. Increasing the cooling water temperature improved the thermal and overall exergetic efficiencies, and even at an inlet temperature of 60°C, the electrical efficiency was over 20%. These findings provide valuable insights for evaluating and optimizing the performance of PV-TE systems through the lens of exergy analysis.

The potential of nanofluids as a cooling medium for PV/T systems and how they can contribute to improving the exergy efficiency of the system has been studied by Aberoumand et al. [173]. The study investigates the effect of using Ag/water nanofluid on the performance of a PV/T system. The findings indicate that the utilization of nanofluids for cooling purposes has a substantial positive effect on both energy and exergy efficiencies. This effect becomes more prominent as the concentration of nanofluid and flow rate increase. By employing a 4 wt% nanofluid with turbulent flow, the power output of the panel witnessed an approximate 35% and 10% increase compared to scenarios without cooling and with water cooling, respectively. Furthermore, the exergy efficiency exhibited a 50% and 30% improvement in comparison to scenarios without cooling and with water cooling, respectively. It can be noted that the research provides a useful case study to support the importance of exergy analysis in assessing the operational effectiveness of PV/T systems and identifying specific areas for optimization. Table 6 provides a summary of recent research on exergy analysis of solar heating devices. These investigations illustrate various types of solar thermal collectors, highlighting exergy efficiency as a crucial performance metric. The findings demonstrate that exergy analysis can facilitate the optimization of the design and operation which entails fine-tuning various parameters and variables to achieve the highest level of performance and efficiency of solar heating devices, resulting in enhanced energy efficiency and decreased environmental consequences.

6.2. Energy Analysis. In traditional PV systems, only solar radiation a portion of the input energy is transformed into electrical energy, while the remaining energy is discharged as heat waste. Conversely, thermoelectric (TE) systems generate electrical energy by exploiting the temperature gradient in a material. By integrating PV and TE materials, PV-TE systems can harvest both electrical and thermal energy [180]. As a result, PV-TE systems can extract more energy from the same amount of solar radiation, leading to higher energy conversion efficiencies compared to either PV or TE systems alone. For instance, a PV-TE system can attain

Table 6: Studies on the exergy analysis of solar heating devices [174].

Ref	Heating device	Exergy efficiency	Key findings
Akpinar and Koçyiğit [175]	Flat plate solar heaters	44%	Exergetic efficiency rises as the air mass flow rate and time are increased.
Alta et al. [176]	Flat plate solar air heaters	39%	The inclusion of fins in solar air heaters was observed to be beneficial and more efficient than those without fins.
Dikici and Akbulut [177]	Solar-assisted heat pump	30.80%	Solar collector's exergy losses were 1.92 kW.
Kara et al. [178]	Solar-assisted heat pump	23.81%	Max exergy losses were predominantly observed in the compressor, followed by the condenser and solar collector.
Gunerhan and Hepbasli [179]	Solar water heating system	16.17%	The solar collector was responsible for the greatest exergy destruction

an overall energy conversion efficiency of up to 30%, which is notably superior to traditional PV systems [181]. Moreover, PV-TE systems can enhance the overall energy yield and efficiency of hybrid renewable energy systems by working together with wind turbines or energy storage systems to optimize energy utilization and minimize waste. Furthermore, PV-TE systems can facilitate energy generation decentralization and increase energy access in underserved communities. This is particularly pertinent in rural areas or developing nations where access to dependable electricity is scarce. In summary, the energy aspect of PV-TE technologies presents considerable potential for increasing energy conversion efficiency, maximizing energy utilization, and extending energy access. Table 7 presents a comparison of the energy conversion efficiency of photovoltaic, thermoelectric, and PV-TE systems. PV-TE systems are capable of harnessing both electrical and thermal energy, resulting in higher energy conversion efficiencies than traditional PV or TE systems. The table highlights the potential advantages of PV-TE technology for energy generation and utilization.

6.3. Economic Analysis. PV-TE technologies must be considered from an economic perspective for their successful deployment and adoption. Despite the initial costs of PV-TE systems being higher than those of traditional solar or thermal systems, their potential long-term economic benefits make them an attractive option for households and businesses. The primary economic benefit of PV-TE systems is their ability to generate both electrical and thermal energy simultaneously, resulting in higher energy conversion efficiency and reduced energy costs [182]. Furthermore, by generating energy on-site, PV-TE systems can provide a reliable and consistent source of energy, reducing the risks associated with fluctuations in energy markets and increasing energy security. In addition to technological advancements and increased demand leading to cost reductions, government incentives and subsidies in many countries have made PV-TE systems more affordable for homeowners and businesses. However, the feasibility of PV-TE systems depends on various factors such as location, system size, and available incentives. The economic benefits of PV-TE systems, such as cost savings and increased energy security, make them a promising option for individuals and businesses looking to reduce their energy costs in the long run. Achirgbenda et al. [1] conducted a study on the economic viability of a hybrid PV/diesel/biomass gasifier system to power a remote system in Nigeria using HOMER Pro software and found that the system had a payback period of 1 year and yearly excess electricity of 411,771 kWh/yr, making it economically and technically feasible for similar remote applications with similar load and weather conditions. The study by Narducci and Lorenzi [183] discusses the economic analysis of hybrid thermoelectric-photovoltaic (HTEPV) solar harvesters and their competitiveness with existing PV technologies. An economic feasibility indicator is utilized to evaluate the economic viability of hybridization, revealing that while HTEPV frequently achieves improved solar power conversion, the expenses associated with power generation may not always warrant their implementation at the current technological stage. Montero et al. [184] in their research show that hybrid PV-TEG systems are not yet economically competitive with PV systems in the Atacama Desert; however, the computed levelized cost of energy (LCOE) for the HPV-TEG system is relatively comparable to the current LCOEs observed for PV systems in the Chilean energy market, indicating that HPV-TEG systems may become competitive in the future. Li et al. proposed a new design for a PV-TE system that utilized a microchannel heat pipe to reduce the number of required TEG modules, resulting in significant cost savings. Their analysis showed that the additional investment in TE could be recovered in six years. The newly developed PV-TE system demonstrates enhanced cost-effectiveness compared to the conventional PV system starting from the sixth year [185]. Thus, from the various literatures analyzed, it suggests that while PV-TE systems have the potential to increase solar harvester efficiency, their economic feasibility is highly dependent on factors such as material costs, system efficiency, and local energy prices. Further research is needed to optimize the design of PV-TE systems and reduce costs to make them more economically competitive with traditional PV systems. However, some studies have shown promising results and suggest that PV-TE systems could be a viable option in certain locations and circumstances.

6.4. Environmental Analysis. The environment is a crucial aspect to consider in the development and implementation of energy technologies, including PV-TE systems. PV-TE

Table 7: Assessment of energy conversion efficiency of PV, TE, and PV-TE systems.

PV-TE system type	Energy conversion efficiency	Advantages	Limitations
Standalone PV-TE system	Up to 30%	Harnesses both electrical and thermal energy and has higher efficiency than traditional PV systems	Higher cost compared to traditional PV systems
Hybrid renewable energy system with PV-TE	Increased overall energy yield and efficiency	Maximizes energy utilization and can contribute to the decentralization of energy generation	More complex system design and may require additional components and maintenance
PV-TE for rural or underserved communities	Increased energy access	Can be especially relevant in developing countries or rural areas where access to reliable electricity is limited	May require significant upfront investment and ongoing maintenance costs

systems offer numerous environmental advantages compared to conventional energy systems. One of the most notable benefits of PV-TE systems is their ability to mitigate greenhouse gas emissions. By generating both electricity and thermal energy simultaneously, PV-TE systems can substantially decrease reliance on conventional fossil fuel-based energy sources. This can lead to decreased emissions of harmful pollutants such as carbon dioxide, sulfur dioxide, and nitrogen oxides, which contribute to climate change and air pollution. Furthermore, PV-TE systems have the potential to conserve natural resources and reduce environmental impacts associated with nonrenewable energy source extraction and use. PV-TE systems generate energy from renewable sources, such as the sun, without requiring any fuel or water, thereby lessening the environmental impact of resource extraction and consumption. Furthermore, PV-TE systems can aid in sustainable building and urban design. For instance, PV-TE systems can be integrated into the facades and roofs of buildings, reducing the need for traditional building materials and lowering energy consumption. Additionally, PV-TE systems can provide decentralized and off-grid energy access to remote and underserved communities, reducing the environmental impact of energy transportation and distribution. The environmental benefits of PV-TE systems are significant and provide a strong impetus for further research and development. Investigating the latest advancements in PV-TE technologies with respect to the environment can identify opportunities to maximize the environmental benefits of these systems while minimizing any potential negative impacts. A review by Kostić and Aleksić [186] summarizes the progress and potential of PV/T water systems over the last decade, emphasizing their ability to convert solar radiation into thermal and electrical energy simultaneously, making them a suitable alternative for a range of applications, and stressing the need for improving their efficiency, reducing costs, and promoting clean and environmentally friendly energy. Also, Jia et al. [187] reviewed various research works on photovoltaic-thermal (PV/T) systems, including their development and applications under different environmental conditions, highlighting the need for accurate modeling, exploration of new materials, enhancement of system stability, and the design of energy storage systems to develop novel PV/T systems for improved energy efficiency. Notwithstanding its comprehensive coverage of PV/T systems, this review article fell short in providing a thorough analysis of the economic viability and feasibility of these systems as well as the potential obstacles that could impede their widespread adoption, thereby leaving room for further research and inquiry in these areas.

7. Summary and Outlook

The review work presented here sheds light on the remarkable promise of photovoltaic-thermoelectric systems in the realm of renewable energy generation. However, as with any innovative technology, PV-TE systems are not devoid of challenges, and addressing these hurdles is crucial for their successful integration into the renewable energy landscape.

One of the paramount challenges pertains to the availability of data for machine learning models. The integration of machine learning techniques to optimize PV-TE systems relies heavily on robust, high-quality data. These models require extensive datasets for training and validation to make accurate predictions and decisions. However, acquiring such datasets for PV-TE systems can be an intricate task. Unlike mature technologies with established datasets, PV-TE systems are relatively nascent, and comprehensive data might be limited. This scarcity poses a hurdle for researchers aiming to employ data-driven optimization techniques effectively. To overcome this challenge, future research endeavors in the PV-TE field must prioritize the development of effective data collection strategies. This includes establishing standardized protocols for data acquisition and sharing, potentially through collaborative efforts among research institutions and industry stakeholders. Additionally, efforts should be directed towards creating simulation datasets [188] that can supplement the lack of real-world data, enabling researchers to explore and refine machine learning models.

Another significant challenge is the complexity of experimentation and modeling. Achieving an optimal balance between extensive experimentation and detailed modeling is an ongoing struggle. Experimental validation is resource-intensive and time-consuming, particularly when dealing with complex PV-TE systems. Conversely, relying solely on modeling can lead to overly simplified representations that do not capture the intricacies of real-world operation. In response to this challenge, researchers must embrace a holistic approach. Future investigations should aim to strike a harmonious equilibrium between experimentation and modeling. This involves designing experiments that are purposefully aligned with the objectives of the modeling efforts. By doing so, researchers can maximize the utility of their experiments while harnessing the predictive power of modeling to explore system behavior under various conditions.

Furthermore, the sustainability of PV-TE systems hinges not only on their technical prowess but also on economic viability. An important concern lies in the cost and energy efficiency of thermoelectric systems, especially when combined with already expensive PV systems. The added expense and potential compromises in energy efficiency could raise questions about the long-term sustainability of PV-TE technology in real-world applications. In this context, the review work validates the need for rigorous economic and environmental assessments of PV-TE systems. While the review discusses the potential advantages of PV-TE, it also calls attention to the importance of evaluating their economic and environmental impacts comprehensively [189]. This includes considering factors such as the initial investment, maintenance costs, and energy efficiency gains while also assessing the potential for reducing greenhouse gas emissions.

However, this review mentions other techniques like PV/T systems and PV cooling, which have been extensively researched and shown satisfactory outcomes in enhancing overall PV system efficiency. These alternative approaches may offer economically viable and energy-efficient solutions, potentially competing with PV-TE systems in certain applications. In the pursuit of sustainable energy solutions, it is imperative to not only focus on technological advancements but also to critically evaluate the cost-effectiveness and energy efficiency of these innovations. The review work provides a foundation for this assessment, highlighting the need for a balanced consideration of economic, environmental, and technical factors to determine the suitability and sustainability of PV-TE systems in the broader context of renewable energy utilization.

8. Conclusion and Future Work

The integration of PV-TE technologies has the capability to transform renewable energy generation by addressing the challenges of energy storage and efficiency. This review paper has provided a detailed overview of the latest advancements in PV-TE technologies, including the use of PCM for thermal energy storage, the use of encapsulated PCM for thermal storage and efficiency, and the use of hybrid PCM to enhance overall performance, machine learning techniques for efficient optimization, and the integration of thermoelectric modules into tandem perovskite silicon solar cells. The implementation of PCM has shown potential to enhance the efficiency of PV-TE systems by storing surplus energy produced during peak hours and releasing it during low-demand hours. Encapsulation of PCM has also demonstrated the ability to enhance thermal conductivity and decrease PCM leakage, thus improving overall system efficiency. The use of hybrid PCM has the potential to enhance system performance by balancing energy storage capacity and thermal conductivity. Furthermore, machine learning techniques have been successfully employed to optimize PV-TE system performance with encouraging outcomes ranging from the use of various algorithms such as ANN, DNN, and Snake Optimizer. The integration of thermoelectric modules into tandem perovskite silicon solar cells also presents an opportunity for improving system efficiency.

The review paper suggests various potential directions for future research to advance the field of photovoltaic-thermoelectric (PV-TE) technologies. One possible gap is the development of new phase change materials (PCMs) with improved thermal properties that are better suited for use in PV-TE systems. Another area for exploration is the further optimization of machine learning techniques to efficiently optimize PV-TE systems using more diverse algorithms as only a few have been explored. Additionally, the integration of thermoelectric modules into other types of solar cells may enhance their efficiency and is worth investigating. Finally, conducting more experimental studies to validate simulation results obtained from software tools such as COMSOL and ANSYS could improve our understanding of these complex systems. Pursuing these future directions has the potential to advance the field of PV-TE technologies and make them more applicable to real-world applications.

In summary, the advancements in PV-TE technologies have taken a crucial step towards achieving sustainable and efficient energy generation. Ongoing research and development in this area are highly recommended to further suggest more numerical and experimental optimization processes for PV-TE systems.

Nomenclature

T_i: PCM initial temperature
T_m: Melting temperature
C_{ps}: Specific heat capacity in solid state
C_{pl}: Specific heat capacity in liquid state
B: Melt fraction
l: Specific latent heat
T_f: Final temperature
n: Sample number
λ: Regularization factor
φ: Mapping function
α: Seebeck coefficient
σ: Electrical conductivity
k: Thermal conductivity
zT: Thermoelectric figure of merit
η: Efficiency
P: Load
$\dot{Q}$: Heat absorbed at the hot side
T: Temperature
T_h: Temperature on the hotter side
T_c: The temperature on the cooler side
w: Weight
b: Bias.

Abbreviations

PV: Photovoltaics
TEM: Thermoelectric module
TEGs: Thermoelectric generators
FEM: Finite element method

ANSYS: Analysis of systems software
COMSOL: Computational sciences and multiphysics modeling software
CFD: Computational fluid dynamics
ML: Machine learning
PV-TE: Photovoltaic thermoelectric
TES: Thermal energy storage
PCM: Phase change material
STEG: Solar thermoelectric generator
LHSS: Latent heat storage system
Q: Heat flow (W)
PCES: Phase change energy storage
SL: Supervised learning
SVM: Support vector machines
USL: Unsupervised learning
BIPV: Building integrated photovoltaic
mPCM: Microencapsulated phase change material
DNN: Deep neural network
CPV: Concentrated photovoltaic
MOGA: Multiobjective optimization genetic algorithm
MPPT: Maximum power point tracking
MLPNN: Multilayer perceptron neural network
SOANN: Snake optimizer based neural network
PSC: Perovskite solar cell
LCOE: Levelized cost of energy.

Data Availability

The data is available upon request.

Conflicts of Interest

We hereby declare that there are no known conflicts of interest related to this publication and there has been no significant financial support that could have influenced the outcome of this work. We have carefully considered the protection of intellectual property associated with this work and confirm that there are no obstacles to its publication, including any issues related to timing or intellectual property. We have adhered to the intellectual property regulations of our respective institutions. The corresponding author serves as the main point of contact throughout the editorial process, responsible for communication with the other authors regarding progress, submission of revisions, and final approval of proofs. We confirm that a current and accurate email address has been provided for the corresponding author, and the email account is set up to receive communications from the journal: chika.maduabuchi.191341@unn.edu.ng, Chika Maduabuchi, corresponding author.

Authors' Contributions

All named authors have read and approved the manuscript, and there are no other individuals who meet the criteria for authorship that have not been listed. The order of authors in the manuscript has been agreed upon by all of us.

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