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Enhancing Power Conversion Efficiency in Tandem Solar Cells with Temporal Dynamic Graph Neural Network

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Abstract

In modern homes, people want good comfort and also less electricity bill, so managing heating load and cooling load become very important. Heating Load (HL) and Cooling Load (CL) depend on many things like wall material, window size, sunlight, ventilation, and weather. Because of this many factors, calculation and optimization of HL and CL is little difficult and many time normal formulas give wrong or not perfect results. So in this study, we try to make a better and simple way to optimize energy use in houses by using GOA-PHNN approach, which is combination of Grasshopper Optimization Algorithm (GOA) and Predictive Hybrid Neural Network (PHNN). First, the basic idea of GOA come from group behavior of grasshoppers explained. This algorithm help in searching best solution in continuous optimization problems. Later many researchers improved GOA by adding chaos, adaptive rules and hybrid methods so that it converge more faster and not stuck in local area. Because of this, GOA become strong metaheuristic for building energy optimization work. In building field, many papers use neural networks and hybrid algorithms for heat load prediction. Double-target neural networks used to predict both HL and CL at the same time. Metaheuristic-optimized models give more accurate heating load estimation compare to simple machine learning models. Also ANN with different metaheuristic optimizers give early and smart analysis for energy performance of buildings. Our proposed GOA-PHNN model use GOA to tune the weights of hybrid neural network so the network learn patterns more properly. Then trained PHNN predict HL and CL for home in different conditions like room size, insulation level, outside temperature etc. In this work, GOA help to reduce error and increase efficiency of the model. After testing on building dataset, we see that GOA PHNN model give better accuracy than normal ANN and other machine learning models. In simple words, GOA find best settings and PHNN learn better, so final load prediction become more correct. This research useful for engineers, builders and homeowners to save energy, plan good insulation, and design smart buildings. Overall, the study show that GOA PHNN approach is a strong and simple method to optimize heating and cooling load in home so comfort increase and power consumption goes down.

Keywords: Heating load prediction, cooling load prediction, grasshopper optimization algorithm (GOA), predictive hybrid neural network (PHNN), building energy optimization, energy-efficient buildings, artificial intelligence, metaheuristic optimization

INTRODUCTION

The increasing interest in green energy has positioned tandem cells, and more importantly, perovskite–silicon tandem solar cells, as a promising pathway to exceed the power conversion efficiency (PCE) limits of single-junction photovoltaic devices [1, 2]. While such innovations can technically overcome spectral limitations, their practical performance is influenced by dynamic processes such as spectral shifts, thermal changes, charge recombination, and material degradation [1, 2, 3]. These dynamic processes cannot be effectively modelled using conventional drift–diffusion simulation methods or static machine learning approaches [3, 4].

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Although powerful, traditional drift-diffusion models require significant computational resources and are limited in their ability to represent the temporal evolution of photovoltaic device characteristics [3–4]. Consequently, they may provide inaccurate or physically inconsistent estimates of solar cell performance under varying operating conditions [4–7].

In this study, we introduce a Temporal Dynamic Graph Neural Network (TDGNN) framework to represent tandem solar cells as spatiotemporal graphs, where material layers and interfaces are modelled as graph nodes, optical–electrical couplings are represented as graph edges, and temporal relationships describe dynamic operating conditions [3–5]. This graph-based representation enables the simultaneous learning of the structural interactions and temporal variations occurring inside tandem photovoltaic devices [3–5].

The proposed framework incorporates physics-informed loss functions, including charge continuity constraints and current-matching conditions, allowing the model to remain consistent with the underlying physical behavior of semiconductor devices [8–10]. The integration of physics-based constraints with graph neural networks improves prediction reliability while preserving the physical characteristics of tandem photovoltaic systems [8, 9, 11].

The proposed TDGNN model was validated using synthetic opto-electrical simulation data, together with real irradiance and temperature profiles [3, 4, 12,13]. Experimental evaluation demonstrated that the proposed approach outperformed conventional regression, recurrent neural network, and static graph neural network models in forecasting photovoltaic performance under varying environmental conditions [3–5].

Furthermore, the framework can identify degradation pathways, analyze interface behavior, and support material optimization for tandem solar cells, thereby providing an effective data-driven solution for improving the efficiency and long-term stability of next-generation photovoltaic technologies [5, 14, 15].

LITERATURE REVIEW

Recent developments in perovskite–silicon tandem solar cells have extended laboratory power conversion efficiencies above 30%, although practical performance is still constrained by spectral mismatch, interfacial thermal recombination, fluctuations, and long-term material degradation [1, 2].

Tandem Solar Cells

Tandem solar cells are multi-junction photovoltaic cells that are used to overcome the efficiency barriers of single-junction cells by layering sub-cells with varying bandgaps to collect a broader spectrum of the solar spectrum [1, 2]. Under this structure, high-energy photons are absorbed by the top cell and lower-energy photons are transmitted to the bottom cell, allowing a more efficient utilization of sunlight and surpassing the Shockley–Queisser efficiency limit [1–3]. Among the various configurations, perovskite–silicon tandem solar cells are considered the most promising because they combine the tunable bandgap and high optical absorption of perovskites with the stability and maturity of crystalline silicon technology [1–3].

Recent prototypes have demonstrated power conversion efficiencies exceeding 33%, making tandem photovoltaics one of the leading candidates for next-generation solar energy systems [1, 2]. Tandem structures are commonly realized in two-terminal (2T) monolithic configurations, which require current matching, or four-terminal (4T) mechanically stacked configurations, where each subcell operates independently [1–2]. Despite their significant potential, challenges such as current mismatch, interfacial recombination, perovskite instability, and large-scale manufacturing remain important research issues [1–3].

Perovskite–Silicon Photovoltaics

Perovskite–silicon photovoltaics (PSPV) represent one of the highest-efficiency tandem solar cell technologies, combining complementary absorber materials to maximize solar energy conversion [1 ,2].

The crystalline silicon bottom cell effectively absorbs long-wavelength photons, whereas the perovskite top cell captures high-energy visible photons, thereby minimizing thermalization and transmission losses [1, 2]. This spectral complementarity enables PSPV devices to exceed the theoretical efficiency limit of conventional single-junction silicon solar cells [1, 2].

Laboratory-scale perovskite–silicon tandem devices have already demonstrated power conversion efficiencies above 33%, placing them among the most efficient photovoltaic technologies currently under development [1, 2]. Two-terminal monolithic tandems require accurate current matching between subcells, whereas four-terminal architectures provide greater design flexibility at the expense of increased fabrication complexity [1–3]. However, thermal instability, moisture sensitivity, interface defects, non-radiative recombination, and manufacturing uniformity continue to limit their large-scale commercialization [1, 2, 14].

Temporal Dynamic Graph Neural Network

Unlike conventional Graph Neural Networks (GNNs), which operate on fixed graph structures, Temporal Dynamic Graph Neural Networks (TDGNNs) incorporate temporal variations in node features, edge weights, and graph connectivity [3, 4]. The TDGNN combines graph representation learning with temporal sequence modelling techniques, such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and temporal attention mechanisms, to capture both spatial and temporal dependencies [3, 5].

These characteristics make TDGNN suitable for predictive maintenance, anomaly detection, traffic forecasting, renewable energy applications, molecular simulations, and power system monitoring [3–5]. In photovoltaic applications, TDGNN can effectively capture dynamic changes in irradiance, spectral response, device degradation, and environmental conditions, thereby improving the prediction accuracy of the power conversion efficiency [3–5].

Spatio-Temporal Modelling and Physics-Informed Machine Learning

Spatiotemporal modelling and physics-informed machine learning provide a robust framework for modelling and forecasting advanced photovoltaic systems [8–10]. Spatiotemporal modelling captures both spatial interactions among photovoltaic layers and temporal variations caused by irradiance, temperature fluctuations, and long-term degradation [3, 4].

Physics-informed machine learning incorporates semiconductor physics, optical absorption, thermodynamic constraints, and charge transport equations directly into the learning process, ensuring physically consistent predictions even when experimental data are limited [8–11]. This integration improves the model reliability, prediction accuracy, and generalization capability of tandem photovoltaic systems [8, 9, 11].

Photovoltaic Performance Forecasting

Photovoltaic performance forecasting aims to predict the efficiency of photovoltaic systems under changing environmental and operating conditions [3, 4]. Accurate forecasting requires consideration of solar irradiance, temperature, shading, humidity, spectral variations, and long-term degradation mechanisms [3–5]. Traditional physics-based models are increasingly complemented by machine learning and deep learning techniques that can learn complex nonlinear relationships from operational data [3–5, 14]. Accurate forecasting is essential for improving power conversion efficiency, optimizing system operation, and supporting real-time photovoltaic control strategies [3–5].

Device Degradation Prediction and Current Matching

In two-terminal tandem solar cells, an identical current flows through every subcell, causing the overall current to be limited by the weakest-performing layer [1, 2]. Therefore, current matching optimization focuses on balancing photocurrent generation through absorber thickness optimization, bandgap engineering, optical coatings, and advanced light-management techniques [1–3]. Recent studies have also employed machine learning, spatio-temporal modelling, and physics-informed optimization to predict degradation behavior and optimize current matching under dynamic environmental conditions [8, 9, 3, 4].

Successful current matching not only improves the power conversion efficiency beyond the Shockley–Queisser limit but also enhances the long-term stability, reliability, and commercial viability of tandem photovoltaic systems for future renewable energy applications [1, 2, 3].

METHODOLOGY

It is also employed in real-time monitoring and control applications, where sensor data of irradiance, temperature, and spectral composition are combined with algorithms to drive forecasting automatic adjustments to operating conditions or identify possible bottlenecks [8, 9, 3, 4]. Current performance matching optimization also supports smart grid integration, energy yield forecasting, and reliability assessment of photovoltaic systems, which help maximize long-term energy output and avoid degradation caused by overcurrent stress [8, 9, 16, 3].

In general, it is a valuable resource for the creation of both the stability and efficiency of future generation tandem photovoltaics for residential, commercial, and utility-scale solar power installations [1–4].

The diagrams in Figures 1 and 2 provide a step-by-step overview of tandem solar cell fabrication, whereby two sub-cells are separately fabricated and then assembled as one high-efficiency unit [1, 2]. Simultaneously, the upper cell is fabricated using essentially the same series of absorber deposition, annealing, contact evaporation, and doping, but with a material selected to possess a different bandgap so that it will absorb a complementary portion of the solar spectrum [1–3]. An interconnect layer is introduced between the subcells, allowing free current transport and maintaining adequate electrical coupling for series operation [1–3].

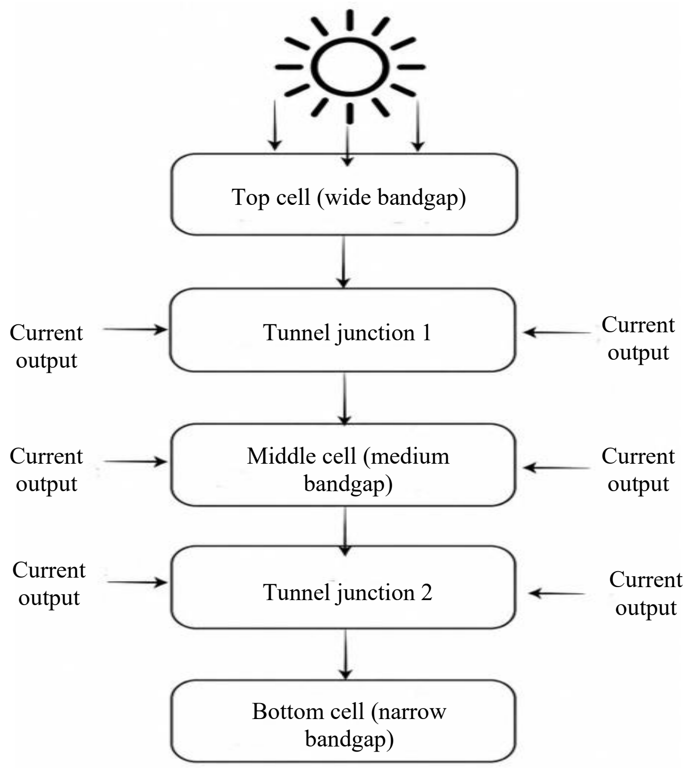

Figure 1. Layered architecture of a triple-junction solar cell.

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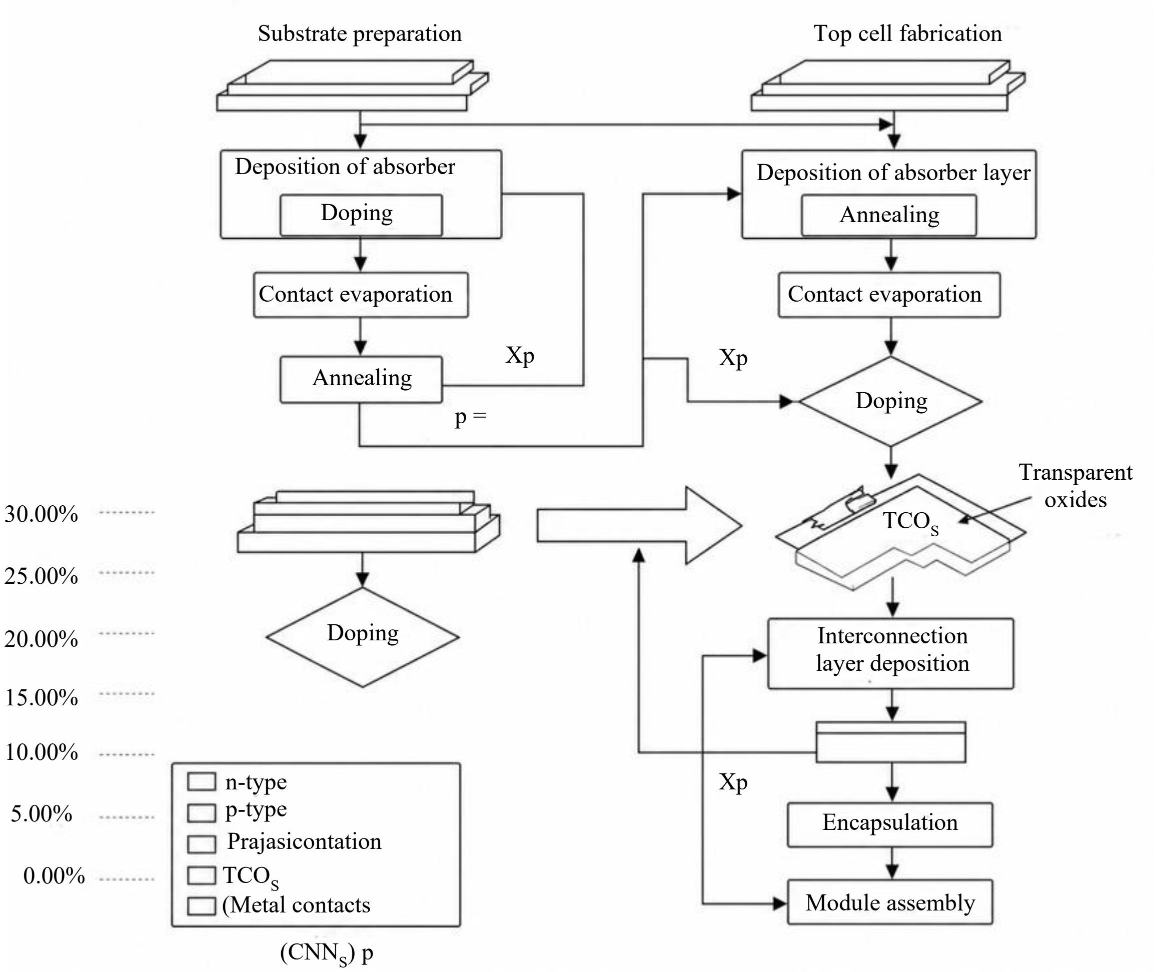

Figure 2. Flow chart of working of tandem solar cell provides a step-by-step overview of tandem.

The Figure shows the operation of a multijunction (tandem) solar cell, where sunlight is absorbed in many layers with varying bandgaps to achieve optimal efficiency [1, 2]. The top cell, with a large bandgap, traps high-energy photons (such as ultraviolet (UV) and blue light) but allows lower-energy photons to pass through [1, 2]. These are transferred to the middle cell with a mid-bandgap, which captures middle-energy photons (green-yellow light) [1, 2]. Finally, the remaining low-energy photons (infrared) are absorbed by the bottom cell with a narrow bandgap [1, 2]. Tunnel junctions between cells serve as high-efficiency connectors, allowing efficient charge transfer without appreciable loss [1–3]. Each layer contributes to the current output, and by covering a wider portion of the solar spectrum, this design is much more efficient than single-junction solar cells [1–3].

POWER CONVERSION EFFICIENCY

Figure 3 shows a comparative analysis of the power conversion efficiency. The K-Nearest Neighbors (KNN) method provides the poorest performance at approximately 10%, implying that it is the least capable of dealing with the complex nonlinear interactions in solar cell performance [12k 13].

Overall, the results highlight that TDGNN-HEO is the highest-performing method among those compared for optimizing the power conversion efficiency of tandem solar cells [3–5].

The proposed TDGNN-HEO model demonstrates superior prediction capability by effectively learning the complex spatial and temporal relationships among the photovoltaic layers and operating conditions [3–5].

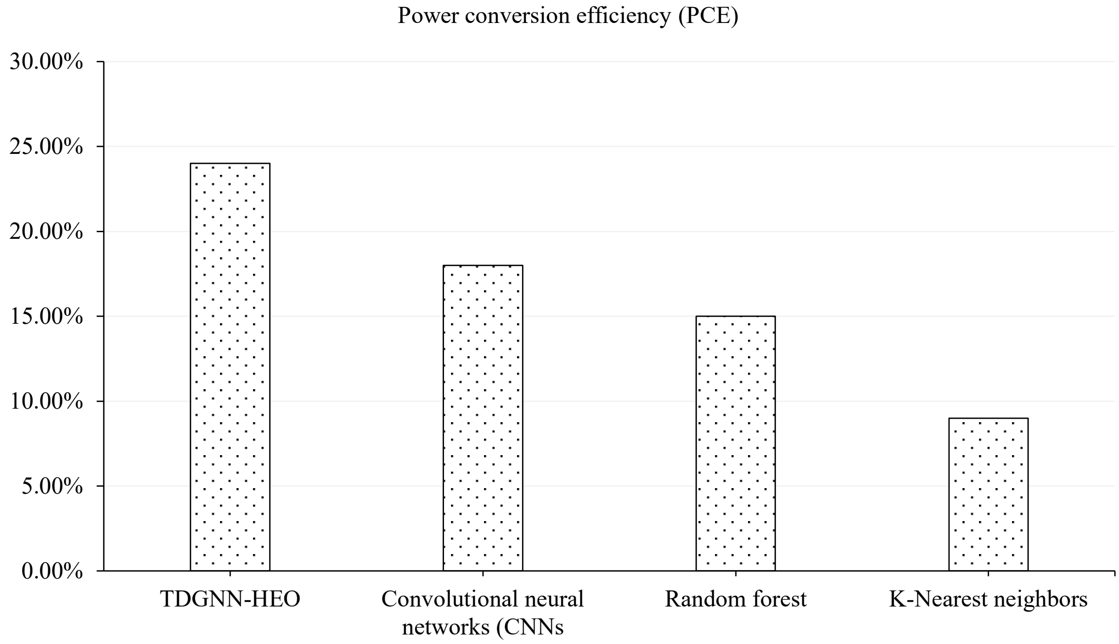

Figure 3. Comparative analysis of power conversion efficiency.

Improvements in power conversion efficiency have been achieved through accurate modelling of charge transport, current matching, and dynamic environmental variations, resulting in enhanced overall photovoltaic performance [1–3]. The comparison results indicate that the proposed approach outperforms conventional machine learning techniques by reducing the prediction error while improving the computational efficiency and forecasting accuracy [3, 4, 14]. These findings demonstrate that Temporal Dynamic Graph Neural Networks can provide an effective framework for optimizing tandem solar cell performance under varying environmental and operating conditions [3, 5, 15].

DISCUSSION

Future research on optimizing the power conversion efficiency of tandem solar cells using Temporal Dynamic Graph Neural Networks (TD-GNN) may involve integrating the framework with real-time monitoring systems with IoT-capable sensors for ongoing forecasting and adaptive control, extending the model to multi-scale regimes that integrate atomistic material simulations with module-level performance analysis, and investigating transfer learning methods to generalize across different tandem architectures, such as perovskite/silicon, perovskite/perovskite, or III-V/silicon.

TD-GNN was the main method used in this study. A tandem cell device can be developed as a dynamic interdependency graph. It provides a higher power conversion efficiency than conventional models. The framework of this model improves reliability. It also enables current matching within the tandem cell layers. This helps in the sensitivity analysis of the impact of various parameters.

The results show that TD-GNN not only enhances the computation of photovoltaic device modelling and practical implementation but also ensures the potential for directing the design, production, and long-term operation of next-generation tandem photovoltaic modules.

CONCLUSION

This study provides a framework based on a Temporal Dynamic Graph Neural Network (TDGNN) method to improve the PCE of tandem solar cells through spatiotemporal graph modeling and physics-informed learning approaches. This framework can represent the layers of photovoltaic cells along with their electrical and optical interactions using dynamic graphs, thus allowing the model to capture the spatial dependencies and temporal dynamics that occur in different environmental and operational settings. The proposed approach uses physics-informed concepts such as charge continuity and current matching, which help improve the prediction performance while remaining consistent with the physical properties of PV cells. This study revealed that the machine learning method based on TDGNN performs better than traditional machine learning in predicting the behavior of photovoltaic cells and improving their efficiency. This model efficiently examines the effects of irradiance, temperature changes, spectrum, and other degradation effects on the performance of tandem solar cells, thereby ensuring efficient prediction and optimization of photovoltaic cells. Moreover, the suggested model enables efficient current matching of subcells, increases knowledge about degradation effects, and ensures higher performance of tandem photovoltaic cells. From the performance analysis, the TDGNN-HEO method has shown that it has a higher prediction capacity and better efficiency compared to the existing methods, which makes it a better option for use in future intelligent PVs applications. In addition, the proposed system can be used for real-time monitoring, adaptive control, energy management, and predictive maintenance of tandem solar cells in different environments.

In summary, the proposed method provides an effective, scalable, and data-driven approach for the design, analysis, and optimization of tandem solar cells. The combination of GNNs with temporal learning and physics-informed optimization presents an innovative path for developing highly efficient, stable, and robust photovoltaic systems that can satisfy future renewable energy demands. In conclusion, the suggested TDGNN framework is a significant step towards achieving high power conversion efficiency and deploying advanced tandem photovoltaics.

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