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Artificial Intelligence applied in renewable energy sources characterization

SUMMARY

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Abstract

This thesis investigates advanced artificial-intelligence (AI) methodologies intended to improve the characterization of photovoltaic (PV) systems and ultra-short-horizon solar irradiance forecasting under real operating conditions. The work is motivated by two persistent challenges in PV engineering: the difficulty of extracting physically meaningful and numerically reliable parameters for equivalent-circuit PV models from measured current–voltage characteristics, and the difficulty of accurately forecasting solar irradiance over horizons of 1–30 minutes under rapidly changing atmospheric conditions. These challenges are caused by the nonlinear behavior of PV devices, the strong coupling between model parameters, and the rapid and nonstationary variability of irradiance caused by cloud-driven atmospheric dynamics, all of which limit the effectiveness of conventional parameter-identification and forecasting approaches.

Firstly, the thesis presents a structured review and critical analysis of AI methods applied in renewable-energy systems, with particular emphasis on PV technologies, and synthesizes recent advances in PV parameter-extraction techniques for single-diode, double-diode, and triple-diode formulations (SDM/DDM/TDM). The review identifies persistent gaps in the literature, including convergence inefficiency, premature stagnation, limited robustness under diverse operating conditions, increasing computational difficulty for higher-order models, and inconsistent benchmarking practices that hinder fair comparisons. These findings establish the scientific and methodological foundation for the developments proposed in the subsequent chapters.

Secondly, the thesis develops and implements two optimization techniques based on metaheuristic algorithms for PV parameter extraction. The first is a hybrid SSA–GSK framework that integrates the population dynamics of the Salp Swarm Algorithm (SSA) with Gaining–Sharing Knowledge (GSK) operators in order to improve refinement capability and convergence stability. The second is a PID-based Search Algorithm (PSA), which adapts the principles of incremental PID control to optimization and combines them with exploration-enhancing mechanisms to guide candidate solutions through nonlinear and multimodal search spaces. Together, these methods are specifically designed to address the structural difficulties of PV parameter extraction, including nonlinearity, parameter interaction, multimodality, and increasing model complexity.

Thirdly, the proposed algorithms are evaluated within a coherent and reproducible validation protocol using both experimentally measured PV devices and widely used benchmark datasets, covering different PV technologies and case studies at both cell and module levels. The evaluation covers SDM, DDM, and TDM formulations and uses a unified RMSE-based objective function supported by complementary statistical indicators to ensure transparent evaluation of fitting accuracy, repeatability, and scalability. The results demonstrate that PSA provides the most reliable and scalable performance as model complexity increases, especially for DDM and TDM formulations where parameter coupling becomes stronger, while the hybrid SSA–GSK framework clearly improves performance compared with

standalone SSA and remains competitive across all datasets. These findings confirm that the proposed algorithms strengthen the robustness of PV parameter extraction across diverse devices, operating conditions, and model structures.

Fourthly, the thesis extends the operational dimension of PV systems by proposing a horizon-adapted hybrid CNN–TCN–XGBoost framework for ultra-short-horizon solar irradiance forecasting, with lead times between 1 and 30 minutes. Representation learning through convolutional networks and temporal convolutional networks is used to capture both local irradiance variations and broader short-term temporal dependencies, while horizon-specific XGBoost components provide lead-time-aware refinement. Validation through aggregated-period and regime-based analyses demonstrates strong overall forecasting performance, low bias, and controlled degradation as forecast horizon increases. In the aggregated 2018 evaluation, the proposed framework reduced nRMSE by about 7.7% at 2 minutes and by about 22.4% at 10 minutes relative to the PV 2-state benchmark. The regime-based analysis further showed that forecasting performance is strongly governed by atmospheric stability, with the best performance obtained under clear-sky conditions and the most difficult behavior observed under highly variable cloud-driven regimes. The 2021 case studies reinforced these findings, showing that the proposed framework is generally the most robust and often the most accurate, while also indicating that the hardest ramp-driven conditions remain challenging as the forecasting horizon increases.

The thesis contributes: (i) the improvement and implementation of two metaheuristic algorithms, PSA and the hybrid SSA–GSK, for robust PV parameter extraction in SDM, DDM, and TDM formulations; (ii) a transparent benchmarking framework that clarifies the influence of device type, model complexity, and evaluation conditions on extraction performance; and (iii) a hybrid CNN–TCN–XGBoost forecasting architecture that improves ultra-short-horizon solar irradiance prediction across different atmospheric regimes. Overall, these contributions strengthen both the physics-grounded modelling layer and the data-driven operational prediction layer of PV characterization, while providing a foundation for future work on deployment-oriented PV digital twins, on-site parameter identification, and the extension of forecasting over multiple time horizons.

1. Introduction

The global shift from fossil-fuel-based energy systems toward sustainable, low-carbon alternatives has increased the importance of renewable energy sources (RES) [1]. Renewable energy now supports climate goals, economic growth, infrastructure development, and energy resilience by reducing emissions, diversifying the energy mix, and limiting exposure to fuel-market volatility [2]. For example, IRENA reported that 91% of newly commissioned renewable power projects in 2024 produced electricity more cheaply than the lowest-cost fossil-fuel alternative, avoiding about USD 467 billion in fossil-fuel costs [3]. Within this transition, Artificial Intelligence (AI) has become an important tool for improving the characterization, operation, forecasting, and management of renewable-energy technologies [4-7].

This thesis focuses specifically on the AI-based characterization of PV systems, particularly photovoltaic cells (PVC) and panels (PVP), and on the application of ML techniques for solar irradiance forecasting. Nevertheless, it is situated within a broader technical landscape in which AI tools support planning, optimization, fault detection, and operation across renewable-energy systems. Although AI-based approaches are also applied in other renewable-energy technologies including wind, hydropower, biomass, and hybrid RES configurations, solar PV has attracted the greatest attention from AI researchers, as evidenced by bibliometric analyses and PV-focused AI reviews. This prominence reflects the rapidly increasing penetration of PV in modern energy systems, declining module costs, and the complex nonlinear behaviors exhibited by PV devices, which make them particularly well suited to data-driven modeling approaches [4, 8-10].

PV technology is considered a key pillar of the renewable-energy transition due to its modularity, scalability, decreasing investment cost, and suitability for both utility-scale and distributed applications [11-14]. However, PV performance is strongly affected by irradiance variability, temperature changes, shading, soiling, manufacturing tolerances, and long-term degradation caused by ultraviolet exposure, thermal cycling, moisture ingress, and mechanical stress [11-17]. These factors create the need for accurate characterization methods that can identify PV model parameters and adapt to real operating conditions.

Equivalent-circuit models and I–V characteristics are commonly used to model PVP behavior. The single diode model (SDM), double diode model (DDM), and three diode model (TDM) describe I–V and P–V behavior, but their key parameters, such as photogenerated current, diode saturation current, series/shunt resistances, and ideality coefficients, cannot be measured directly and must be extracted from measured I–V curves [18-20]. Classical methods such as Newton–Raphson, Lambert-W-based formulations, and iterative curve fitting often require accurate initial guesses, strong assumptions, and high-quality data [21, 22].

To overcome these limitations, a large body of work has applied metaheuristic algorithms to PV parameter extraction. Metaheuristic algorithms including Differential Evolution (DE), Artificial Bee

Colony (ABC), Simulated Annealing (SA), Harmony Search (HS), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), and numerous hybrid variants have proven capable of solving nonlinear optimization problems without requiring gradient information or strict assumptions [20-22]. These methods are derivative-free and can search high-dimensional spaces, making them suitable for nonlinear PV parameter identification [21, 23, 24]. Recent studies show that AI-based and metaheuristic approaches can improve accuracy, convergence, and robustness compared with conventional numerical methods, especially for noisy or real-world data [19, 20, 23, 24]. However, challenges remain, including premature convergence, high computational cost, inconsistent performance across datasets, and difficulty with multi-objective formulations [21-24].

In parallel with parameter extraction, solar irradiance forecasting is another essential part of PV characterization because irradiance directly controls PV power generation and affects grid reliability, market operation, reserve scheduling, load balancing, and energy-storage management [25, 26]. Traditional solar irradiance forecasting approaches, including persistence-based strategies, statistical time-series models such as autoregressive integrated moving average (ARIMA), and physics-based models derived from numerical weather prediction, often struggle with nonlinear and rapidly changing atmospheric conditions [25, 26]. AI-based models, including Random Forest (RF), Gradient Boosting (GB), and k-Nearest Neighbors (kNN), Gated Recurrent Unit (GRU), Convolutional Neural Networks (CNN), and hybrid CNN–LSTM have shown improved forecasting accuracy and better ability to capture temporal and meteorological patterns [25-33].

Despite these advances, important gaps remain. PV parameter extraction and solar irradiance forecasting are often studied separately, although both are connected within PV characterization [20, 21, 25]. Forecasting performance depends on accurate PV modelling, while parameter extraction can benefit from better understanding of environmental effects [20, 25]. In addition, limited generalizability across PV technologies, climates, and locations, together with data scarcity, sensor noise, inconsistent measurements, incomplete datasets, and weak interpretability, still limits real-world AI deployment in PV systems [25-27, 33, 34].

1.1 Research Gaps

Despite the rapid development of AI applications in RES, important limitations remain in PV characterization, especially in PV parameter extraction and ultra-short-term solar irradiance forecasting. Many AI- and metaheuristic-based parameter extraction methods are still computationally demanding, sensitive to tuning, and not sufficiently validated across different PV technologies and operating conditions. Similarly, many AI-based forecasting models struggle under rapidly changing atmospheric conditions and show inconsistent performance across different sky regimes.

1.1.1 Research Gaps in AI/Metaheuristics-Based PV Parameter Extraction

Although many metaheuristic algorithms have been applied to extract PVC and PVP parameters, several challenges remain. Many methods require large populations and high iteration numbers, which increases computational time and limits practical use in real-time or embedded PV systems. Premature convergence is also a common issue, especially when exploration and exploitation are not well balanced, leading to parameter sets that may not accurately represent the full I–V curve.

Another limitation is the weak generalization of many algorithms across different PV technologies, irradiance levels, and temperature conditions. In addition, extending the extraction process from SDM to more complex models such as DDM and TDM increases the number of parameters and strengthens parameter correlations, making convergence more difficult. Existing studies also often use inconsistent datasets, metrics, stopping criteria, and parameter bounds, which makes fair comparison difficult. These gaps motivate the development of more efficient, robust, and consistently benchmarked metaheuristic methods for PV parameter extraction.

1.1.2 Research Gaps in AI-Based Solar Irradiance Forecasting

Ultra-short-term solar irradiance forecasting is important for PV operation, storage dispatch, ramp-rate mitigation, and grid control. However, many existing AI-based models have limited ability to capture rapid cloud-driven irradiance variations, especially under partly cloudy or unstable atmospheric conditions. Abrupt transitions between clear and cloudy states create sharp irradiance ramps that are difficult to forecast accurately at minute-scale horizons.

Moreover, forecasting models often perform well under stable clear-sky conditions but degrade during cloudy or highly variable periods. Therefore, achieving reliable performance across different sky conditions remains a key challenge. This thesis addresses these gaps by developing advanced metaheuristic methods for PV parameter extraction and a hybrid AI framework for ultra-short-term solar irradiance forecasting, with the aim of improving accuracy, robustness, and practical applicability in renewable-energy systems.

1.2 Aim and Objectives of the Thesis

Building on the gaps identified above, this thesis aims to develop, implement, and evaluate advanced AI-driven methods for PV characterization, specifically targeting PV parameter extraction and ultra-short-term solar irradiance forecasting, with the goal of improving the accuracy, reliability, and real-world usefulness of AI within renewable energy applications.

Specific Research Objectives:

To achieve this aim, the thesis is structured around the following specific research objectives:

O1. To review and analyze AI methods applied in renewable-energy applications, particularly in PV technologies.

O2. To review and analyze recent advancements in PV parameter-extraction models and algorithms.

O3. To develop, modify, and implement metaheuristic-based techniques for robust and accurate PV parameter extraction across diverse operating conditions.

O4. To develop and implement AI-based models for short-horizon and ultra-short-horizon solar irradiance forecasting.

O5. To validate and benchmark the proposed PV parameter-extraction methods and solar irradiance forecasting models against established reference models.

1.3 Structure and Content of the Thesis

This PhD thesis is organized into six chapters, progressing from the general background and state of the art to the development, implementation, and evaluation of AI-based methods for PV device characterization and solar irradiance forecasting.

Chapter 1 establishes the context and motivation of the thesis. It introduces the global transition toward RES and explains the role of AI in addressing the nonlinear and data-intensive challenges of modern energy systems. The chapter then focuses on PVC and PVP, identifying the main challenges in PV modelling, parameter extraction, and solar irradiance forecasting. It also defines the research gaps, overall aim, and specific objectives of the thesis.

Chapter 2 presents a review of intelligent computational methods in renewable-energy applications, with emphasis on PV technologies. It discusses machine learning, deep learning, and metaheuristic optimization, then focuses on PV modelling and metaheuristic-based parameter extraction. SDM, DDM, and TDM models are critically reviewed in terms of accuracy, robustness, and computational efficiency, providing the foundation for the methods developed in Chapter 3.

Chapter 3 develops and implements metaheuristic-based techniques for PV parameter extraction. It formulates the parameter-identification problem, including objective functions, parameter bounds, and performance metrics. Based on the limitations identified in Chapter 2, the chapter introduces new or modified algorithms designed to improve convergence behavior, exploration–exploitation balance, accuracy, and robustness across different operating conditions.

Chapter 4 validates the proposed metaheuristic algorithms using representative PV datasets, test cases, and benchmark methods. It presents numerical results for different PVC and PVP under various operating conditions and evaluates convergence behaviour, computational cost, robustness, and accuracy compared with state-of-the-art approaches.

Chapter 5 focuses on AI-based solar irradiance forecasting. It defines the short- and ultra-short-horizon forecasting problem, describes the datasets and input variables, and presents the developed forecasting models, including their architectures, training strategies, and pre-processing steps. The chapter evaluates the results under different meteorological conditions using standard error metrics and compares the proposed models with reference methods from the literature.

Chapter 6 summarizes the main conclusions, original contributions, and limitations of the thesis. It highlights the contributions of the proposed metaheuristic parameter-extraction algorithms and AI-based irradiance forecasting models, and proposes future research directions, including extension to other PV technologies, operating conditions, and integration into broader renewable-energy management frameworks.

2. Artificial Intelligence for Photovoltaic Modelling and Parameter Extraction

Accurate modelling of PV systems requires the precise identification of model parameters, which is a challenging task due to the nonlinear characteristics of PV devices and their strong dependence on operating conditions. Traditional analytical and numerical parameter extraction techniques often suffer from convergence issues, sensitivity to initial conditions, and reduced robustness when applied to complex PV models. To overcome these limitations, metaheuristic optimization algorithms have been increasingly adopted as effective tools for PV parameter extraction.

In this chapter, an overview of AI methods relevant to RES is presented, with particular emphasis on metaheuristic algorithms used for PV modelling and parameter identification. The discussion is restricted to the optimization techniques and modelling approaches that are directly employed throughout this thesis. Special attention is devoted to the application of metaheuristic algorithms to the three models, where parameter extraction is considered a nonlinear optimization problem.

The PV models and metaheuristic-based parameter extraction methods reviewed in this chapter serve as the theoretical foundation for the novel algorithms proposed in Chapter 3. Existing approaches are critically analyzed in terms of accuracy, robustness, and computational efficiency, highlighting their limitations and open challenges. This analysis provides the motivation for the development of improved metaheuristic parameter extraction techniques that are introduced and validated in the subsequent chapters of this thesis.

2.1 Artificial Intelligence in Renewable Energy Systems

2.1.1 AI applications with emphasis on PV systems

This thesis builds on these developments but narrows the focus to two critical aspects in which AI can have a particularly strong impact and where significant research gaps remain: (i) the application of intelligent and metaheuristic methods for PV model parameter extraction, and (ii) the design of data-driven models for ultra-short-term solar irradiance forecasting. These two themes constitute the core technical contributions of the work, which are explored thoroughly in the upcoming sections.

2.2 Equivalent-Circuit Models for PV Devices

2.2.1 Single-diode model (SDM)

In the SDM formulation, the PVC is modeled as a current source connected in parallel with one diode, a shunt resistance R_{sh} and a series resistance R_{s}. Due to its favorable compromise between structural simplicity and predictive capability, this model is the most commonly adopted in both industrial practice and academic parameter-extraction studies [35, 36]. In this model, five parameters must be identified for a given operating condition: the I_{ph} current, the I_{sd} current, the n, the R_{s} and R_{sh} in order to achieve optimal performance from the PVC.

2.2.2 Double-diode model (DDM)

The DDM extends the SDM by introducing an additional exponential diode branch to represent recombination effects occurring within the depletion region of the p–n junction. In this way, this configuration reflects diffusion processes in the quasi-neutral regions as well as generation–recombination phenomena in the space-charge region, together with the parasitic series and shunt resistances. As a result, it provides a more realistic description of PVC behavior than the SDM, at the cost of additional parameters and higher computational complexity [36]. In this formulation the PVC is characterized by seven unknown parameters that must be identified for each operating condition, which $\{I_{\mathrm{ph}},\ I_{\mathrm{sd1}},\ I_{\mathrm{sd2}},\ n_1,\ n_2,\ R_{\mathrm{s}},\ R_{\mathrm{sh}}\}$.

2.2.3 Triple-diode (TDM)

Although the SDM and DDM models are sufficient for many crystalline-silicon modules, more detailed equivalent circuits are often required to capture non-ideal effects observed in advanced or highly stressed devices. In particular, the TDM introduces a third exponential diode branch to represent additional recombination and leakage mechanisms (for example at grain boundaries, defect clusters or degraded regions) that cannot be accurately described by only two diodes [37]. For a given irradiance and temperature, the "full" TDM therefore involves 9 parameters to be identified, which are $(I_{\mathrm{ph}},\ I_{\mathrm{sd}_1}, I_{\mathrm{sd}_2}, I_{\mathrm{sd}_3},\ n_1, n_2, n_3,\ R_{\mathrm{s}}, R_{\mathrm{sh}})$.

2.2.4 PV module modelling

In practical applications, PVCs are interconnected to form modules, strings, and arrays to achieve the voltage and power specifications required by load demands or grid integration. A PVP typically comprises multiple cells arranged in series, and, in some cases, several such series strings may be connected in parallel to enhance the delivered current. Therefore, the equivalent-circuit models introduced for a single cell can be extended to the module level by considering the series-parallel configuration of the cells and introducing appropriate module-level parameters [37, 38]. In the SDM five parameters must be extracted for the module, for DDM seven parameters must be extracted, and for TDM nine parameters must be extracted.

2.3 Critical Analysis and Identified Gaps in PV Parameter Extraction

Recent PV parameter-extraction research shows clear progress in accuracy and modelling coverage, especially as studies extend from SDM toward DDM, TDM and module-level formulations [39]. However, computational cost and convergence inefficiency remain major barriers, because very low RMSE values often require large populations, high iteration counts or large evaluation budgets [40-48].

Premature convergence and imperfect exploration–exploitation balance also remain persistent problems. If exploration collapses too early, optimization can stagnate in local minima and produce parameter sets that do not reproduce the full I–V characteristic reliably [42]. Robustness and generalization across PV technologies and operating conditions are also not consistently demonstrated, especially when moving across different irradiance–temperature ranges [40-47, 49].

There is also a persistent trade-off between model richness and extractability. Moving from SDM to DDM/TDM improves the ability to represent recombination and leakage mechanisms, but it enlarges the decision space and increases sensitivity to noise, initialization and parameter coupling [50].

2.3.1 Motivation for the proposed metaheuristic methods

Motivated by these gaps and trends, this thesis adopts two complementary research directions for the PV parameter-extraction problem. First, it modifies, and implements a hybrid metaheuristic-based technique that combines global search with an additional refinement mechanism, with the aim of improving convergence speed and reducing sensitivity to local minima and parameter coupling. Second, it develops and implements a new standalone metaheuristic algorithm tailored to the PV parameter-extraction landscape, designed to provide stable convergence and consistent parameter estimates while maintaining practical computational cost across diverse operating conditions. This direction is motivated by comparative findings that many existing approaches can be sensitive to algorithm settings and may exhibit variability in convergence behavior across datasets.

Both approaches, the hybrid method and the newly modified and implemented metaheuristic algorithms are therefore introduced to address the documented limitations in robustness, scalability, and computational efficiency for the three models' parameter identification, and they are presented and discussed in detail in Chapter 3.

2.4 Conclusion

This chapter reviewed the key foundations of PV modelling and parameter identification, focusing on how I–V/P–V characteristics vary with irradiance, temperature, partial shading, soiling, and long-term degradation [51-53]. These conditions justify the use of equivalent-circuit models, mainly SDM, DDM, and TDM, which provide an accuracy–complexity hierarchy for PV simulation and control [35-38, 54-58]. However, moving from SDM to DDM and TDM increases the difficulty of parameter extraction due to stronger parameter coupling, higher dimensionality, multimodal/non-convex error surfaces, and trade-offs between accuracy, robustness, and computational cost [50, 59-62].

The review also showed that classical analytical and deterministic methods, although simple and fast, may become unreliable with limited or noisy data, complex models, poor initialization, or weak identifiability based only on datasheet points [63-66]. Therefore, PV parameter identification is commonly formulated as a global optimization problem. Metaheuristic algorithms are well suited for this task because they are stochastic, derivative-free methods that balance exploration and exploitation in complex search spaces, especially for DDM and TDM fitting [7, 20, 39, 67]. Comparative studies usually assess these methods using accuracy indicators such as RMSE, convergence behaviour, statistical stability, and computational cost [19, 67]. The review also highlighted the growing use of hybrid metaheuristic approaches that combine global search with analytical transformations to improve stability and reduce computational burden [68-70].

The findings of this state-of-the-art investigation were also disseminated through a peer-reviewed journal article in Energy Strategy Reviews, which reviewed artificial-intelligence applications in renewable energy, including PV parameter extraction and solar irradiance forecasting [7].

Based on the identified gaps in robustness, scalability, computational efficiency, and reproducibility for SDM, DDM, and TDM identification, Chapter 3 presents the proposed solutions. These include a hybrid metaheuristic identification technique with an additional refinement mechanism to improve convergence and reduce sensitivity to local minima, and a modified standalone metaheuristic algorithm designed to provide stable and consistent parameter estimates at practical computational cost across different datasets and operating conditions.

3. Metaheuristic-Based Techniques for PV Parameter Extraction

3.1 Chapter Overview

Accurate extraction of PV parameters is essential for reliable simulation and control of PVC and PVP. In practice, parameter identification is challenging because PV equivalent-circuit models are nonlinear, the optimization landscape is typically multimodal, and parameter coupling becomes stronger as the model dimensionality escalates from SDM, DDM to TDM. These characteristics can cause conventional optimization methods to converge slowly or become trapped in local minima, and can require large evaluation budgets to obtain stable estimates [39, 42].

This chapter focuses on the development, modification, and implementation of two metaheuristic-based techniques for PV parameter extraction: a PID-based Search Algorithm (PSA) and a hybrid SSA–GSK framework. The PV parameter-extraction problem is first formulated in terms of decision variables, objective functions, and parameter constraints. The proposed algorithms are then described in detail, including their update equations, constraint-handling mechanisms, and implementation procedures. Experimental evaluation and benchmarking are presented in Chapter 4.

3.2 Hybrid SSA–GSK Metaheuristic Algorithm

This section presents the proposed hybrid SSA–GSK optimization framework, which combines the chain-based exploration mechanism of SSA with the learning-and-exchange operators of GSK [71]. The motivation for hybridization is to exploit the complementary behavior of the two algorithms: SSA provides a simple population structure with effective global movement driven by a leader–follower chain, while GSK introduces structured knowledge exchange through its junior and senior learning schemes. Within the proposed framework, the SSA population and follower-update mechanism are retained, whereas the leader update is redesigned using the knowledge-sharing operators of GSK in order to strengthen exploitation and improve convergence stability.

Let a population of N salps be initialized within the feasible bounds $[lb_j, ub_j]$. Each salp position corresponds to a candidate parameter vector of the PV model being identified. At each iteration, the population is evaluated and ranked according to fitness, and the best current solution is taken as the reference solution (food source). In classical SSA, the leader position is updated using the SSA leader rule; however, in the hybrid SSA–GSK framework, the leader's new position is generated using GSK-based learning operations, while the remaining salps (followers) continue to update their positions through the SSA follower rule.

To construct the GSK-based leader update, the algorithm first determines how many dimensions of the decision vector are updated using the junior scheme and how many are updated using the senior scheme. The leader vector is then updated dimension-wise by applying junior updates to the selected D_{junior} dimensions and senior updates to the remaining D_{senior} dimensions.

For the dimensions assigned to the junior scheme, the leader update follows the GSK junior learning operator. After ranking individuals from best to worst, the algorithm identifies suitable knowledge sources around the selected individual and selects an additional random individual x_r (distinct from the chosen neighbors). For the junior dimensions, the candidate update is computed using [71]:

$$x_i^{\text{new}} = x_i + k_f[(x_{i-1} - x_{i+1}) + (x_i - x_r)]. \tag{1}$$

For the dimensions assigned to the senior scheme, the update is generated using the GSK senior learning operator. Two individuals are sampled from the best and worst segments of the ranked population, and a representative individual x_m is selected from the middle segment. The candidate update for the senior dimensions is computed using [71]:

$$x_i^{\text{new}} = x_i + k_f\left[(x_{p\text{-best}} - x_{p\text{-worst}}) + (x_i - x_m)\right]. \tag{2}$$

Once the junior and senior dimension updates are computed, a complete candidate leader vector is formed. The candidate leader is then evaluated, and a greedy acceptance rule is applied: the updated leader is accepted only if it improves the fitness value compared with the current leader; otherwise, the current leader is retained. This acceptance step prevents deterioration and ensures monotonic improvement of the best solution whenever an improved update is found.

After the leader is updated using the GSK-based procedure above, the remaining salps (followers) are updated using the SSA follower rule which maintains the chain structure. The behavior of the hybrid method is influenced by the GSK control parameters, particularly the knowledge factor k_f and the proportion p used to define elite and poor groups in the senior phase. The intensity is directly governed by these parameters of knowledge transfer in the leader update and, consequently, the convergence behaviour of the overall hybrid algorithm.

The SSA–GSK experiments reported in this thesis were conducted using the following parameter settings: population size $N = 100$, knowledge rate $k_r = 0.7$, knowledge factor $k_f = 0.225$, top and bottom proportion $p = 0.1$, and a maximum number of iterations $Max_{iter} = 1100$.

For clarity, the corresponding flowchart is shown in Figure 1.

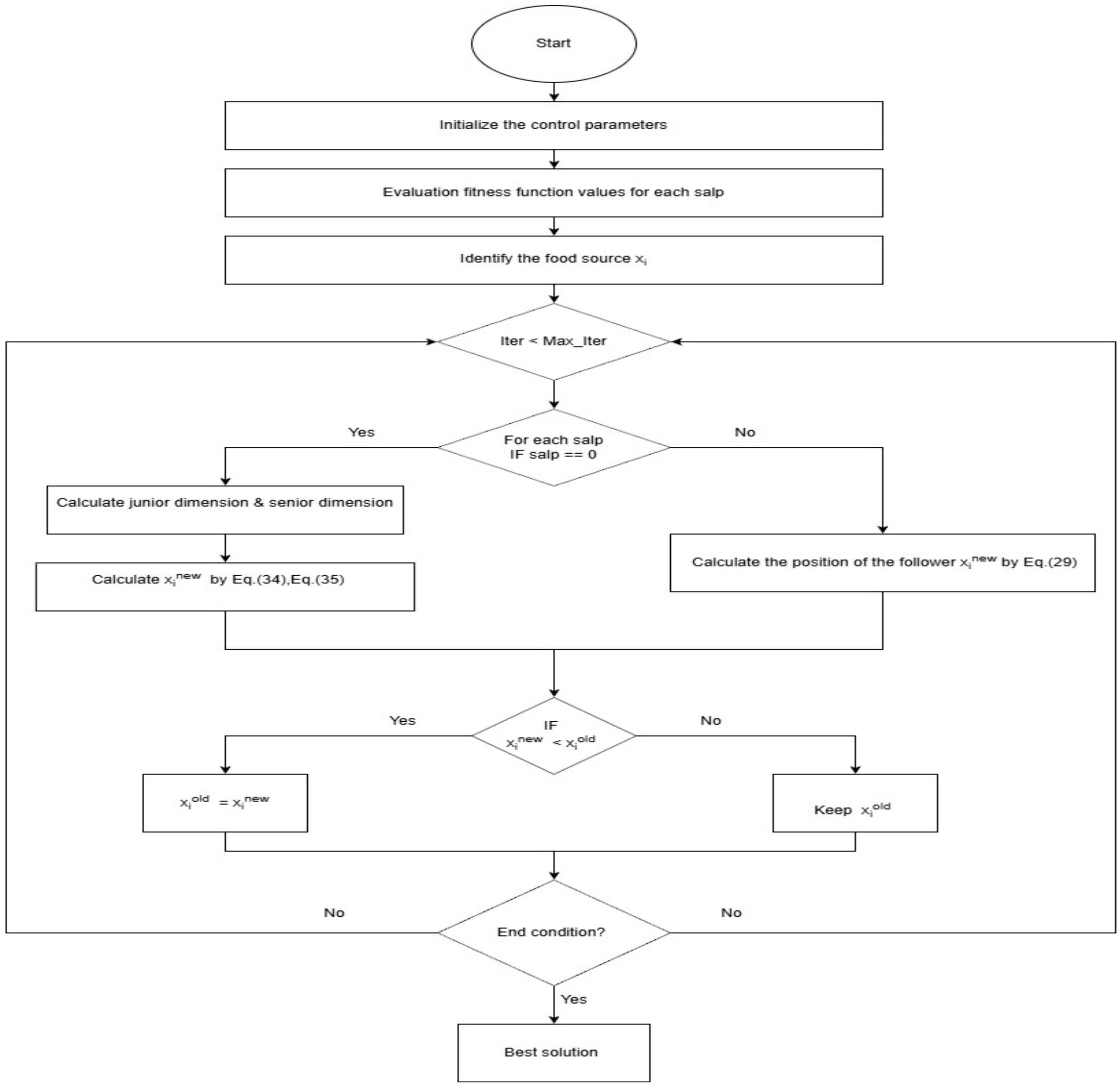

Figure 1 Flowchart of Hybrid SSA-GSK

3.3 PID-Based Search Metaheuristic Algorithm

Although the hybrid SSA–GSK framework strengthens the exploration–exploitation balance by combining complementary search mechanisms, additional improvements are still required as some convergence and efficiency challenges may still arise, especially under varying operating conditions and for more complex PV models. These considerations motivated the development, modification, and implementation of a PID-based Search Algorithm (PSA), which is designed to provide more consistent convergence behavior and robust parameter estimation for SDM, DDM and TDM.

PSA is designed to provide accurate parameter identification while controlling computational cost through an explicit balance between population size and iteration budget [72, 73]. PSA is motivated by incremental PID control concepts, where the control action is expressed as a change relative to the previous state. In classical control, PID regulation combines proportional, integral, and derivative terms to reduce a deviation between a target value and a measured value. PSA transfers this idea into an optimization setting by treating the best solution found so far as a moving reference and using PID-inspired correction terms to guide the population toward that reference in a stable and controlled manner.

In PSA, the optimization population is updated using two complementary components. The first component is a PID-based correction step that drives solutions toward the current best solution. The second component is a Lévy-flight-based exploratory step (referred to here as a "zero-output" term) intended to enhance global search capability and reduce the risk of stagnation in local minima. A time-varying mixing factor controls the relative influence of exploitation (PID correction) and exploration (Lévy flight) during the search.

The population is initialized randomly within the lower and upper bounds of each decision variable [72, 73]:

$$x_{ij} = (u_j - l_j)\, r_1 + l_j \tag{3}$$

where $X_{i,j}$ is the value of the j-th variable for the i-th candidate solution, l_j and u_j are the lower and upper bounds, and $r_1 \in [0,1]$ is a random number.

At each iteration, PSA calculates the deviation between each candidate solution and the current best solution [72, 73]:

$$e_k(t) = x^*(t-1) - X(t-1) \tag{4}$$

Where $x^*(t)$ denotes the best solution vector at iteration t, and $X(t)$ denotes the matrix collecting all population vectors at iteration t.

The PID-based correction is then calculated using proportional, integral, and derivative terms [72, 73]:

$$\Delta u(t) = K_p\, r_2\, [e_k(t) - e_{k-1}(t)] + K_i\, r_3\, e_k(t) + K_d\, r_4\, [e_k(t) - 2e_{k-1}(t) + e_{k-2}(t)] \tag{5}$$

Where K_p, K_i, and K_d are the proportional, integral, and derivative coefficients, while r_2, r_3 and r_4 are random vectors used to add controlled stochastic behavior.

To improve exploration, PSA also uses a Lévy-flight term [72, 73]:

$$o(t) = \left[\cos\left(1-\frac{t}{T}\right) + \lambda r_5 \mathrm{L}\right] e_k(t) \tag{6}$$

Where $r_5 \in [0,1]$ is a random vector and λ is a generation-dependent scaling factor

The final solution update combines the PID correction and Lévy exploration using a mixing factor η [72, 73]:

$$x(t+1) = x(t) + \eta\, \Delta u(t) + (1-\eta)\, o(t) \quad (7)$$

For all PSA experiments reported in this thesis, the population size and iteration budget are fixed to $N = 100$ and $Max_{iter} = 1100$. The PID coefficients are set to $K_p = 1.2$, $K_i = 2$, and $K_d = 0.75$, which were selected through repeated empirical testing across the considered PV parameter-extraction cases to obtain stable convergence and low fitting error. The Lévy parameter is set to $\beta = 2$ to enable occasional long jumps while maintaining controlled search behavior.

For completeness, the flowchart of PSA is provided in Figure 2.

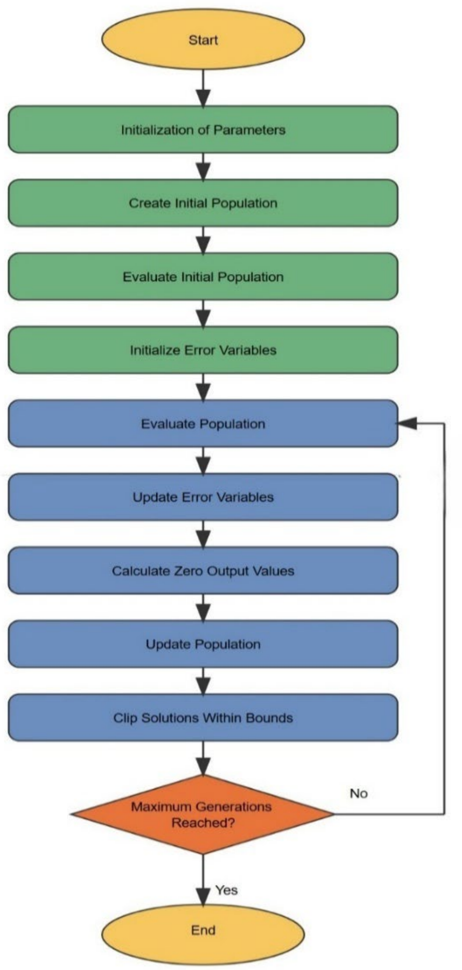

Figure 2 PSA flowchart

3.4 Performance Metrics and Statistical Evaluation

To evaluate the extracted parameters for the three models using the proposed PSA and hybrid SSA–GSK algorithms, the optimization problem is formulated to minimize the mismatch between the measured current values obtained from experimental or benchmark I–V datasets and the corresponding current values predicted by the selected PV model using the estimated parameter vector. In this thesis, the RMSE is adopted as the primary objective function. In addition to RMSE, the mean bias error (MBE), the standard deviation (STD), and the absolute error (AE) [45, 74] are considered.

The RMSE for a candidate parameter vector X is defined as [45, 74]:

$$RMSE(X) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(I_{c,i}-I_{m,i}\right)^2} \tag{8}$$

The MBE is computed as [45, 74]:

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(I_{c,i}-I_{m,i}\right) \tag{9}$$

The STD is computed as [74]:

$$STD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left[\left(I_{c,i}-I_{m,i}\right)-MBE\right]^2} \tag{10}$$

Finally, the AE is defined as [45]:

$$AE = \sum_{i=1}^{n} \mid I_{c,i}-I_{m,i} \mid \tag{11}$$

3.5 Conclusion

Chapter 3 presented two metaheuristic-based techniques for PV parameter extraction and documented the methodological choices used throughout the thesis. The first contribution is the hybrid SSA–GSK framework, designed to combine SSA's population structure with GSK's knowledge-learning operators to strengthen exploitation and late-stage refinement. In the proposed hybrid, the SSA follower rule is retained, while the leader update is redesigned using GSK junior/senior learning operators, supported by improvement-preserving selection and explicit boundary handling to maintain feasibility and stable refinement near convergence [43, 71, 75].

The second contribution is the PSA, which adapts incremental PID correction concepts to optimization by using the current best solution as a moving reference. PSA updates candidate solutions through a PID-driven exploitation step combined with a Lévy-flight exploration term, with a time-varying mixing factor to regulate exploration versus exploitation over iterations. Practical implementation aspects relevant to reproducibility, initialization within bounds, feasibility enforcement, and full-loop runtime accounting, were also specified [72, 73].

The scientific contributions arising from this development work were disseminated through two peer-reviewed journal publications. Specifically, the PSA-based approach was published in Applied Sciences, while the hybrid SSA–GSK approach appeared in the Environmental Engineering and Management Journal. These publications document the theoretical development of the proposed methods and confirm the originality and scientific relevance of the algorithmic contributions presented in this chapter [71, 73].

Building on the problem formulation, algorithm designs, and metrics established in Chapter 3, Chapter 4 performs the experimental validation and benchmarking of the proposed methods. The chapter reports numerical results using the RMSE/MBE/AE criteria defined here and compares the proposed techniques against reference approaches under SDM, DDM, and TDM settings, while also examining convergence behavior and computational cost.

4. Experimental Evaluation and Benchmarking

4.1 Chapter Overview

This chapter evaluates the performance of the two-metaheuristic parameter-extraction techniques developed in Chapter 3: the PSA and the hybrid SSA–GSK framework. The evaluation is conducted for the PV equivalent-circuit models considered in this thesis, namely the SDM, DDM, and TDM, depending on the suitability of each formulation for the corresponding device and dataset. The purpose is to verify that the proposed methods can identify physically meaningful parameter sets that enable accurate reproduction of the measured I–V characteristics.

4.2 PV Datasets and Test Cases

The evaluation uses PV datasets chosen to support both practical validation and benchmarking against established literature. For clarity, the test cases are organized into two dataset groups based on their source. The first group consists of experimental datasets measured under laboratory or natural conditions, including monocrystalline silicon (mSi) and multijunction solar cell (MJSC) devices. The second group comprises benchmark datasets adopted from specialized literature, which described in section 4.2.2

Across both dataset groups, the extracted parameter sets are validated through quantitative comparison between the model-predicted I–V curves to the measured data, using statistical tests, and the same evaluation workflow is applied consistently to assess performance across different PV technologies, device types (cell/module), and operating conditions.

4.2.1 Experimental datasets

The experimental validation in this thesis is based on in-house I–V measurements acquired for two PV device types: a commercial mSi cell with an active area of approximately 3 cm × 3 cm, and a commercial InGaP/InGaAs/Ge triple-junction MJSC with an active area of approximately 1 cm × 1 cm. For the MJSC, the junction band-gap energies are 1.86 eV (InGaP), 1.40 eV (InGaAs) and 0.67 eV (Ge). For each technology, multiple samples were initially characterized and a representative device was selected for the detailed I–V measurement campaigns reported in this chapter [76].

All laboratory I–V measurements were acquired using the SolarLab measurement platform, which is designed to measure I–V characteristics while controlling irradiance and cell temperature. The SolarLab hardware configuration and the main elements of the measurement workflow are shown in Figure 3. The platform records irradiance and temperature simultaneously with each electrical trace so that every I–V curve is paired with its corresponding operating conditions. Temperature control is implemented as a closed-loop procedure, where the device is driven to a target setpoint and held stable while the I–V characteristic is swept under approximately constant temperature conditions. To reduce disturbances from stray light, reflections, and short-term thermal fluctuations around the device, the measurement region is enclosed within a light-shielding black cover during acquisition [76].

Within this experimental set, the mSi analysis in the present chapter focuses on an I–V characteristic measured at a representative one-sun operating point, specifically 1000 W/m² irradiance and 27 °C cell temperature. In addition, three dedicated datasets were measured for the MJSC under 1000 W/m² irradiance and one-sun conditions at three temperature levels, denoted as Case A (41.5 °C), Case B (51.3 °C) and Case C (61.6 °C). These measurements were conducted under natural sunlight using the RELab system, with each measured I–V dataset comprising 29 V–I data points [76].

Figure 3 Experimental setup [77]

4.2.2 Benchmark datasets from the literature

In addition to the in-house measurements, this thesis evaluates the proposed extraction algorithms using five well-established benchmark I–V datasets from the PV modelling literature: RTC France silicon cell, amorphous silicon cell (aSi), Photowatt PWP201 module, PVM 752 GaAs thin-film module, and STM6-40 module. These datasets are commonly used because they provide reproducible measured I–V points under defined irradiance and temperature conditions, allowing direct comparison with published parameter-extraction studies. The RTC France dataset contains 26 points measured at 1000 W/m² and 33 °C [78], while the aSi dataset contains 46 points at 1000 W/m² and 25 °C [45]. At module level, the PWP201 dataset includes 25 points at 1000 W/m² and 45 °C [78], the PVM dataset contains 44 points at 1000 W/m² and 25 °C [45], and the STM6-40 dataset includes 20 points at 1000 W/m² and 51 °C [79]. These datasets are used consistently for SDM, DDM, and TDM parameter extraction, supporting reproducible validation and comparison of the proposed algorithms across different PV technologies and operating conditions.

4.3 Experimental Protocol and Benchmarking Setup

4.3.1 Algorithm configuration

To ensure a fair comparison, PSA and SSA–GSK were executed using the same computational budget, with a population size of 100 and a maximum number of 1100 iterations. For SSA–GSK, the knowledge rate (k_r), knowledge factor (k_f) and top/bottom proportion (p) were set to 0.7, 0.225, and 0.1, respectively. For PSA, the PID gains were defined as K_p = 1.2, K_i = 2, and K_d = 0.75, while the Lévy exponent β was set to 2. In both algorithms, the termination criterion was fixed at T = Max_iter.

4.4 Results and Discussion

This section summarizes the parameter-extraction results obtained with the two proposed metaheuristic techniques, PSA and the hybrid SSA–GSK, across the PV test cases considered in this thesis. Each dataset was evaluated under the SDM, DDM, and TDM, and the discussion focuses on fitting accuracy, stability, convergence behaviour, and computational cost. RMSE is used as the main curve-fitting indicator, supported by MBE, STD, AE profiles, I–V/P–V reconstructions, convergence curves, and execution-time analysis.

Table 1 Summary of the main Chapter 4 parameter-extraction results

Dataset / condition	Best PSA RMSE results	Main result from the comparison
mSi cell, 1000 W/m², 27 °C	SDM: 5.63096×10^{-4}; DDM:2.6216×10^{-4}; TDM:2.625428×10^{-4}	PSA was close to the best SDM result and became clearly superior in DDM/TDM; it reduced RMSE vs SSA–GSK by 16.47% in SDM, 69.40% in DDM, and 49.73% in TDM.
RTC France cell, 1000 W/m², 33 °C	SDM: 9.8602×10^{-4}; DDM:9.7078×10^{-4}; TDM:9.7630793×10^{-4}	PSA reached the SDM optimum group and produced the best DDM/TDM-level accuracy with near-zero bias, while SSA–GSK improved over SSA but remained behind PSA.
aSi cell, 1000 W/m², 25 °C	SDM: 4.6123×10^{-5}; DDM:4.0943×10^{-5}; TDM:9.0459057×10^{-6}	PSA achieved the best reported TDM fit and strongly benefited from the higher-order model, reducing RMSE by 90.94% relative to SSA–GSK in TDM.
MJSC cell, 41.5 °C / 51.3 °C / 61.6 °C	TDM: 7.83176×10^{-5}; 7.53160×10^{-5}; 6.74823×10^{-5}	PSA achieved the best fits across temperatures and model orders; in TDM it reduced RMSE vs SSA–GSK by 67.40%, 78.23%, and 91.98%.
PVM panel, 1000 W/m², 25 °C	SDM: 2.2780×10^{-4}; DDM:1.6579×10^{-4}; TDM:1.11712928×10^{-4}	PSA provided the most accurate and stable estimation, with the TDM giving the lowest RMSE and reduced localized errors near the knee region.
PWP201 panel	SDM/DDM/TDM: 2.42507×10^{-3}	PSA reached essentially the same optimum across SDM/DDM/TDM, showing that added model complexity did not significantly reduce RMSE for this case.
STM6-40 panel, 1000 W/m², 51 °C	SDM: 1.72981×10^{-3}; DDM:1.6892×10^{-3}; TDM:1.68836049×10^{-3}	PSA matched the best SDM group and improved over SSA–GSK by 14.99%, 18.55%, and 23.62% from SDM to TDM.

The I–V reconstruction related to mSi shown in Figure 4 confirms the almost complete overlap between the measured curve and the PSA-estimated SDM, DDM, and TDM characteristics, especially near the knee region where diode nonlinearity becomes dominant. The convergence behaviour in Figure 5 shows that PSA reduces RMSE rapidly during the early iterations and then enters a stable refinement phase. The SDM reaches its plateau earlier, whereas DDM and TDM continue improving for a longer period because of their larger search spaces. This confirms that the multi-diode models provide better fitting accuracy but require deeper exploitation to reach the best basin of attraction.

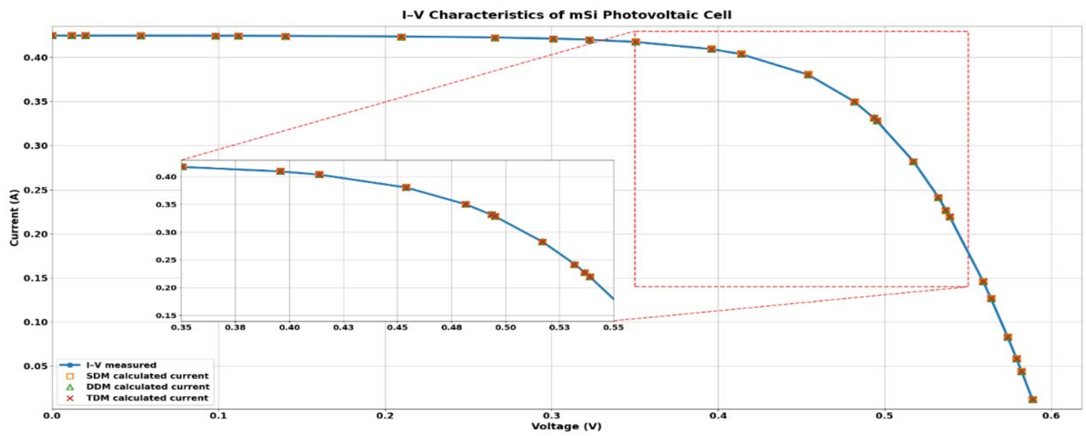

Figure 4 I–V characteristics of the mSi PV Cell

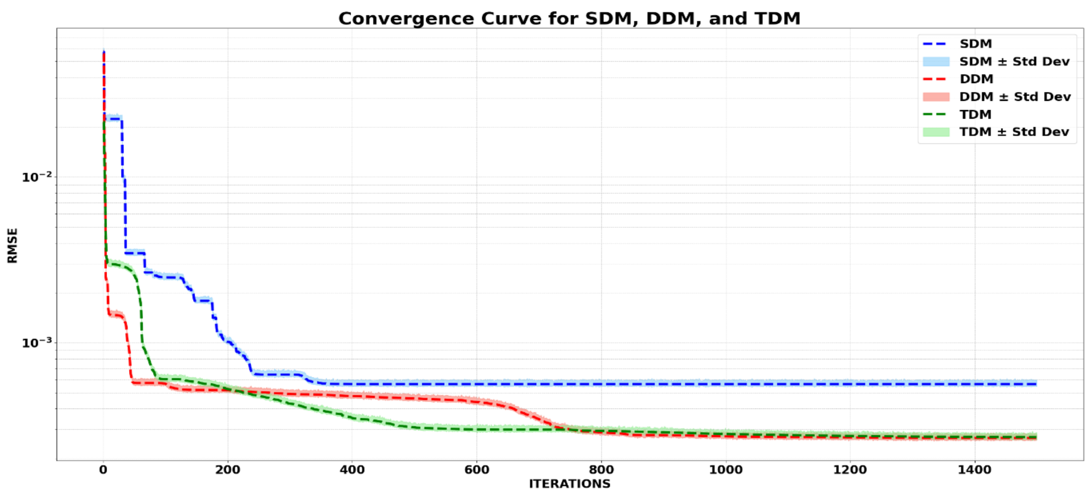

Figure 5 mSi PV cell Convergence Curve

In case of MJSC, PSA delivered the best fits across 41.5 °C, 51.3 °C, and 61.6 °C for SDM, DDM, and TDM, while maintaining small bias and stable dispersion. In the TDM, PSA reduced RMSE relative to SSA–GSK by 67.40%, 78.23%, and 91.98% for the three temperatures. Figure 6 shows that PSA RMSE decreases with temperature for the three PV representations, indicating stable behavior under the tested thermal conditions.

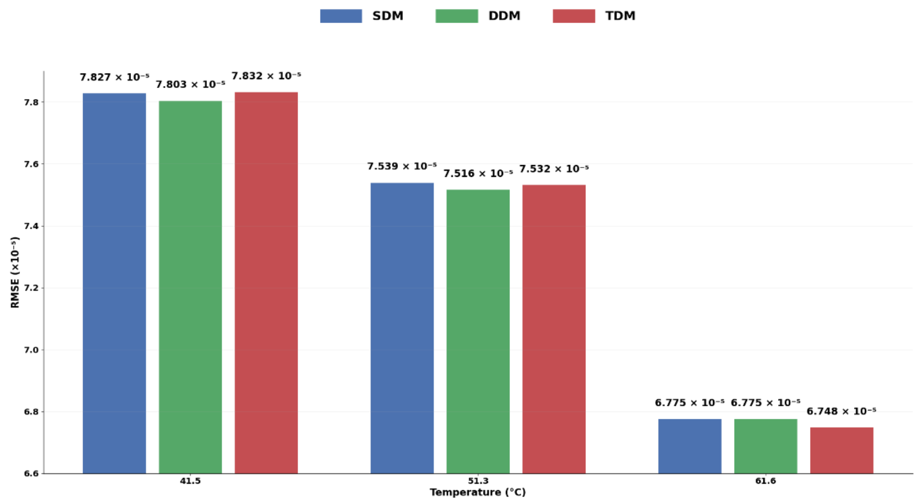

Figure 6 MJSC RMSE of PSA algorithm in the function of the temperature

4.5 Conclusion

Chapter 4 provided the main experimental validation of the proposed parameter-extraction methods. Across all tested PV cells and panels, PSA was the most reliable and scalable method, especially for DDM and TDM, where parameter coupling and nonlinearities are stronger. It either matched the best RMSE plateau or achieved the best performance in higher-order models, while maintaining near-zero bias, stable dispersion, and reliable convergence. SSA–GSK consistently improved over plain SSA, confirming the value of hybridization, but it generally remained behind PSA when minimum error and maximum repeatability were required. Overall, Chapter 4 confirms that PSA provides accurate, physically meaningful, and computationally stable parameter extraction across different PV technologies, model orders, and operating conditions, while SSA–GSK represents a useful improvement over the original SSA framework.

The research findings associated with the algorithm development in Chapter 3 and the validation and benchmarking investigations in Chapter 4 have been disseminated through two journal publications. In particular, the proposed PSA was published in Applied Sciences, whereas the hybrid SSA–GSK approach was published in the Environmental Engineering and Management Journal. Together, these publications present the proposed methods and their comprehensive assessment using SDM, DDM, and TDM test cases [71, 73].

Building on these modelling and parameter-identification foundations, Chapter 5 shifts from device-level characterization to data-driven operation-level prediction by addressing AI-based solar irradiance forecasting. It defines the short-term and ultra-short-term forecasting tasks considered, introduces the datasets and input variables, and presents the developed AI forecasting models (architectures, training strategies, and the pre-processing pipeline). The chapter then evaluates performance under diverse meteorological conditions using standard forecasting error metrics.

5. AI-Based Solar Irradiance Forecasting Models

5.1 Chapter Overview

Chapter 5 shifts from device-level PV characterization to operation-level prediction by addressing ultra-short-horizon solar irradiance forecasting at lead times of 1–30 minutes. This task is important for real-time PV plant operation, storage dispatch, ramp-rate mitigation, and fast ancillary services. The chapter formalizes the forecasting problem, reviews the state of the art, and proposes a hybrid CNN–TCN–XGBoost nowcasting framework. The central idea is that the parameter-extraction framework developed in Chapters 3 and 4 remains valuable for physical interpretation and future physics–AI integration, while the main forecasting pathway adopted in this chapter is data-driven because minute-scale irradiance variability is dominated by rapid cloud-driven dynamics.

5.2 Forecasting Problem Definition

Solar irradiance forecasting aims to estimate future solar irradiance using the information available at the current time. In this thesis, the target is future irradiance at forecast horizons of 1, 2, 3, 4, 5, 7, 10, 15, 20, and 30 minutes. The forecasting problem and the supervised learning representation are summarized by the following important equations [80, 81]:

$$\hat{G}(t+\tau) = f_\theta(\Omega(t), \tau), \qquad \tau \in (1, \dots, 30)\text{min} \tag{12}$$

$$X_t = \left[x_t, x_{t-\Delta t}, \cdots, x_{t-(L-1)\Delta t}\right], \hat{G}(t+\tau) = f_\theta(X_t), \tag{13}$$

Here, $\Omega(t)$ is the information set available at issuance time, X_t is the lookback input sequence, and f_θ is the learner. Direct multi-horizon learning is preferred because recursive strategies may accumulate error as the lead time increases [81, 82].

5.3 Two Pathways for Solar Irradiance Forecasting

5.3.1 Pathway A: physics-informed solar irradiance forecasting via extracted parameters

The physics-informed pathway uses irradiance and temperature forecasts together with calibrated SDM/DDM/TDM parameters to compute PV power. The extracted parameters from Chapters 3–4 can therefore support physically consistent power estimation. However, at 1–30-minute horizons the main uncertainty is not usually the PV conversion model but the irradiance forecast itself, because cloud advection and cloud evolution generate fast ramps that are difficult to predict without high-frequency local sensing [81, 83, 84].

5.3.2 Pathway B: data-driven solar irradiance forecasting from measurements

The data-driven pathway learns the mapping from recent measurements directly to future solar irradiance. This is the primary pathway adopted in this chapter because recent GHI, DHI, meteorological variables, PV operating variables where available, and cyclic time descriptors contain short-term information about the present cloud state, ramp dynamics, and local persistence. The general supervised form is:

$$G(t+\tau) = f_\theta(G(t), G(t+\tau),\ \dots, G(t-(L-1)\tau), z(t), z(t+\tau)) \tag{14}$$

where $G(t)$ aggregates the measured variables at time t. In ultra-short horizons, $G(t)$ typically includes at least recent solar irradiance, and $\mathrm{z}(\cdot)$ represents exogenous variables (temperature, wind speed, humidity, sky-condition proxies, time-of-day encodings). This formulation is consistent with the dominant data-driven forecasting paradigm summarized in PV forecasting reviews [85].

5.4 Proposed CNN–TCN–XGBoost Hybrid Nowcasting Framework

To overcome the challenges of solar irradiance forcasting, this thesis introduces a hybrid CNN–TCN–XGBoost nowcasting architecture. The proposed design combines deep temporal feature learning with boosting-based regression in order to improve accuracy and robustness across both stable and volatile atmospheric regimes. Under clear-sky conditions, solar irradiance typically evolves smoothly and can often be captured by simpler models. However, in cloudy or transitional conditions, the irradiance signal becomes highly non-stationary, with abrupt fluctuations that require models capable of learning both short-term patterns and longer temporal dependencies. The proposed hybrid framework is designed specifically to handle this variability by separating representation learning from horizon-specific numerical prediction.

In the proposed model architecture, the CNN is used to capture fast, local variations in high-frequency irradiance and meteorological measurements, which are commonly associated with abrupt irradiance changes and short-lived irradiance ramps. These convolutional representations are then passed to a deep TCN, which learns longer-range temporal dependencies through causal and dilated convolutions, enabling the model to integrate information over a wider historical context without relying on recurrent structures. Rather than producing the final forecasts directly from the deep network, the framework uses the CNN–TCN output as a compact set of learned features that summarize the recent irradiance dynamics. These extracted features are then provided to XGBoost regressors that operate in a horizon-specific manner, allowing each lead time to be modeled with a dedicated regressor that can correct residual errors and refine numerical outputs. This combination leverages the complementary strengths of DL for feature extraction and GB for robust regression and error correction, thereby mitigating weaknesses typically found in purely statistical approaches, physical models, or standalone ML methods.

To evaluate performance consistently across operationally relevant intra-hour lead times, forecasts are generated for multiple horizons, specifically 1, 2, 3, 4, 5, 7, 10, 15, 20, and 30 minutes ahead. This multi-horizon design enables an assessment of both accuracy and stability as the lead time increases, which is essential for determining whether the proposed solution remains reliable beyond the very short-term regime.

A flowchart of the proposed hybrid model is provided in Figure 7.

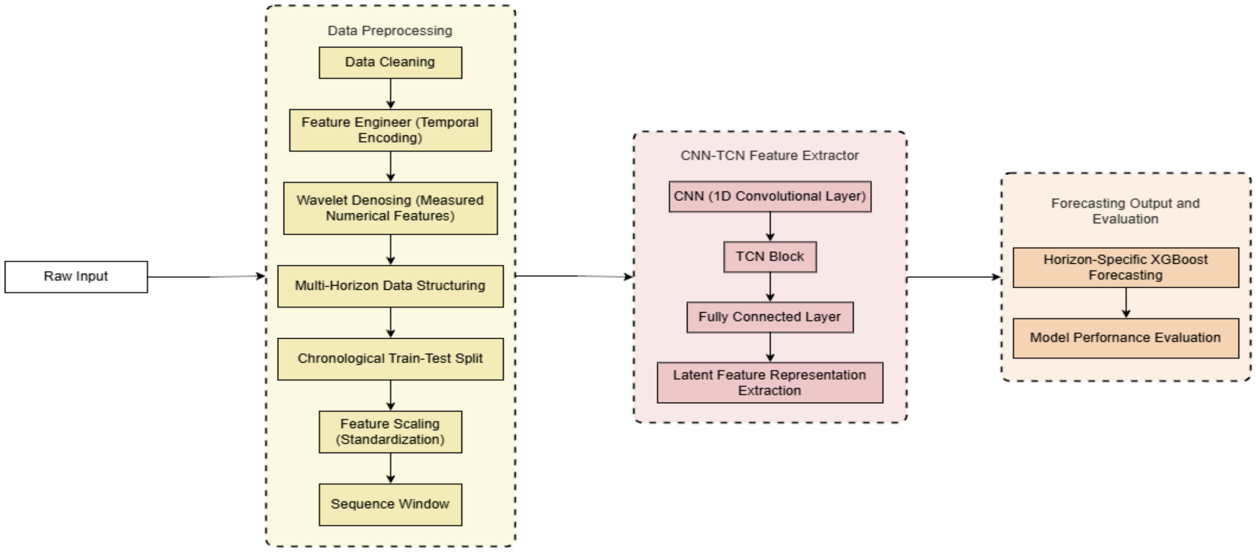

Figure 7 Methodological workflow of the proposed hybrid solar irradiance forecasting model

5.4.1 Datasets and Data Characteristics

Two measurement datasets are used. The 2018 dataset contains May 2018 measurements sampled every 15 s at the Solar Platform of the West University of Timișoara, Romania, and includes GHI, DHI, air temperature, wind speed, and relative humidity. The days include a mix of clear-sky, cloudy/overcast, and highly variable regimes. The training subset covers the first twelve days of May (01 May–12 May 2018), while the test subset covers the last ten days (22 May–31 May 2018) [86]. The 2021 dataset is sampled every 4 s and includes GHI, DHI, in-plane irradiance, meteorological variables, PV voltage, PV current, and cyclic time features. The 2021 data are organized into BaseData-train, Case-CS, and Case-6D-Mixed to test clear-sky, cloudy/overcast, and highly variable regimes. The 2021 model was trained using the BaseData-train subset, comprising measurements collected between 15 March 2021 and 31 March 2021. The trained model was subsequently evaluated on two test subsets: Case-CS, and Case-6D-Mixed [87].

5.4.2 Performance Evaluation Metrics

Forecasting performance is evaluated using nRMSE, nMBE, MAPE, prediction precision P[TOL], and skill score SS. These metrics quantify global error, systematic bias, relative deviation, the percentage of forecasts inside a tolerance interval, and the improvement relative to the 2-State benchmark [81, 87, 88]:

$$\text{nRMSE} = \frac{\sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(G(t)-\hat{G}(t)\right)^2}}{\bar{G}} \tag{15}$$

$$\mathrm{nMBE} = \frac{\frac{1}{N}\sum_{t=1}^{N}\left(G(t) - \hat{G}(t)\right)}{\bar{G}} \tag{16}$$

$$\mathrm{MAPE} = \frac{100}{N}\sum_{t=1}^{N}\left|\frac{G(t) - \hat{G}(t)}{G(t)}\right| \tag{17}$$

$$\text{Skill Score(SS)} = 1 - \frac{\mathrm{nRMSE}_{\mathrm{model}}}{\mathrm{nRMSE}_{\mathrm{benchmark}}} \tag{18}$$

$$\mathrm{P}[\%] = \frac{100}{N}\sum_{t=1}^{N}\left(\left|\frac{G(t) - \hat{G}(t)}{G(t)}\right| \leq \mathrm{TOL}\right) \tag{19}$$

5.5 Results and Discussion

The proposed model was evaluated on two independent measurement campaigns. Table 2 shows that the framework is computationally suitable for real-time nowcasting: although training is offline, inference requires only about 4.17 ms/window while producing all ten forecast horizons.

Table 2 Computational cost of the proposed framework

Dataset	NN parameters	Training time	Inference time
2018	327,850	326.79 s	4.178 ms/window
2021	328,810	1287.38 s	4.179 ms/window

5.5.1 Evaluation of Forecasting Accuracy across the 2018 Dataset

5.5.1.1 Entire Evaluation of Forecasting Accuracy across Solar Regimes in 2018

Across the full May 2018 evaluation, the proposed model consistently improves the available published comparison horizons against the 2-State benchmark. At 2 min, nRMSE decreases from 0.1780 to 0.16425, corresponding to an improvement of about 7.7%. At 10 min, nRMSE decreases from 0.2220 to 0.1723, corresponding to an improvement of about 22.4%. The proposed model also reduces MAPE from 6.40% to 5.60% at 2 min and from 12.5% to 6.80% at 10 min, while P[5%] increases from approximately 57.5% to 79.81% at 10 min. These results confirm that the CNN–TCN representation and horizon-specific XGBoost regressors improve both accuracy and forecast precision. Table 3 and Figure 13 summarize the performance across representative 2018 atmospheric conditions.

Table 3 Summary of forecasting performance across representative 2018 regimes

2018 case	Regime	Main result of proposed model
22 May 2018	Highly unstable	nRMSE = 0.3734 at 1 min and 0.5239 at 30 min; P[5%] decreases from 64.0% to 47.65%.
23 May 2018	Moderate instability	nRMSE = 0.3160 at 1 min and 0.4903 at 30 min, improving over 22 May as variability decreases.
25 May 2018	Mixed/transition	nRMSE = 0.1737–0.2989 and MAPE remains below 10%, showing strong performance under structured variability.
30 May 2018	Clear-sky	nRMSE = 0.0118–0.025, MAPE = 1.68–2.37%, and P[5%] remains above 84%.

5.5.2 Measurement data from 2021

5.5.2.1 Hybrid Model Accuracy using the BaseData-train

For the 2021 BaseData-train subset, after preprocessing the dataset contained 177,012 samples and was split chronologically into 70% training and 30% validation. The proposed framework achieves nRMSE = 0.21393 at 1 min, increasing gradually to 0.54783 at 30 min. MAPE increases from 8.11% to 22.42%, while P[5%] decreases from 79.99% to 66.11%. The nMBE remains small across horizons, confirming that errors are mainly caused by atmospheric variability rather than systematic bias.

5.5.2.2 Hybrid Model Accuracy under Case-CS

The Case-CS subset evaluates stable clear-sky conditions, where irradiance evolution is governed mainly by deterministic solar geometry. The proposed model reproduces the smooth diurnal profile with high consistency. For 09 July, nRMSE remains within 0.006531–0.009905, and for 22 August it remains within 0.005934–0.009019. The highest clear-sky errors occur on 22 February, where nRMSE increases from 0.01736 at 1 min to 0.03188 at 30 min, but nMBE remains close to zero. These results show that the proposed framework preserves physical consistency under deterministic regimes.

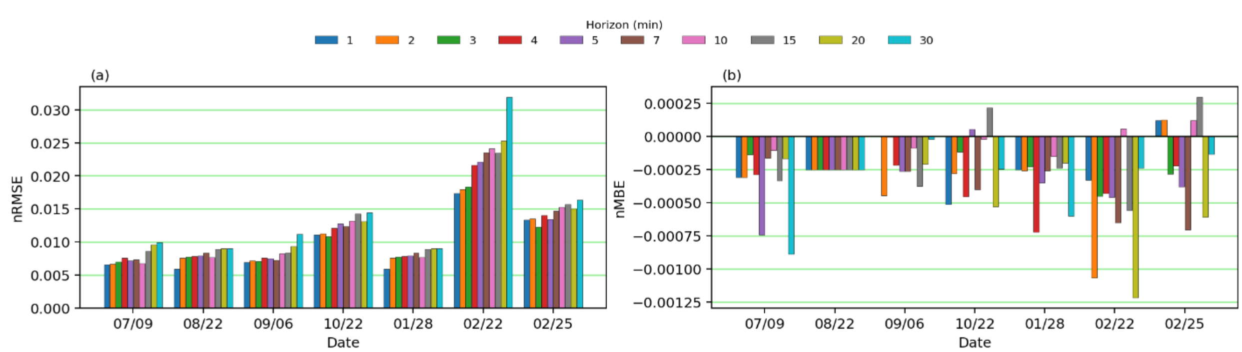

Figure 8 Evaluation of the Hybrid model for the Case-CS dataset

5.5.2.3 Hybrid Model Accuracy and Benchmark Comparison during 2021 (Case-6D-Mixed)

The Case-6D-Mixed subset provides the strongest operational validation because it includes clear-sky, overcast, transitional, and highly variable days. On 05 April, the proposed model gives the best 1-min nRMSE (0.2187) compared with 2-State (0.2510), although its longer-horizon advantage becomes less consistent. On 20 April, a cloud-driven regime makes forecasting difficult, but the proposed model remains competitive and matches 2-State at 30 min (nRMSE = 0.9460) while staying below ARIMA (1.0900). On 08 May, the highly variable regime confirms the robustness of the model: at 10 min, nRMSE is 0.4698 compared with 0.7560 for 2-State. On 11 May, the clear-sky case shows the strongest performance, with nRMSE = 0.00395 at 10 min. On 19 May, the proposed model outperforms both benchmarks at 30 min with nRMSE = 0.7685 versus 0.8880 and 1.0930. On 21 May, the model is strongest at short and intermediate horizons, but the benchmarks become more competitive at 30 min.

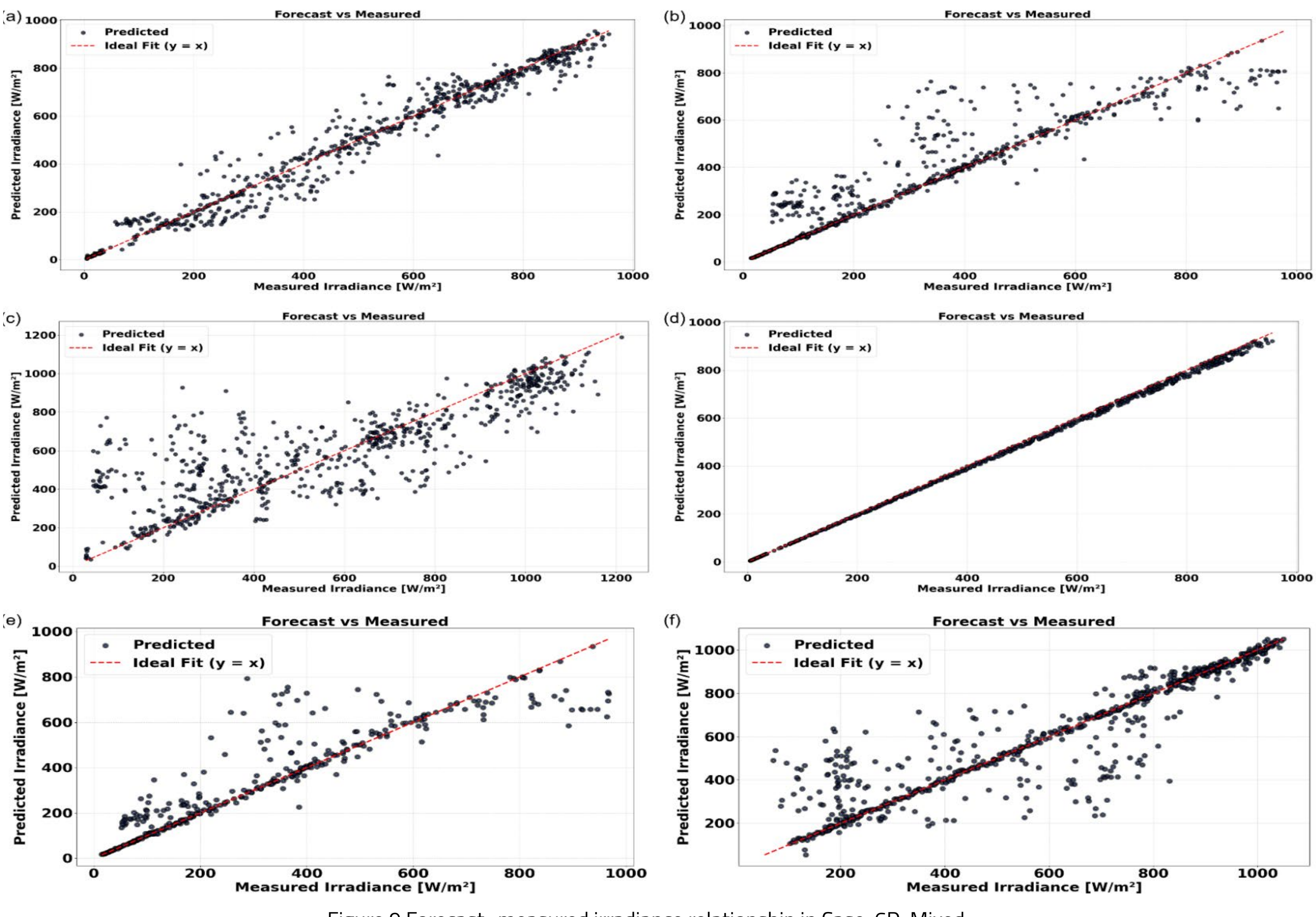

Figure 9 Forecast–measured irradiance relationship in Case-6D-Mixed

5.6 Conclusion

Chapter 5 developed and validated a hybrid CNN–TCN–XGBoost framework for ultra-short-horizon solar irradiance forecasting. The model combines CNN-based local ramp detection, TCN-based temporal memory, and horizon-specific XGBoost regression. The 2018 results demonstrate improved accuracy over the 2-State benchmark, with nRMSE reductions of about 7.7% at 2 min and 22.4% at 10 min. The 2021 results show controlled degradation with horizon on BaseData-train, very low errors under Case-CS clear-sky conditions, and robust performance across Case-6D-Mixed regimes. The main remaining limitation is the difficulty of forecasting abrupt ramp-driven conditions at longer horizons, where stochastic cloud evolution reduces the predictive value of recent measurements. Nevertheless, the results confirm that the proposed method strengthens the data-driven operational prediction layer of PV characterization and provides a practical basis for future deployment-oriented PV digital twins and multi-horizon forecasting systems.

The research outcomes associated with this chapter, including the development of the proposed CNN–TCN–XGBoost hybrid nowcasting framework for ultra-short-horizon solar irradiance forecasting and its validation through comparative benchmarking across multiple forecasting horizons and atmospheric regimes, have been accepted for presentation at the 2026 IEEE Conference on Advanced Topics on Measurement and Simulation (ATOMS 2026), with subsequent publication in the IEEE Xplore-compliant conference proceedings.

6. Conclusion and Future Work

6.1 General Conclusions

This thesis focused on improving photovoltaic-system characterization and short-horizon predictability using advanced AI-based methods. It addressed two complementary challenges in PV engineering: extracting stable and physically meaningful parameters for equivalent-circuit PV models from measured I–V data, and forecasting ultra-short-term solar irradiance under rapidly changing atmospheric conditions.

Chapter 1 introduced the research context, motivation, gaps, and objectives. It highlighted key limitations in PV parameter extraction, including convergence inefficiency, premature stagnation, weak robustness, difficulty with complex models such as DDM and TDM, and inconsistent benchmarking. For forecasting, the main challenges were rapid cloud-driven irradiance variations, abrupt sky transitions, reduced minute-ahead accuracy, and unstable performance across atmospheric regimes.

Chapter 2 reviewed AI applications in renewable energy, with emphasis on PV parameter extraction. It showed that metaheuristic algorithms are suitable for nonlinear PV models, but many existing approaches still suffer from high computational cost, sensitivity to model complexity, and limited robustness, justifying the need for improved hybrid optimization methods.

Chapter 3 presented the main parameter-extraction methods developed in the thesis: the hybrid SSA–GSK algorithm and the PID-based Search Algorithm (PSA). SSA–GSK improved SSA through GSK-based knowledge sharing, while PSA adapted PID-control principles to optimization. Both methods were designed to handle nonlinearity, multimodality, parameter coupling, and increasing PV model complexity.

Chapter 4 validated these methods across SDM, DDM, and TDM models and several PV cells and panels, including mSi, RTC France, aSi, MJSC, PVM, PWP201, and STM6-40. The results showed that both methods produced accurate and physically meaningful parameters, with PSA showing the strongest robustness and scalability, especially for more complex models. The chapter also emphasized that PV parameter-extraction methods should be evaluated not only by RMSE, but also by convergence behaviour, runtime, repeatability, population size, and iteration budget.

Chapter 5 extended the work to operation-level prediction through a hybrid CNN–TCN–XGBoost framework for 1–30-minute solar irradiance nowcasting. CNN captured local irradiance ramps, TCN represented longer temporal dependencies, and horizon-specific XGBoost models refined forecasts for each lead time. The model achieved stable low-bias forecasts and controlled degradation with increasing horizon. In the 2018 case, it reduced nRMSE by about 7.7% at 2 minutes and 22.4% at 10 minutes compared with the PV 2-state benchmark.

Overall, the thesis contributes an AI-based framework for PV characterization by developing PSA and hybrid SSA–GSK for robust PV parameter extraction, establishing a consistent benchmarking approach across PV models and devices, and proposing a horizon-aware CNN–TCN–XGBoost model for ultra-short-term irradiance forecasting. These contributions support both physics-based PV modelling and operational PV prediction, with relevance for adaptive PV digital twins and intelligent PV analytics.

6.2 Achievement of the Research Objectives

The doctoral research was structured around five objectives, and each objective was achieved progressively through the thesis chapters. Objective O1, to review and analyze AI methods applied in renewable-energy applications, particularly in PV technologies, was achieved through Chapters 1 and 2, which positioned the work within the broader renewable-energy and AI literature.

Objective O2, to review and analyze recent advancements in PV parameter-extraction models and algorithms, was achieved in Chapter 2 through the critical discussion of equivalent-circuit models, classical extraction methods, and metaheuristic optimization approaches. This review identified the technical limitations that motivated the algorithmic developments of the thesis.

Objective O3, to develop, modify, and implement metaheuristic-based techniques for robust and accurate PV parameter extraction, was achieved in Chapter 3 through the development of the hybrid SSA–GSK algorithm and PSA. Objective O4, to develop and implement AI-based models for short-horizon and ultra-short-horizon solar irradiance forecasting, was achieved in Chapter 5 through the proposed CNN–TCN–XGBoost framework.

Objective O5, to validate and benchmark the proposed parameter-extraction and forecasting methods against established reference models, was achieved through Chapters 4 and 5. Chapter 4 validated PSA and SSA–GSK across multiple PV devices, model structures, and benchmark algorithms, while Chapter 5 evaluated the forecasting framework across different horizons, years, and atmospheric regimes. In this way, the thesis achieved its aim by combining methodological development with experimental validation.

6.3 Future Research Directions

The results obtained in this thesis open several future research directions. For PV parameter extraction, future work should focus on deployment-oriented optimization frameworks that preserve the robustness of the proposed methods while reducing computational cost. Adaptive stopping criteria, hybrid global–local search, surrogate-assisted optimization, and hardware-aware implementation could make continuous or field-level parameter estimation more practical.

Another direction is the development of adaptive model-selection frameworks capable of choosing between SDM, DDM, and TDM according to data quality, operating conditions, and engineering purpose. This would move the present work from robust optimization of fixed circuit models toward more context-aware PV modelling.

For forecasting, the proposed CNN–TCN–XGBoost framework can be extended by integrating richer input sources such as sky-camera imagery, all-sky imagers, satellite products, and numerical weather prediction outputs. This would be particularly useful under unstable atmospheric regimes, where abrupt irradiance ramps remain difficult to predict. Future work should also consider probabilistic forecasting to provide prediction intervals, uncertainty information, and ramp-risk indicators for storage scheduling, reserve allocation, and grid-support applications.

Finally, the stronger integration of PV parameter extraction and irradiance forecasting into a unified adaptive PV digital twin represents an important long-term direction. In such a framework, extracted parameters would provide physical calibration, while forecasting residuals and operating anomalies could trigger adaptive re-identification of the PV model. Modern AI agents could also assist this process by selecting models, adjusting optimization settings, monitoring convergence, and combining heterogeneous data sources. Therefore, the thesis provides a foundation for future AI-enabled PV modelling, forecasting, and digital-twin development.

6.4 Valorization of the Research Results

The complete list of publications and scientific dissemination activities associated with this doctoral work is provided below:

- Bennagi, A., O. AlHousrya, D.T. Cotfas, and P.A. Cotfas, Comprehensive study of the artificial intelligence applied in renewable energy. Energy Strategy Reviews, 2024. 54: p. 101446.
  https://doi.org/10.1016/j.esr.2024.101446
  Journal Impact Factor: 9.9 (2026), Q1.
- Bennagi, A., AlHousrya, O., D.T. Cotfas, and P.A. Cotfas, Parameter extraction of photovoltaic cells and panels using a pid-based metaheuristic algorithm. Applied Sciences, 2025. 15(13): p. 7403.
  https://doi.org/10.3390/app15137403
  Journal Impact Factor: 2.5 (2026), Q2.
- Bennagi, A., AlHousrya, O., D.T. Cotfas, and P.A. Cotfas, HYBRID SALP SWARM-GAINING AND SHARING KNOWLEDGE (SSA-GSK) METAHEURISTIC ALGORITHM FOR EXTRACTING PHOTOVOLTAIC CELL PARAMETERS. Environmental Engineering & Management Journal (EEMJ), 2025. 24(5). https://doi.org/10.30638/eemj.2025.085
  Journal Impact Factor: 0.9 (2026), Q4.
- Bennagi, A., AlHousrya, O., D.T. Cotfas, P.A. Cotfas, and M. Paulescu, Multi-Horizon Solar Irradiance Forecasting under Variable Sky Conditions through CNN-TCN Feature Learning and XGBoost. Currently under review at Unconventional Resources Journal.
  Journal Impact Factor: 4.6 (2026), Q1.

- Bennagi, A., AlHousrya, O., D.T. Cotfas, P.A. Cotfas, and M. Paulescu, A Hybrid CNN-TCN-XGBoost Model for Multi-Horizon Solar Irradiance Forecasting. Accepted for presentation at the 2026 IEEE Conference on Advanced Topics on Measurement and Simulation (ATOMS 2026), with subsequent publication in IEEE Xplore-compliant proceedings.
- AlHousrya, O., Bennagi, A., P.A. Cotfas, and D.T. Cotfas, A novel Hybrid ant colony algorithm for solving the shortest path problems with mixed fuzzy arc weights. Alexandria Engineering Journal, 2024. 109: p. 841-855. https://doi.org/10.1016/j.aej.2024.09.089
  Journal Impact Factor: 6.8 (2026), Q1.
- AlHousrya, O., Bennagi, A, P.A. Cotfas, and D.T. Cotfas, A Hybrid Machine Learning and IoT System for Driver Fatigue Monitoring in Connected Electric Vehicles. Machine Learning with Applications, 2026: p. 100845. https://doi.org/10.1016/j.mlwa.2026.100845
  Journal Impact Factor: 4.9 (2026), Q1.
- AlHousrya, O., Bennagi, A, P.A. Cotfas, and D.T. Cotfas, The Role of the Industrial IoT in Advancing Electric Vehicle Technology: A Review. Applied Sciences, 2025. 15(17): p. 9290. https://doi.org/10.3390/app15179290
  Journal Impact Factor: 2.5 (2026), Q2.
- AlHousrya, O., Bennagi, A, P.A. Cotfas, and D.T. Cotfas. IoT-Enabled Driver Health Monitoring System Using Multi-Modal Sensors and Cloud Integration. in 2025 IEEE 31st International Symposium for Design and Technology in Electronic Packaging (SIITME). 2025. IEEE. https://doi.org/10.1109/SIITME67657.2025.11293652
- AlHousrya, O., Bennagi, A., P.A. Cotfas, and D.T. Cotfas, Vision-Based Driver Drowsiness Detection Using Eye-State Analysis and Lightweight CNNs. Accepted for presentation at the 2026 IEEE Conference on Advanced Topics on Measurement and Simulation (ATOMS 2026), with subsequent publication in IEEE Xplore-compliant proceedings.
- Participation in the UNITA project workshop, where the implementation and research results related to parameter-extraction algorithms were disseminated, including the PSA and the Hybrid SSA-GSK metaheuristic algorithms.

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