

UNIVERSITÉ DU QUÉBEC EN OUTAOUAIS

**COMPUTATIONAL INTELLIGENCE BASED MODELING
OF UAV-INTEGRATED PV MODULE IN ICING CONDITION**

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Abstract

The integration of photovoltaic (PV) systems into unmanned aerial vehicles (UAVs) offers promising advantages, such as enhanced flight endurance and energy efficiency. However, the dynamic and environmental complexities introduced by UAV motion and adverse conditions, such as in-flight icing, necessitate advanced modeling and optimization approaches to investigate the behavior of the UAV-integrated PV module and its optimal performance. This thesis develops a comprehensive framework that addresses these challenges by incorporating a set of analytical, mathematical, optimization, and computational intelligence-based methods.

Using rotational matrix concepts, the tilt and azimuth angles of the PV module are calculated based on the UAV's yaw, pitch, and roll angles, while the Grey Wolf Optimization algorithm is employed to adaptively adjust the PV module's ideality factor. This enables accurate prediction of the maximum power point (MPP) under real-time operational conditions. Additionally, multi-input multi-output (MIMO) and multi-input single-output (MISO) ML models are introduced, trained on datasets representing historical environmental and flight-condition data. These datasets are processed using advanced optimization methods, such as the Whale Optimization Algorithm (WOA) and Dogleg Trust Region Algorithm (DTRA), to extract moving PV system parameters for various conditions.

The thesis further examines the critical issue of atmospheric in-flight icing, which obstructs sunlight and affects the UAV-integrated PV module's performance. By segmenting the operational curve of the PV module into ice-covered and normal zones, a computational framework is developed to model the impact of icing, incorporating its effects into irradiance calculations. Advanced computational intelligence methods are used to predict PV performance under conditions such as partial shading and

sunlight variations induced by UAV movement. This integrated approach provides robust methodologies for modeling and optimizing UAV-integrated PV systems, addressing the challenges of dynamic movement and icing condition simultaneously. The results offer valuable insights for advancing solar-powered UAV technologies and ensuring their reliable performance in diverse operating scenarios.

Résumé

L'intégration des systèmes photovoltaïques (PV) dans les véhicules aériens sans pilote (UAV) offre des avantages prometteurs, tels qu'une endurance de vol accrue et une meilleure efficacité énergétique. Cependant, les complexités dynamiques et environnementales liées au mouvement des UAV et aux conditions défavorables, comme le givrage en vol, nécessitent des approches avancées de modélisation et d'optimisation pour étudier le comportement des modules PV intégrés aux UAV et optimiser leurs performances.

Cette étude développe un cadre global qui répond à ces défis en intégrant un ensemble de méthodes analytiques, mathématiques, d'optimisation et basées sur l'intelligence computationnelle. En utilisant les concepts de matrices de rotation, les angles d'inclinaison et d'azimut du module PV sont calculés en fonction des angles de lacet, de tangage et de roulis de l'UAV, tandis que l'algorithme d'optimisation Grey Wolf est utilisé pour ajuster de manière adaptative le facteur d'idéalité du module PV. Cela permet une prédiction précise du point de puissance maximale (MPP) dans des conditions opérationnelles en temps réel.

De plus, des modèles d'apprentissage automatique multi-entrées multi-sorties (MIMO) et multi-entrées une sortie (MISO) sont introduits et entraînés sur des ensembles de données représentant les conditions environnementales et de vol historiques. Ces ensembles de données sont traités à l'aide de méthodes d'optimisation avancées, telles que l'algorithme d'optimisation des baleines (WOA) et l'algorithme Dogleg Trust Region (DTRA), afin d'affiner l'extraction des paramètres du système PV et d'améliorer la précision prédictive des modèles dans des scénarios de vol dynamiques.

L'étude examine également le problème critique du givrage atmosphérique en

vol, qui obstrue la lumière du soleil et affecte les performances du module PV. En segmentant la courbe de fonctionnement du module PV en zones couvertes de glace et zones normales, un cadre computationnel est développé pour modéliser l'impact du givrage, en intégrant ses effets dans les calculs d'irradiance. Des méthodes avancées d'intelligence computationnelle sont utilisées pour prédire les performances du module PV dans des conditions telles que l'ombrage partiel et les variations de lumière dues au mouvement de l'UAV.

Cette approche intégrée fournit des méthodologies robustes pour modéliser et optimiser les systèmes PV intégrés aux UAV, en relevant les défis du mouvement dynamique et des conditions environnementales défavorables, y compris le givrage. Les résultats offrent des perspectives précieuses pour faire progresser les technologies des UAV alimentés par l'énergie solaire et garantir leurs performances fiables dans divers scénarios d'exploitation.

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Dedication

This thesis is dedicated to

My Beloved Wife, Sepideh

This work is as much yours as it is mine.

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List of Abbreviations

AAM	Advanced Air Mobility
ALO	Ant Lion Optimizer
AM	Air Mass
ANN	Artificial Neural Network
AOI	Angle of Incident
BaT	Bagged Trees
BNN	Bi-layered Neural Network
Bot	Boosted Trees
CGSVM	Coarse Gaussian Support Vector Machine
CSVM	Cubic Support Vector Machine
DSPO	Derivative Search Based Political Optimization
DNI	Direct Normal Irradiance
DTRA	Dogleg Trust Region Algorithm
EDE	Empirical Driven Equations
EGPR	Exponential Gaussian Process Regression
ETR	Ensemble Tree Regression
FGSVM	Fine Gaussian Support Vector Machine
GA	Genetic Algorithm
GPR	Gaussian Process Regression
GWO	Grey Wolf Optimization
HFP	Hybrid Flower Pollination
IC	Incremental Conductance
IL	Interactions Linear

ISHTS	Improved Simultaneous Heat Transfer Search Algorithm
LE	Leading Edge
LR	Linear Regression
LSRK	Least Squares Regression Kernel
LSVM	Linear Support Vector Machine
M5/2GPR	Matern 5/2 Gaussian Process Regression
MAE	Mean Absolute Error
MFO	Moth-Flame Optimization
MG SVM	Medium Gaussian Support Vector Machine
MIMO	Multi-Input Multi-Output
MISO	Multi-Input Single-Output
ML	Machine Learning
MNN	Medium Neural Network
MPP	Maximum Power Point
MPPT	Maximum Power Point Tracking
MRMR	Minimum Redundancy - Maximum Relevance
MSE	Mean Squared Error
MVO	Multiverse Optimization
NASA	National American Space Agency
NATO	North Atlantic Treaty Organization
NNN	Narrow Neural Network
NREL	National Renewable Energy Laboratory
PV	Photovoltaic
PSO	Particle Swarm Optimization
P&O	Perturb and Observe
QSVM	Quadratic Support Vector Machine
RQGPR	Exponential Gaussian Process Regression
RMSE	Root Mean Squared Error

RL	Robust Linear
SDEC	Single Diode Equivalent Circuit
SEGPR	Squared Exponential Gaussian Process Regression
SL	Stepwise Linear
STC	Standard Test Condition
SVM	Support Vector Machine
SVMK	Support Vector Machine Kernel
TDR	Traveling Distance Rate
TNN	Tri-layered Neural Network
TSA	Tunicate Swarm Algorithm
UAV	Unmanned Aerial Vehicle
UAM	Urban Air Mobility
WEP	Wormhole Existence Probability
WNN	Wide Neural Network
WOA	Whale Optimization Algorithm

1. Introduction

1.1. Overview

Integration of solar photovoltaic (PV) technology into vehicles has been gaining worldwide popularity to meet all or a part of the vehicle's energy requirements and to extend its range of mission [1]. Among various vehicles, unmanned aerial vehicles (UAVs) attract significant attention from academic researchers and industrial specialists due to their wide range of applications. UAVs are facing issues related to their power constraints as they need to either land for recharging or be replaced by another UAV to continue the mission. Requiring a UAV to return every few hours for recharging can become highly expensive [2]. Extending the UAV's endurance, operation range, and flight time is a main challenge to make its mission optimal. To this aim, the immediate solution that comes to mind is adding more batteries [3]. Although adding more or larger batteries would supply additional energy to a UAV, this approach is not feasible due to weight limitations. The increased weight negatively impacts the UAV's endurance, making it an ineffective solution [4]. To address this challenge, integrating a PV system into UAVs has been proposed as a promising solution [5]. By incorporating solar cells, a UAV could harness and store solar energy in its battery system for use during nighttime flights, eliminating the need to return for recharging [6]. In addition, the integration of solar technology into UAVs offers several advantages such as providing a clean source of energy with a high energy-to-weight ratio and low maintenance need for UAVs by enhancing various factors such as battery recharging cycles, and its endurance and the less frequent need for takeoff and landing [1].

Solar-powered aircrafts represent an innovating concept and cutting-edge technology, often considered the future of aviation. The limitless availability of solar energy makes this green technology promising in terms of cost-effectiveness, safety, sustainability, and providing clean transportation. By converting solar energy into power, these aircrafts can achieve extended flight endurance. During periods of low sunlight or nighttime, they rely on stored energy from batteries to stay airborne. Although the initial cost for designing solar-powered UAVs is high, they are more fuel-efficient and require less maintenance compared to traditional fuel-powered UAVs. Over time, by eliminating the need for jet fuel, solar-powered UAVs can save millions of dollars and contribute to environmental conservation [7].

Solar-powered UAVs can operate in various weather conditions and locations. However, if used in cold regions or at higher altitudes, they may encounter mechanical and electrical challenges, such as in-flight icing. Atmospheric in-cloud icing poses a significant threat to all types of aircraft, particularly fixed-wing UAVs, which are limited by icing in their operational range [8]. While icing is a well-studied issue in general aviation [9], less researches have focused on UAVs. One key difference is that most UAVs, except for the largest, fly at much lower speeds and altitudes and are smaller in size compared to traditional aircraft. In-flight icing on UAVs (or any aircraft) occurs when freezing liquid droplets accumulate on the fuselage, propellers, sensors, and other components as the UAV passes through clouds or precipitation [9] [10].

The use of a UAV-integrated PV system in its best conditions involves an in-depth investigation, going beyond what is currently available in the literature. The movement of the PV modules makes the analysis and modeling challenging. The operation of PV systems in their maximum power point (MPP) operational point is an important concept to enhance their energy efficiency. It is more crucial for the solar UAV's PV

system moving in different directions to track the MPP leading to an optimal performance. Additionally, extracting unknown electrical parameters of a PV module for the purpose of determining its behavior in variable irradiance conditions plays an important role to perform energy loss studies, to design the whole electrical and electronics system related to the PV modules and eventually to achieve an effective control program. Traditionally, these parameters can be derived through the PV module manufacturer's datasheet under only one operating condition, known as standard test condition (STC). However, the extracted parameters under the STC condition are only valid for that specific condition. Extracting the parameters of a solar module is a complex optimization problem [11]. This task is generally approached using two primary strategies including analytical techniques and numerical computations [12].

Moving of the UAV-integrated PV module and various flight condition add complexities to the analysis of the behavior of PV modules particularly, in icing conditions making its utilization in energy harvesting more difficult. This complexity can be considered from two prospective. Firstly, movement causes constantly changing conditions, from ambient environment to flight dynamics and in-flight icing. Secondly, performing an analysis on a moving PV module needs an approach to extract the system parameters independently without need to any prior experimental measurements. In the context of variable and complex conditions, machine learning (ML) approaches can be a promising solution and provide the needed prediction of the desired parameters for various conditions of PV module utilization. These models can learn from numerous data points and predict the behavior of the system based on the performed training. In terms of individually extracting system parameters, utilizing metaheuristic methods would be highly advantageous. These methods can be utilized in the dataset processing phase to prepare reliable data for the machine learning training phase.

The current body of research on UAV-integrated PV systems primarily focuses on the overall performance of solar UAVs, considering both the electrical and mechanical systems. These studies often treat the integrated PV system only as a component of the entire system, overlooking the complexities and detailed behavior of the PV module that arise from continuous UAV movement and variable environmental conditions. Additionally, the operation of the PV system at its MPP, which is critical for energy efficiency, becomes even more challenging for a moving UAV that is constantly exposed to varying irradiance and environmental conditions. Furthermore, conventional methods for extracting the unknown parameters of PV modules depend on manufacturer-provided data under STC and prior experimental measurements. However, these methods are not reflective of the real-world conditions UAVs face, including normal operational fluctuations and in-flight icing phenomena.

This research addresses these gaps by developing an adaptive, computationally intelligent framework for predicting the behavior of UAV-integrated PV modules under various flight conditions, including in-flight icing. To this end, this research projects incorporate the following main steps/objectives:

- 1- With regard to the first objective, a computational model for MPP of a UAV-integrated PV system is developed. The initial phase of this objective, which is foundational for the subsequent steps of whole research, involves interpreting the movement of UAV-integrated PV module in a 3D space into the key placement angles of the PV system: tilt and azimuth. This is accomplished by proposing a method that utilizes UAV dynamic equations and leverages rotational matrix concepts. The trained computational model processes UAV movement parameters and historical meteorological data using a set of empirical PV system equations, the grey wolf optimization (GWO) algorithm, and several multi-input single-output

(MISO) machine learning models to predict the MPP power of the UAV-integrated PV modules.

- 2- The second objective focuses on parameter extraction for the UAV-integrated PV system using computational intelligence techniques. This involves processing meteorological and UAV movement data through the whale optimization algorithm (WOA), particle swarm optimization (PSO), and two sets of empirical PV cell equations. These methods will enable the training of multiple MISO models and a multi-input multi-output (MIMO) artificial neural network (ANN).
- 3- As a third objective, a computational-based performance analysis of the UAV-integrated PV module, considering the effect of in-flight icing, is conducted. This work begins by presenting equations that describe ice formation on the UAV wings, derived from previous icing tests and utilizing curve-fitting approach. Moreover, a new approach is needed to interpret the non-uniform UAV integrated PV module ice pattern to equal uniform ice coverage which will be discussed. The UAV movement and meteorological data is then processed using various optimization techniques, including multiverse optimization (MVO), GWO, WOA, and moth-flame optimization (MFO) algorithms. The datasets processed by the mentioned approaches will be utilized to train multiple MIMO and MISO models to predict the performance of the integrated PV module in two operational zones: non-shaded and ice-shaded areas

1.2. Motivation of Research and Problem Statement

As highlighted in the introduction, integrating PV modules as a power source for UAVs is an emerging research area that has drawn attention. This integration introduces several challenges in analyzing and evaluating the performance of the integrated PV modules. While numerous studies have explored the performance of PV

panels in fixed applications, to the best of our knowledge none have addressed the performance of PV systems under varying conditions, particularly regarding their placement and environmental factors. These challenges are further amplified when the system operates in a 3D space, requiring precise analysis. Understanding movement in a 3D space is crucial, as these concepts can be extended to other types of applications, such as the integration of PV technology into surface vehicles like cars, trucks, and buses.

Moreover, while the mechanical aspects of in-flight icing have been extensively researched, there is no existing literature that examines the impact of this phenomenon on the performance of UAV-integrated PV module. Given this gap, the methods and approach proposed in this research could serve as a valuable reference for future studies on the implementation of PV technology in various types of vehicles under various weather conditions.

According to the aforementioned challenges, three primary problems are considered in this research. First, existing PV panel modeling studies, typically designed for fixed applications, do not account for the movement of a PV panel, especially when analyzing the MPP of a PV module. Second, PV module parameter extraction methods, such as analytical and optimization-based approaches, are tailored for static applications and struggle under dynamic conditions, particularly in UAV-integrated PV systems. These conventional methods fall short because they cannot handle the varying parameters and non-linear characteristics that arise when PV modules move in 3D space on UAVs. Moreover, all these methods require prior experimental measurements to extract the unknown parameters of the PV module, while, obtaining such measurements and processing them at the same time is not

feasible in a moving application. Finally, the third problem addresses the challenges of studying PV module performance in solar-powered UAVs, particularly under in-flight icing, which leads to non-uniform coverage of the PV module and dynamic movement. Ice accumulation on PV modules obstructs sunlight, which affects the operation of the PV module. This issue is further complicated by the UAV's movement, leading to inconsistent sunlight exposure, which makes accurate analysis challenging.

1.2.1. Problem 1: Lack of a Specific Method to Determine the MPP Characteristics of a UAV-Integrated PV System

A large number of PV panel modeling methods have been investigated and proposed in recent years for the fixed application of PV systems. These methods can be classified as analytical models [13]-[16] and optimization-based models [17],[18]. Analytical modeling techniques compute the PV system parameters based on the PV cell's physics rules and the governing equations, while optimization-based methods extract the PV parameters based on an objective function which tries to tune the PV system parameters to reach the pre performed experimental measurements of the PV system in some limited conditions. Although all the mentioned modeling studies improve the PV modeling procedure by considering various scenarios, they neglect the random movements of the PV panels in UAVs.

Given the fact that the UAV-integrated PV model's specifications change based on the UAV's movement, there is no research in the literature to address this issue. In this context, ML methods are expected to come up with appropriate solutions to this challenge. There are some studies in the literature that use ML approaches to model PV systems in various conditions and deal with the system complexities [19]-[22], mostly for the fixed application of the PV panels.

According to the limitations of traditional fixed PV system modeling and the potential for ML methods to address complexities, the use of a UAV-integrated PV system demands even further investigation. In fact, the design and implementation of a UAV-integrated PV system need to meet the technical demands while considering applicable restrictions, such as solar irradiation changes, ambient temperature, and the placement of the PV module with respect to the sun, which may vary according to the drone's movement. Hence, a precise model that represents the PV system's output characteristics in relation to various input parameters is essential. This helps to investigate all restrictions and the exact behavior of the PV system and achieve the solar module's best performance at its MPP.

1.2.2. Problem 2: Limitations of Conventional PV Parameter Extraction Methods for UAV-Integrated PV Modules

In the PV module modeling and I-V characteristic description procedure, the most frequent basic concept is the single-diode equivalent circuit (SDEC) approach [23]. The SDEC is an equivalent circuit of a PV module that includes five unknown parameters and is one of the most accurate among other approaches [24][25]. The extraction of the parameters of a solar module is a complex non-linear optimization problem [11] which can be classified into two main subclasses, namely analytical methods [12] and numerical ones. The analytical methods utilize the equations of the key points of the power-voltage curve of the PV module, including short circuit current, open circuit voltage, and MPP to find out the PV module model's unknown parameters [26][27]. Because of the highly nonlinear properties of the PV module curves, selecting incorrect operational points may lead to considerable errors in extracted parameters. To address the challenges of analytical methods, much effort has been invested into numerical methods for PV module parameter extraction [17][18]. Numerical methods

are based on iterative or optimization algorithms and try to fit all experimentally measured points on the curves of the PV module. Numerous optimization algorithms including PSO [28]-[32] have been proposed for this purpose.

Although the two aforementioned methods including analytical and numerical methods are appropriate for limited circumstances, such as fixed applications of PV modules, they may encounter challenges when the PV module is implemented under uncertain conditions, requiring parameters to be extracted for each circumstance. In the context of variable conditions, ML approaches can be a promising solution and provide the needed prediction of the desired parameters for various conditions of PV utilization. Many researchers use ML approaches to address the challenges associated with PV technology implementation. In [19], the authors review the applications of ML approaches in the field of PV systems including maximum power point tracking (MPPT), fault detection, islanding detection, sizing method, and PV performance forecasting. In [33], [20]-[22], researchers employed an artificial intelligence in the field of PV technology power studies. The availability of a representative model for UAV-integrated PV systems is crucial for their optimal utilization. To harness the advantages of integration of a PV system to a UAV, an efficient and comprehensive model which is able to predict the unknown parameters of the UAV-Integrated PV system is needed. Such a model plays a crucial role in the design, simulation, control, and performance evaluation of the PV system. After performing a comprehensive literature review, to the best of our knowledge, this is the first time a method is proposed that is independent of any prior experimental tests and capable of independently extracting the unknown parameters of a PV module. This capability allows the method to be employed in modeling a moving PV system, which becomes highly complex when integrated with UAVs due to the rotation of UAVs in 3D space.

1.2.3. Problem 3: Lack of Methodology for Analyzing In-flight Icing Effects on UAV-Integrated PV System Parameters

Solar-powered aircrafts represent an innovative and advanced technology given the unlimited supply of solar radiation. They use converted solar energy into the electricity to expand flight endurance. When sunlight is inadequate or during nighttime, these aircrafts utilize stored energy from batteries to sustain their operations. While solar-powered UAVs entail higher costs for development and research due to the sophisticated technology involved, they offer greater fuel efficiency and require less maintenance compared to fuel-powered UAVs. By eliminating the need for fuel, solar-powered UAVs have the potential to save significant amounts of money over time and contribute to environmental preservation.

Previously done researches indicates that icing conditions can occur at any time and in any location worldwide on the UAVs [34][35]. The effects of icing on UAVs, urban air mobility (UAM), and advanced air mobility (AAM) applications have become a growing concern in recent years [36][37]. Adverse weather, particularly atmospheric in-flight icing, poses a severe hazard to these aircraft, limiting their operational envelope and flyability [38]. Icing on aerodynamic surfaces of UAVs increases drag, decreases lift and the stall angle, and changes the mass of the aircraft [38][39]. In response to the need to understand the impact of in-flight icing on the mechanical performance of UAVs, researchers have conducted extensive studies [40].

In addition to the mechanical obstacles, in-flight icing can also impact the performance of any system integrated with a UAV, including the PV system in solar UAVs. Ice formation on the panels can block sunlight from reaching the cells, thereby impeding electricity generation. Whether the shading is complete or partial, it can lead

to a decrease in the electricity output of the panels, with the reduction rate disproportional to the shaded area [41]. Understanding the effects of shading is essential to assess the impact of snow on PV modules. The obstruction of light has always been a significant issue for photovoltaics, leading to extensive research on the effects of shading and soiling. Authors of [42] and [43] explored the behavior of various types of PV cells in low light conditions. Researches indicates that partial shading has a more detrimental effect on PV system performance than uniform shading [44][45]. In order to consider the application of PV systems in cold regions, some studies have specifically focused on the effect of snow on the performance of PV panels. [17][18][21][22].

The challenges of assessing the impact of ice on PV modules become more complex when the module's movement, influenced by the UAV's motion, is taken into account. A moving PV module is exposed to varying levels of sunlight at any given moment, leading to fluctuating output from the PV module. Analyzing this dynamic system requires advanced computational methods rooted in computational intelligence science. These methodologies have proven to be effective in addressing the uncertainty associated with such issues. Computational intelligence-based approaches demonstrate strong performance in evaluating the effects of snow, the movement of PV modules, and the optimization of PV systems.

1.3. Objectives of Research

The integration of PV technology into UAVs offers potential to enhance their endurance and performance. This integration is becoming increasingly attractive as the performance of PV cells improves. Therefore, establishing an accurate modeling

strategy enables assessing the performance of UAV-integrated PV systems under varying flight conditions and environmental settings, including the potential obstacle of in-flight icing that can give rise to issues related to partial shading condition. The primary aim of this research is to predict the performance of UAV-integrated PV systems in challenging weather conditions by developing machine learning models through data processing using mathematical and optimization methods. To achieve this goal, the following specific objectives have been defined for each phase of the project.

1.3.1. Computational Intelligence-based MPP Modeling of UAV-integrated PV System

Efficient energy harvesting is an important concern for UAV-integrated PV systems during flight. During UAV flight, it moves in six degrees of freedom, enabling full 3D movement. This motion, combined with Earth's rotation relative to the sun, results in variable sunlight exposure on the integrated PV module. Additionally, factors such as ambient temperature, UAV speed, and flight altitude impact the PV module's temperature. These variables collectively affect the performance of the UAV's PV system.

One of the important aims of this objective is to develop a method to interpret the movement of UAV-integrated PV module to the basic PV module placement parameters and then predict the MPP behavior of the UAV-integrated PV module under various flight conditions. This predicted MPP power serves as a reference for the power electronics converter to control the PV module at its optimal operational point. Furthermore, considering the diode ideality factor as a variable parameter in the variable condition of the flight of UAV is another part of this objective.

1.3.2. Objective 2: Computational Intelligence-based Parameter Extraction of

UAV-integrated PV System

The precise modeling of the UAV-integrated PV systems is central for their implementation on UAVs, especially due to their continuous movement. Accurate modeling is essential for developing control methods, conducting performance studies, and designing the whole system considering PV system parameters. UAV's movement and varying flight and environmental conditions lead to changes in the output and key parameters of the UAV-integrated PV module. These parameters, which represent important characteristics of the PV module, are crucial for assessing its behavior, output, and overall performance. Identifying the unknown parameters of a PV module is particularly important for UAVs due to their continuous movement, as accurate modeling is essential for control methods, performance studies, and system design. To enable this identification for varying flight and environmental conditions of UAV-integrated PV modules, the second objective of this thesis is defined. The aim of Objective 2 is to predict five unknown parameters under different flight and environmental scenarios by leveraging the power of computational intelligence and optimization methods.

1.3.3. Objective 3: Computational Intelligence-based Parameter Extractions of the UAV-integrated PV System Considering In-flight Icing Phenomenon

In cold, humid conditions, icing commonly affects an aircraft's wings, fuselage, control surfaces, and propulsion systems when supercooled water droplets in the air collide with the aircraft, forming ice. The shape and extent of this ice buildup depend on various factors, including aircraft parameters like flight speed and the surrounding meteorological conditions. This phenomenon, known as in-flight icing, can reduce the irradiance reaching the UAV-integrated PV module surface. Combined with other UAV flight and environmental variations, in-flight icing adds complexity to the

behavior of the UAV-integrated PV module. The behavior of a PV module is determined by its equivalent circuit parameters, and identifying these parameters reveals its performance, especially under movement and icing conditions. Therefore, the third objective of this research is to predict the parameters of the UAV-integrated PV module, taking into account in-flight icing and variations in the UAV's flight and environmental conditions.

1.4. Methodology

To achieve the objectives outlined in this thesis, this study employs a range of advanced computational methods and scientific analyses. These include proposing analytical methods based on the PV module governing equation and mathematical concepts, employing metaheuristic optimization algorithms, nonlinear equation-solving techniques, machine learning model training, and model validation using analytical and experimental approaches. A concise overview of the proposed methodologies is provided below.

1.4.1. Methodology of Objective 1

In the first objective of this thesis, a dataset comprising one year of environmental data from the Canadian Capital Region, combined with a randomly generated UAV movement dataset, is processed using a series of methods to prepare a target dataset for training ML models capable of predicting the MPP properties of the UAV-integrated PV module. Initially, the rotation and movement of the UAV-integrated PV module is translated into the basic placement angles of a PV module through trigonometric analysis based on the concept of rotational matrices. Subsequently, the diode ideality factor, considered a variable parameter, is computed

for each data point in the dataset using the GWO algorithm. Additionally, a set of PV module empirical equations is employed to calculate the MPP properties of the UAV-integrated PV module for each data point. The outputs of the calculations are then used to train 23 different ML regression models to identify the most suitable model for predicting MPP properties under any UAV placement or movement conditions. Additionally, a hybrid MPPT method is proposed and validated on the hardware setup to show the functionality of the proposed method. Finally, a series of experimental measurements and hardware tests are conducted to validate the performance of the proposed method.

1.4.2. Methodology of Objective 2

In the second objective, the same dataset used in the first objective is processed through a group of various methods, including an analytical method based on the rotational matrices to interpret the movement of the UAV as the basic placement parameters of the PV system, two sets of PV module empirical derived equations (EDEs), a nonlinear equation solver, and a metaheuristic optimization algorithm to extract the five unknown parameters of the PV module system. Both sets of EDEs calculate the MPP properties of the PV panel, with the second set consisting of a system of equations that includes all five unknown parameters. The second set of EDEs is solved using a nonlinear solving method, specifically the dogleg trust region algorithm, and incorporated into the objective function of the WOA. By comparing the results of the two sets of EDEs, the unknown parameters are extracted for the entire dataset. The resulting dataset, containing the five extracted parameters for all data points, is then used to train MISO and MIMO machine learning models. A total of 130 MISO models and one ANN-based MIMO model are trained. The best-performing models are selected based on their accuracy, and an experimental test is designed to validate the

performance of the proposed method.

1.4.3. Methodology of Objective 3

In the third objective, after considering the movement of the UAV-integrated PV module as described in the first methodology, the effect of non-uniform in-flight icing on the irradiance reaching the PV module surface is analyzed. To this aim, an icing pattern formula is proposed, derived using a curve-fitting approach, and a new analytical method is introduced to model the non-uniform icing pattern as an equivalent uniform icing pattern. Partial coverage of the PV panel due to icing alters its operational curve, creating distinct zones. The impact of these zones is addressed by proposing a framework for parameter extraction analysis and ML model training for each zone separately. Four different metaheuristic optimization methods including WOA, GWO, MVO, and MFO are employed to extract the parameters of the UAV-integrated PV module in the ice-covered zone, with the best method selected based on error metrics. Furthermore, 140 ML models are trained and evaluated to predict the parameters of the UAV-integrated PV module under icing conditions. To enhance the performance of the trained models and reduce their complexity and dependency on parameters, the minimum redundancy - maximum relevance (MRMR) method is utilized as a feature extraction technique. Finally, the performance of the proposed method is validated through experimental tests.

1.5. Statement on the Originality of the Thesis

1.5.1. Contributions of Computational Intelligence-based MPP Modeling of UAV-Integrated PV System

Considering the project's objective of analyzing the UAV-integrated PV

module and the inherent properties of the UAV, which moves continuously in 3D space, the first step in analyzing the electrical properties of the integrated PV module is to establish a method to convert the UAV's operational angles into the standard placement angles of a PV module. To the best of our knowledge, this research proposes, for the first time, a method capable of performing this conversion. The proposed method is based on the principles of rotational matrices. A rotation matrix is a mathematical tool used in linear algebra to perform rotations within a coordinate system. In this study, the Tait-Bryan rotation matrix [46], which incorporates the Roll, Pitch, and Yaw sequences, is employed to compute the new body frame.

In the majority of research studies, the diode ideality factor of the PV module is treated as a constant parameter. However, in this study, due to the continuous movement of the UAV and its integrated PV module, determining the diode ideality factor of the module is essential. This factor is the sole parameter associated with the equivalent circuit of the PV module in the utilized equations. Hence, through the application of a PV module governing equation and leveraging the capabilities of a meta-heuristic optimization algorithm, the diode ideality factor of the UAV-integrated PV module is calculated adaptively for each operational angle of the UAV.

Moreover, as the final contribution in this topic, the MPP properties of the UAV-integrated PV system for various conditions of movement and flight is getting predictable using a series of ML trained models. This prediction can then be utilized to regulate the MPPT power electronics boost converter linked to the PV module, enabling the system to optimize power harvesting under various operational conditions of the UAV-integrated PV module.

1.5.2. Contributions of Computational Intelligence-based Parameter Extraction

of UAV-Integrated Photovoltaic System

To the best of our knowledge, this is the first time a method is introduced in the literature that can independently derive the unknown parameters of a PV system. This capability allows the method to be applicable in UAV or any other vehicle scenarios where the PV system undergoes continuous movement. Past studies have extracted PV system parameters by utilizing metaheuristic methods based on experimental measurements as references for their optimization techniques.

The novel method proposed in this research capitalizes on a new approach to interpreting UAV movements by employing rotational matrices to compute the operational angles of the PV modules. This strategy, combined with the innovative use of PV panel governing equations, metaheuristic optimization, and a nonlinear equation solver, proposes a precise and independent method for extracting PV module parameters under varying environmental and flight conditions. Unlike conventional methods, this approach does not require prior experimental measurements or data for accurate parameter extraction. Instead, it can independently derive the unknown parameters of the UAV-integrated PV system.

1.5.3. Contributions of Computational Intelligence-based Parameter Extractions of the UAV-integrated PV System Considering In-flight Icing Phenomenon

The first contribution of this section is the introduction of a new approach to incorporate the effect of in-flight icing into the calculations of irradiance hitting the UAV-integrated PV module. To the best of our knowledge, this is the first time in the literature that the impact of in-flight icing on a UAV-integrated PV system has been considered.

Ice formation on the wings of the UAV, where the PV system is installed, depends on the type of ice, can act as an obstacle, causing varying degrees of light to hit the cell surface. This ice formation, as mentioned earlier, leads to a partial shading effect. Aside from the challenges posed by partial shading on the PV module, it also impacts the operational curve of the PV module. Partial shading restricts the current flow through a cell string, resulting in changes on the operational curve of the PV module. To consider this effect on the UAV integrated PV panel parameters, a method is proposed to segment the curve into two zones: the ice-covered zone and the normal zone. Subsequently, the unknown parameters of the ice-covered UAV-integrated PV module are determined by combining the results from each zone.

1.6. Thesis Outline

The chapters of this thesis are organized as follows:

Chapter 2 provides a literature review that offers foundational insights into the concepts addressed in this dissertation. This chapter focuses on studies related to the fundamental concepts underlying this thesis.

Chapter 3 proposes a trigonometric analysis combined with the concept of rotational matrices to translate the movement of a UAV-integrated PV system into the placement parameters of a PV module. Additionally, it introduces the use of the GWO algorithm, in conjunction with the EDEs of PV modules, to compute the ideality factor of the moving PV module. A total of 23 ML regression models are trained to predict the MPP properties of the PV module and the effectiveness of the proposed method is validated through experimental measurements and hardware implementation.

Chapter 4 develops a novel method involving analytical techniques, optimization algorithms, nonlinear solvers for unconstrained problems, and both MIMO and MISO ML methods to predict the five unknown parameters of the UAV-integrated PV module. PSO and the WOA are utilized as optimization techniques, while the dogleg trust region algorithm (DTRA) is employed as the nonlinear solver. A total of 130 regression ML models and one ANN MIMO model are trained. The performance of the proposed method in predicting the five unknown parameters is verified through experimental tests.

Chapter 5 introduces a novel approach using curve fitting to model the in-flight icing phenomenon on UAV wings. A new analytical method is proposed to translate the effects of non-uniform ice on the PV module into an equivalent uniform ice pattern, which is incorporated into the governing equations of the PV module. Furthermore, four metaheuristic optimization algorithms WOA, GWO, MFO, and MVO are utilized to extract the five unknown parameters of the UAV-integrated PV module under icing conditions. These parameters are used to train 140 machine learning models to predict the parameters of UAV-integrated PV modules under in-flight icing conditions. The MRMR method is employed to simplify the ML models and enhance their performance. The proposed approach is validated through experimental tests.

Chapter 6 summarizes the work presented in this thesis, highlights the research contributions, and outlines the topics for future investigation.

1.7. List of Publications

A list of the papers derived from this dissertation, which are published so far or

have been submitted, is given as follows:

[1]: M. Saeedinia, B. Hashemi, A. -M. Cretu and S. Taheri, "A Novel Computational Intelligence-Based Parameter Extraction of UAV-Integrated Photovoltaic System," in *IEEE Access*, vol. 12, pp. 97664-97677, 2024, doi: 10.1109/ACCESS.2024.3428400.

[2]: M. Saeedinia, S. Taheri, A. -M. Cretu and "Computational Intelligence-based Modeling of UAV-Integrated PV Systems" in *MDPI Solar* (Submitted).

[3]: M. Saeedinia, S. Taheri, A. -M. Cretu and "Computational Intelligence-Based Modeling of a UAV-Integrated PV Module in Icing Conditions" in *IEEE Journal of Photovoltaics* (under review).

2. Literature Review

2.1. Introduction

In this chapter, a literature review relevant to the objectives of this thesis is presented. The research objectives represent a multidisciplinary endeavor, combining cutting-edge topics in various scientific fields. To the best of our knowledge, this is the first time this specific combination of PV, computational intelligence, and UAV sciences has been explored. The literature review provides a comprehensive overview of related studies that are connected to the thesis objectives. Its aim is to introduce the existing body of research, highlight the current gaps and limitations, and define the problems addressed in this work.

The first subsection examines studies on the integration of PV technology with vehicles, specifically focusing on UAVs. It also reviews the challenges faced by UAV-integrated PV systems and explores the analyses required to optimize the use of PV panels on UAVs.

The second subsection reviews research related to parameter extraction for PV systems, commonly referred to as the comprehensive modeling of PV systems. It also discusses studies that employ computational intelligence-based approaches for PV system analysis, which form the foundation for achieving the second objective of this research.

The final subsection reviews solar UAV technologies and examines the in-flight icing phenomenon, a critical issue for UAV-integrated PV systems. It also considers studies that address the challenges posed by snow and ice coverage on PV panels.

2.2. Review of Research Related to the Computational Intelligence based MPP Modeling of a UAV-integrated PV System.

Integration of PV technology into vehicles technologies is an effective solution to meet all or part of a vehicle's energy requirements and extend its operational range. Some studies focus on integrating PV systems with electric vehicles charging stations to supply their energy needs. For instance, [47] and [48] examine the benefits of such systems and their impact on reducing environmental emissions. Additionally, researchers in [49] propose an approach to optimize the location of solar-powered charging stations. While some studies consider PV systems as part of the power infrastructure for vehicles, others take a different approach by directly integrating this technology into the vehicles themselves. This integration can extend the vehicles' operational range [50],[51], reduce their greenhouse gas emissions [52], and allow vehicles to utilize their full power at all speeds with minimal maintenance costs [53][54]. Among the various vehicular systems that leverage PV technology, UAVs are among the most attractive due to their wide range of applications, including power facility inspections, traffic monitoring, geographic studies, surveillance, and more [55]-[57]. Given the limited onboard battery capacity, integrating PV modules into UAVs is a practical solution to enhance flight endurance. This approach has sparked significant research into the control and design of PV modules for UAV integration [5]. The output characteristics of UAV-integrated solar PV systems, such as current,

voltage, and power, are affected by the continuous movement of the UAV [58]. Another crucial parameter that varies with each flight condition is the MPP, which represents the specific point on the current-voltage (I-V) curve where the product of voltage and current yields the highest power output under given conditions [59]. Identifying and maintaining operation at the MPP is essential to extract optimal power, especially in dynamic conditions like UAV flight, where the angle of solar incidence and temperature change constantly [59]-[60]. The task of maintaining operation at the MPP is achieved through MPPT algorithms, which adjust system parameters in real-time to follow the optimal power point. To achieve optimal performance in solar-powered vehicles, researchers have performed related studies which provide valuable insights into the more complex integration problem of a PV module with UAVs, which shows the most complex form of movement among various vehicles. In [61], the variation of the duty cycle is discussed to examine the impact of vehicle movement on the MPP of an integrated PV system, focusing primarily on the movement of a ship while neglecting other parameters beyond ship movement. Similarly, the authors of [62] investigate the effects of vehicle movement on the performance of an integrated PV module through extensive field measurements. This study demonstrates how the movement of surface vehicles can significantly reduce the efficiency of conventional MPPT methods, such as perturb and observe (P&O), dropping efficiency from 95% to 55%. To study the effect of movement of the UAV specifically on the MPPT of its integrated PV system, researchers explored various MPPT techniques. These include conventional methods like P&O and incremental conductance (IC), as well as more progressed approaches such as fuzzy logic-based control [60]. As with any PV system, from fixed installations to those integrated into moving vehicles, MPPT control modules play an important role in UAV power management by continuously adjusting the operating point of the PV system during flight in addition to conventional methods,

some studies propose simplified approaches, such as determining the MPP by regulating the output voltage of a buck-boost converter through a trial-and-error process [7]. These approaches minimize the need for input sensors, reducing both system weight and cost. Proposed solutions in aforementioned researches are using a modified version of the conventional MPPT techniques [58][64]-[55]. Nevertheless, it is important to note that the response time of these methods has to be considered to reach MPP under fast-changing conditions.

Optimal utilization of a UAV-integrated PV system requires a comprehensive examination that goes beyond the scope of existing literature. The design and implementation must address the technical demands while accounting for variables such as solar irradiation, ambient temperature, and the placement of the PV module on the UAV. Although many modeling studies focus on stationary PV systems, they fail to capture the random movements and variable orientations encountered in UAV applications, which involve six degrees of freedom. To design UAV-integrated PV systems capable of maintaining MPP under dynamic conditions, it is crucial to develop accurate models that can predict the system's output characteristics in real time.

To achieve this, the modeling methods of PV modules must first be analyzed. Recently proposed PV panel modeling techniques, capable of capturing the behavior of PV modules based on their unknown parameters, can be broadly classified into analytical models [14] and optimization-based models [17]. Analytical modeling derives PV system parameters using the physical principles of PV cells and their governing equations, while optimization-based methods extract these parameters using objective functions and prior experimental measurements. Although these models address various scenarios, they generally assume fixed PV panels, rendering them

inadequate for applications where random movements and varying operational conditions influence power output.

Given that the specifications of a PV model change dynamically with a UAV's movement and operational conditions, the current literature does not adequately address this challenge. In this context, which involves significant complexity, moving beyond conventional methods is necessary. Computational intelligence-based approaches, including metaheuristic optimization algorithms and ML techniques, are expected to offer effective solutions. Numerous studies have applied such methods to MPPT challenges, utilizing techniques like GA-optimized ANN MPPT [66], fuzzy logic and ANN MPPT [67], PSO-based MPPT [68], and imperialist competitive algorithm-based MPPT [69]. Additionally, some researchers have employed ML approaches to model fixed PV systems under varying environmental conditions, demonstrating their capability to manage system complexities efficiently [70][19].

2.3. Review of Computational Intelligence based Parameter Extraction of a UAV-integrated PV Module

As discussed in the previous sections, integrating UAVs with PV technology offers numerous advantages, such as increased endurance, reduced UAV weight, and lower maintenance requirements. One of the critical steps in optimizing this combined technology is developing a precise model of the UAV-integrated PV module to effectively manage its behavior and gain a comprehensive understanding of its operation. To achieve this, a precise model capable of extracting the unknown parameters of the UAV-integrated PV system is essential. Parameter extraction for photovoltaic cells is a crucial aspect of optimizing, simulating, and evaluating solar PV modules. In PV module modeling and I-V characteristic description, the most widely

used concept is the SDEC approach [24]. The SDEC represents a PV panel as an equivalent circuit with five unknown parameters and is considered one of the most accurate modeling methods [24][25]. To develop a precise model of a PV module, all unknown parameters must be determined. These parameters can initially be derived from the PV module manufacturer's datasheet under a single operating condition, known as the STC. However, the parameters extracted under STC are valid only for that specific condition. As a result, adjusting these parameters to account for varying temperature and irradiance conditions has become a focus of research.

The extraction of solar module parameters under conditions other than STC is a complex, non-linear optimization problem [11]. Solving this problem can be categorized into two main subclasses: analytical methods [12] and numerical methods. Analytical methods rely on equations corresponding to key points of the power-voltage (P-V) curve of the PV module, such as the short-circuit current, open-circuit voltage, and MPP, to determine the unknown parameters of the PV module model [26][27]. However, due to the highly nonlinear nature of PV module curves, selecting incorrect operational points for analysis can lead to significant errors in the extracted parameters. To overcome the limitations of analytical methods, significant efforts have been directed toward numerical methods for PV module parameter extraction [17][18]. Numerical methods use iterative or metaheuristic optimization algorithms to fit all experimentally measured points on the PV module curves. Various optimization algorithms, including PSO [28], genetic algorithm [29], tunicate swarm algorithm [11], ant lion optimizer [30], hybrid flower pollination (HFP) [31], and Improved Simultaneous heat transfer search algorithm (ISHTS) [32], have been proposed for this purpose. In addition to metaheuristic-based parameter extraction algorithms, other strategies involve advanced mathematical modeling of the PV module's operational

curve. For instance, in [71], the linear least squares method is employed to fit the I-V curve of the PV module in two steps, dividing it into a linear part and an exponential part. Furthermore, reducing the number of parameters through a separable non-linear least squares technique and subsequently searching for the unknown parameters is another approach proposed in [72].

Although the aforementioned insights are suitable for limited scenarios, such as fixed PV module applications, they may encounter difficulties under uncertain conditions, such as variable placement and operational settings of PV modules, where parameters must be extracted for each unique combination of weather and placement conditions. Additionally, many of these methods rely on predefined data provided by manufacturers or experimental measurements to determine the unknown parameters of PV modules using various techniques. In dynamic applications such as UAVs, where the placement of the UAV-integrated PV module changes continuously, it is often impractical to perform experimental measurements or electrical analyses for each configuration. In such cases, computational intelligence-based approaches offer a promising solution. These methods can predict the desired parameters for diverse PV utilization conditions without relying on prior experimental measurements. Many researchers have explored ML approaches to address the challenges associated with PV technology implementation. For instance, in [19], the authors review ML applications in PV systems, including MPPT, fault detection, islanding detection, sizing methods, and PV performance forecasting. In [33], researchers utilized an artificial intelligence-based model, derivative search-based political optimization (DSPO), to optimize the dispatch of a multi-area renewable energy system, where PV systems play a critical role. Furthermore, studies such as [20]-[22] have employed various ML methods to model the performance of PV systems in snowy conditions,

albeit without accounting for PV panel movement. Artificial intelligence approaches also provide innovative solutions in UAV control, including the artificial electric field algorithm for path planning [73] and UAV formation control [74][75].

2.4. Review of Research Related to the Computational Intelligence-based Parameter Extractions of the UAV-integrated PV System Considering In-flight Icing Phenomenon

To build a UAV capable of continuous flight, the design of solar-powered UAVs equipped with PV cells, rechargeable batteries, and electronic components to manage electrical power is essential. The relatively low energy density of current battery technology is a primary factor limiting the performance of small-scale electric UAVs [76]. To have sufficient room to install the PV cells, fixed-wing UAVs are typically used, with PV cells integrated on the wings from the leading edge to cover the entire wing surface [77]. Over the years, numerous solar UAVs have been developed. Early models featured 1,000 cells generating 450W of power with 11% efficiency [80]. Subsequent models increased the number of cells and power output, with one model developed in 1981 utilized more than 4000 cells to generate 600W power and one 1983 model incorporating over 16,000 cells to provide 2,500W [79]. Significant advancements occurred between 1993 and 2003, including developments by NASA [80]. Recent innovations include the Solar Impulse II, which uses over 17,000 solar cells to generate 66 kW of power, and the PHASA-35 which is developed for satellite applications with a wingspan of about 35 meters.

According to the explained trend, solar UAVs are increasingly employed in various applications, from surveillance to military operations, where utilizing them in harsh weather conditions is inevitable. One significant challenge that UAVs are faced

with in the harsh environmental condition is in-flight icing, which affects both mechanical and electrical performance. In-flight icing occurs when freezing liquid droplets accumulate on the UAV's fuselage, its integrated PV module, propeller, sensors, and other components. Mechanically, icing increases drag, decreases lift and stall angle, and alters the aircraft's mass, limiting its operational envelope and flyability [38], [81], [82]. Electrically, icing obstructs light from reaching the PV modules surface, affecting their performance.

Scientists and engineers have studied the impact of icing on aerodynamic surfaces such as wings [10], [83], [84], propellers [85]-[87], and engine inlets [88]-[90]. Similar considerations must be applied to understand the impact of icing on UAV-integrated PV modules. Snow and ice can form and accumulate on PV modules, obstructing light and reducing electricity production. However, even with a layer of snow or ice covering the module's surface, some light may still penetrate and reach the PV cells. The penetration of light through snow or ice can be described by the Bouguer-Lambert law [91]. The obstruction of light has consistently been a challenge for PV systems. To quantify the impact of snow on PV modules, it is essential to understand the effects of shading. Uniform shading typically results in a reduction in system output, whereas partial shading introduces complex changes in the electrical current balance due to the conductive properties of the cells.

In the majority of studies, researchers investigate the effect of ice and snow on the performance losses of PV systems. These researches studied the losses across various regions and time periods, highlighting that even minor losses can significantly impact the feasibility and success of a PV project [92]-[96]. The other group of studies primarily focuses on the physical removal of ice from PV systems. This line of research

was begun years ago, with one of the earliest studies [96] proposing a material to facilitate the melting of snow and ice from PV systems. Continuing research on materials designed to help in the removal of snow and ice or to prevent their formation has explored several strategies, including the development of ice-phobic and snow-phobic materials [97][98]. While water-repellent surfaces have achieved notable success, so-called ice-phobic surfaces are less developed. Although certain materials and coatings have demonstrated some degree of ice-phobicity, they are currently unsuitable for photovoltaic applications due to their lack of transparency [99]. Despite the efforts to develop physical approaches to prevent the formation of ice and snow on PV systems, none of these methods have achieved widespread adoption, and icing of PV systems remains a notable challenge [45].

The next group of studies accepts the presence of snow and ice on PV systems and explores the behavior and performance of the PV systems under such conditions. This group represents the most advanced approach among the three, as it employs computational intelligence-based methods to address the complexities introduced by snow or ice on PV modules.

For instance, [28] proposes a model for a snow-covered PV module using PSO and validated it with experimental tests. A comprehensive model for a PV module under partial snow conditions is presented in [18]. Study [100] develops a model based on the Newton-Raphson method to determine the parameters of a PV module under uniform snow coverage. Additionally, [101] introduces a model to predict the performance of a snow-covered PV system while incorporating a snow removal mechanism.

Although these studies represent significant progress in PV research, they are

limited to fixed PV applications. Moreover, all these models rely on prior experimental tests to characterize the PV module's behavior under snow or ice conditions.

3. Computational Intelligence-based Modeling of UAV-Integrated PV Systems

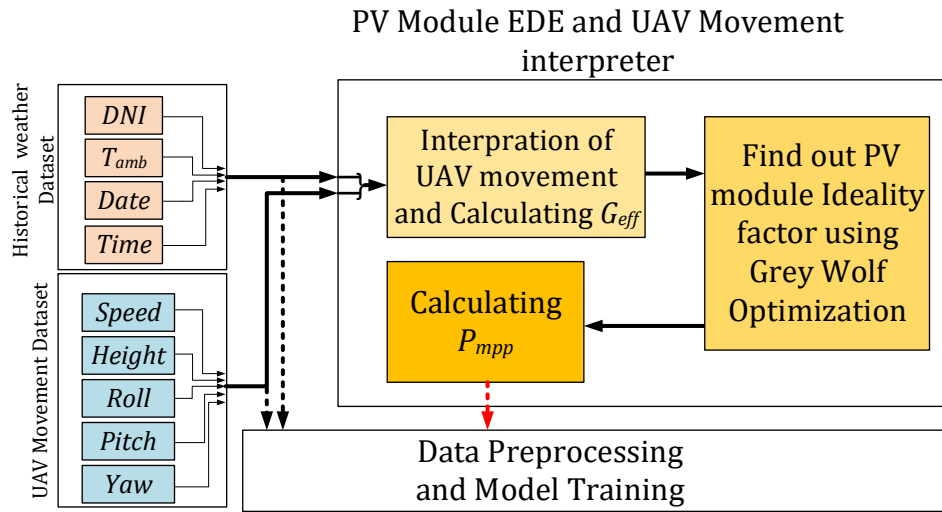
3.1. Introduction

The availability of a representative model for UAV-integrated PV systems is crucial for their optimal utilization. This model should accurately depict the PV panel's behavior under rapidly varying ambient and placement conditions brought on by the movement of the UAV. In addition, two major challenges i.e., shifting the earth's position in relation to the sun during the day and year, and shifting the PV module's placement in relation to the sun depending on the UAV's continual movement should be taken into account. Therefore, this chapter develops a ML-based model to address the UAV-integrated PV system movement. For this purpose, a novel approach is employed to determine the tilt and azimuth angles of a UAV-integrated PV system in relation to the UAV's operation angles. Furthermore, the use of the grey wolf optimization algorithm enables the adaptive calculation of the PV system ideality factor. Additionally, various ML algorithms are trained to predict the MPP properties of the PV system, accounting for the continuous movement of the UAV and the emergence of PV modules in various conditions at every instant. Moreover, the proposed ML-based model is integrated with the incremental conductance MPPT technique, forming a hybrid MPPT to maximize energy harvesting from the UAV-integrated PV system under variable movements. This approach is verified through experimental hardware testing.

3.2. Methodology

3.2.1. Proposed Method Block Diagram

The dynamic nature of a UAV's flight, e.g., continuous change of height, direction, and rotation, introduces significant variability in the PV system's parameters for each movement and meteorological condition. This variability leads to a considerable challenge to maintaining the PV module at its MPP. To cope with this limitation, ML approaches are expected to provide a promising solution. In this study, ML-based models are proposed to predict the MPP properties of the UAV-integrated PV module enabling efficient control of the PV module's performance under varying UAV movements and meteorological conditions. To this aim, a historical meteorological dataset [46] is combined with a randomly generated dataset containing the flight properties of the UAV. These datasets are then processed using the EDE in conjunction with the GWO algorithm to generate the final dataset suitable for training ML models. The schematic representation of this approach is illustrated in Fig. 3.1. The proposed approach can decrease the calculation burden of the controller of the UAV-integrated PV module by providing initial operation point that is either precisely at or in close proximity to MPP. In this section, ML model development, including the preparation of the dataset, utilized machine learning models, and trained models' performance are discussed.



Empirical Driven Equations (EDE)
 G_{eff} : Effective Irradiance Ratio Calculated by (9)
 P_{mpp} : Maximum Power Pont Power Calculated by (8)

Figure 3.1. Proposed method block diagram.

3.2.2. Relationship of UAV Movement in Terms of PV Module Placement Parameters

This section aims to propose a new approach as a solution to incorporate the concept of PV systems into the modeling of moving PV systems. Compared to static PV systems, UAV-integrated PV systems require a kind of modeling to account for dynamic movements. Traditional methods that rely on fixed placements are insufficient for moving systems. This novel perspective enables researchers to explore PV control strategies and studies in the context of UAVs or any other type of vehicles that utilize PV modules as their energy sources. This section provides a detailed analysis of the relationship between UAV movements and PV module placement parameters, highlighting their respective characteristics and interplay. Rotational matrices are used to interpret the UAV's roll, pitch, and yaw angles, which are then translated into operational angles for the PV modules. This relationship is crucial for accurately modeling the dynamic behavior of UAV-integrated PV systems.

The movement of a UAV can be described by the rotation around its principal imaginary axes. These axes are perpendicular to each other at the UAV's center of gravity, referred to as the body coordination frame. The rotation around the body frame z axis, which is perpendicular to the UAV's wings, is called yaw angle (ψ). The rotation around this axis identifies the movement of the aircraft's nose in left-right directions. The rotation of the UAV body around its lateral axis (y) is known as the pitch angle (ϕ). Rotations around this axis indicate the up and down movements of the UAV's nose. And finally, rotating around x axis denotes the roll angle (θ). This axis goes from the nose to the tail of the aircraft. These axes are shown in Fig. 3.2.

The movement of a UAV along/around the introduced axes can be expressed as the tilt and azimuth angles of the PV module installed on the UAV. This phenomenon can be clarified by examining the simplest scenario involving the UAV's body placement during flight, where it rotates around a single axis at a time. For

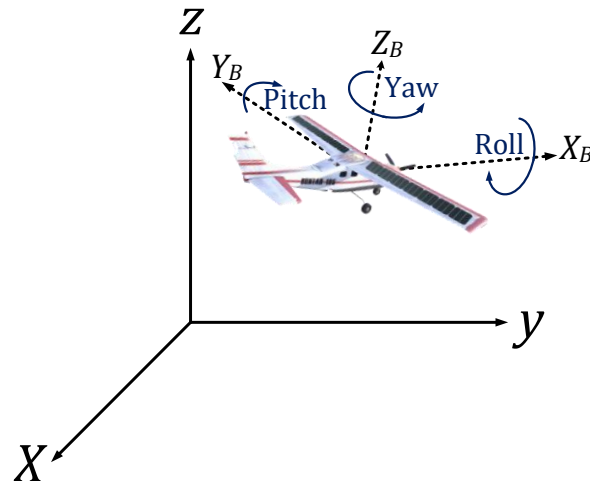


Figure 3.2. UAV body frame, fixed frame, and rotation axes.

instance, the rotation of an aircraft around its roll axis can be expressed as the tilt angle of the integrated solar panel. Moreover, the rotation around the pitch axis can be considered the tilt angle as well, as shown in Fig. 3.3. Actually, the rotation around the roll and pitch axes can both be considered the tilt angle but with different azimuth angles, perpendicular to each other as shown in Fig. 3.4. Moreover, rotating around the Yaw axis leads to changes in the azimuth angle, as shown in Fig. 3.4. c.

To delve deeper into this problem and identify the precise relationship between UAV movements and PV module angles when rotations occur simultaneously around all axes, an in-depth mathematical analysis of their interdependence is required. To analyze the rotational movements of the UAV comprehensively, it is necessary to introduce an additional coordinate system as a fixed frame. This fixed frame serves as

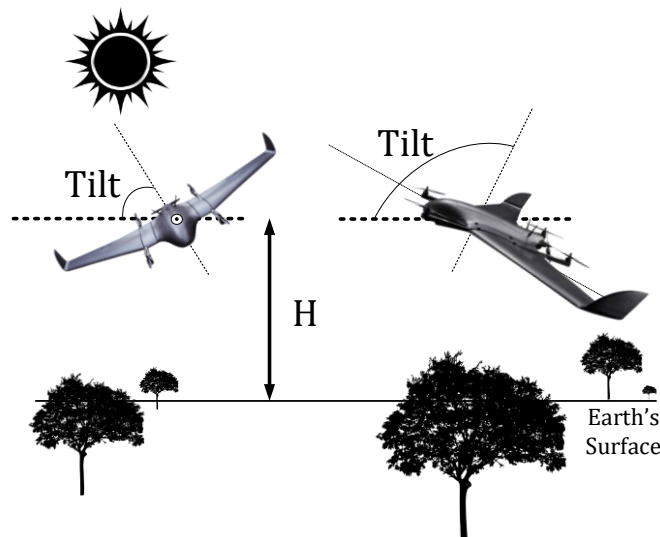


Figure 3.3. Tilt angle of aircraft while rotating around roll and pitch axes.

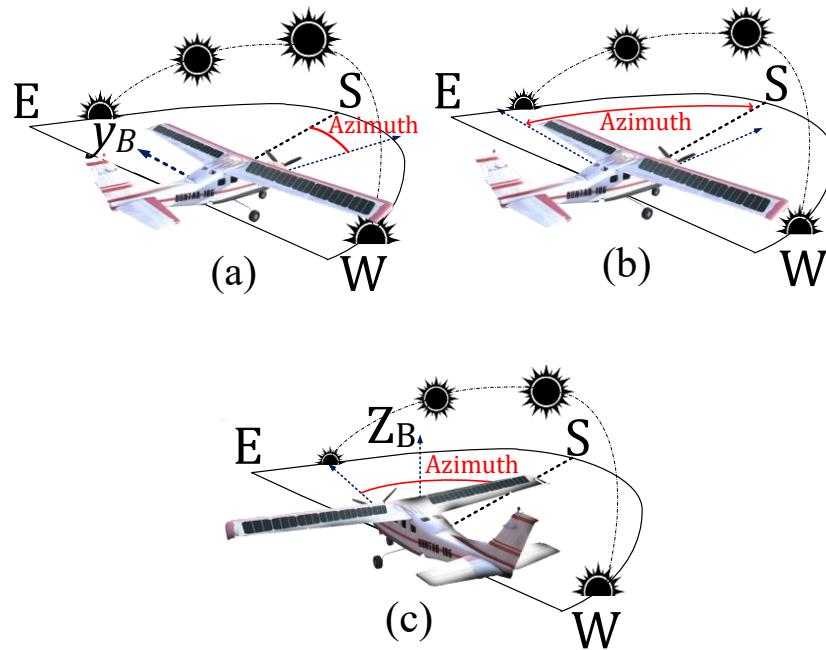


Figure 3.4. Different azimuth angles related to the aircraft's movement. (a) moving along roll axis and rotating around pitch axis. (b) moving along roll axis and rotating around roll axis. (c) moving along roll axis and rotating around yaw axis.

a reference for interpreting all body frame placement caused by various rotations. This fixed frame is known as the world frame. These two frames for a random condition of the UAV flight are shown in Fig. 3.2 as well.

The positioning of the body frame shifts as the UAV maneuvers around its roll, pitch, and yaw axes, leading to altered orientation angles in relation to the fixed frame across different flight scenarios. Establishing a correlation between these frames amidst varying positional conditions requires identifying a trigonometric connection that links their corresponding axes. This objective is accomplished by employing rotational matrices. In this investigation, the Tait-Bryan rotation matrix is utilized, incorporating sequences of roll, pitch, and yaw, to calculate the updated body frame. This rotation matrix is derived as the product of three matrices, each representing elemental rotations about the X, Y, and Z axes of the fixed frame, as follows [102]:

$$\begin{aligned}
R_x &= \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi & \cos\phi \end{pmatrix} \\
R_y &= \begin{pmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta \end{pmatrix} \\
R_z &= \begin{pmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{pmatrix}
\end{aligned} \tag{3.1}$$

$$R_{TB} = R_x R_y R_z$$

where θ , ϕ , and ψ are roll, pitch, and yaw angles of the UAV's body respectively. Also, R_x , R_y , and R_z are rotation matrices around x, y, and z axes, and R_{TB} is Tait Bryan rotation matrix, which is shown as below. Rotation sequence in this work considered as yaw-roll-pitch.

$$R_{TB} = \begin{pmatrix} c\psi c\theta - s\phi s\psi s\theta & -c\phi s\psi & c\psi s\theta + s\phi s\psi c\theta \\ s\psi c\theta + s\phi c\psi s\theta & c\phi c\psi & s\psi s\theta - s\phi c\psi c\theta \\ -c\phi s\theta & s\phi & c\phi c\theta \end{pmatrix} \tag{3.2}$$

where c and s are abbreviations of sine and cosine and θ , ϕ , and ψ are the roll, pitch, and yaw angles of the UAV's body, respectively. In order to achieve a rotated frame, the following relation between the world and body frames is established [102].

$$\begin{bmatrix} x_b \\ y_b \\ z_b \end{bmatrix} = R_{TB} \begin{bmatrix} x \\ y \\ z \end{bmatrix} \quad (3.3)$$

The Z-axis of the body frame, accompanied by its corresponding unit vector (Z_{Bu}), maintains orthogonality in relation to the UAV-integrated PV module, as demonstrated in Fig. 3.5. Since the tilt angle of the PV module denotes the deviation in degrees from the horizontal plane, this angle can be determined by measuring the degree between Z_{Bu} and the horizontal plane. In order to find the mentioned angle, first, the angle between Z_{Bu} and Z_u needs to be examined. Given that the UAV's position does not influence this angle, it can be established by treating the two frames as concentric. Fig. 3.5(a) and Fig. 3.5(b) depict the X-Y plane within both the body and world frames, along with the corresponding angles from two distinct viewpoints. Within these figures, α is the angle formed between Z_{Bu} and Z_u , μ indicates the angle formed by Z_{Bu} with the world frame X-Y plane, and Z_{Bu}' is the projection of Z_{Bu} on the world frame X-Y plane. To calculate the angle between Z_{Bu} and Z_u , the dot product formula and trigonometric functions can be utilized. Based on the earlier discourse concerning rotation matrices and their practical application, Z_{Bu} can be deduced in the fixed frame coordination by applying the rotation equations on Z_u . With Z_u and Z_{Bu} determined, α can be derived as follows:

$$\alpha = \cos^{-1} \left(\frac{z_B \cdot z_U}{|z_B| |z_U|} \right) \quad (3.4)$$

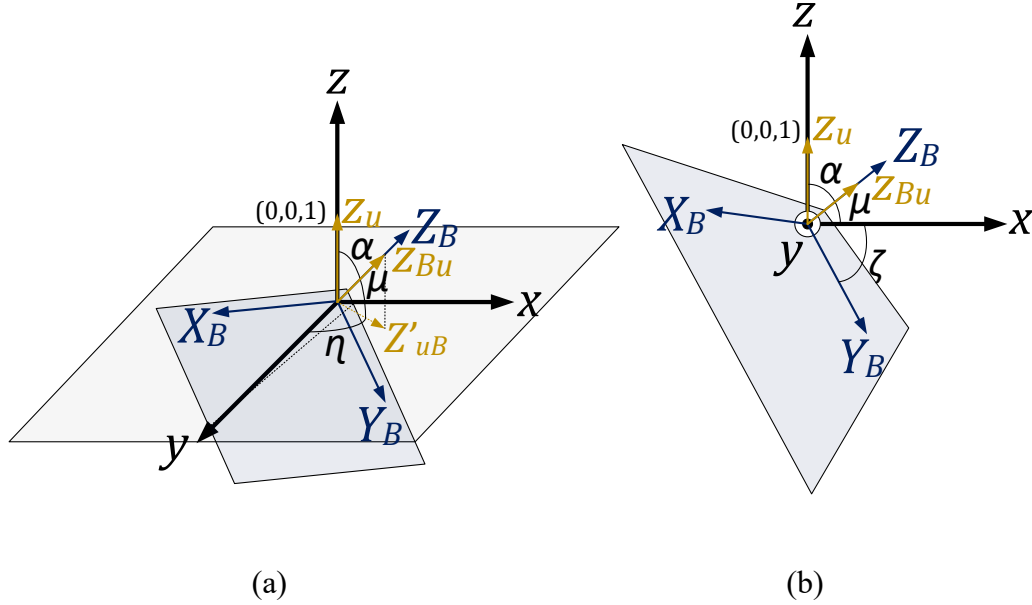


Figure 3.5. UAV body frame and world frame with their unity vector perpendicular to their XY plane and its angles with different axes from two different points of view.

Fig. 3.5 depicts that α and μ constitute a pair of complementary angles, and likewise, ζ and μ form a complementary pair. It is clear that ζ and α denote identical angles, and ζ is derived from the calculation of α . ζ signifies the angle at which the body frame's X - Y plane is formed with the world frame's X - Y plane, providing insight into the PV module's tilt angle. Additionally, the azimuth angle of the PV module, represented by η , can be determined by the angle formed between Z_{Bu} and the world frame's Y axis and calculated as follows:

$$\eta' = \tan^{-1}(y_{\vec{z}_b} / x_{\vec{z}_b}), \begin{cases} \eta = \eta' + 180^\circ & X_{Z'_{BU}} > 0 \\ \eta = \eta' & X_{Z'_{BU}} < 0 \end{cases} \quad (3.5)$$

where $y_{\vec{z}_b}$ and $x_{\vec{z}_b}$ are the X and Y coordination of Z_{Bu} in the world frame X-Y plane.

The angles and their related equations discussed in this section enable the inclusion of UAV movement around its various axes in the PV module equations that are used in the upcoming sections.

As mentioned before, the whole proposed methodology consists of steps including utilizing the PV module EDE, using optimization methods to extract the unknown parameters, and finally training computational intelligence-based models for predicting the performance of the UAV-integrated PV module for any potential placement of the PV module either in the non-ice cover or ice-covered conditions. In this section the concept of EDE is presented.

3.2.3. Module Empirical Derived Equations

Following the interpretation of UAV movement in terms of PV module angles in the preceding section, it is now possible to incorporate UAV movements into the analysis of its integrated PV module output power. In line with the power analysis, it becomes crucial to adaptively determine the diode ideality factor of the PV module in relation to each UAV movement. All of these concepts are elaborated upon in this section.

In most instances, existing literature primarily employs the analysis of PV modules based on the PV module equivalent circuit models, notably the single diode

model [14]. However, the EDE analysis utilized in this thesis is based on the empirical driven equations proposed by [103], which has been derived and validated empirically.

To find MPP voltage and current of the PV module the following equations are proposed [103].

$$I_m = (C_0 G_{eff} + C_1 G_{eff}^2)(I_{m,STC} + k_{Im}(T_c - T_{STC})) \quad (3.6)$$

$$V_m = V_{m,STC} + C_2 a V_t \ln(G_{eff}) + \frac{C_3 (a V_t \ln(G_{eff}))^2}{N_s} + K_{Vm}(T_c - T_{STC}) \quad (3.7)$$

$$P_{mpp} = V_{mpp} I_{mpp} \quad (3.8)$$

where a is the diode ideality factor, and the numerical parameters, including K_{Vm} , K_{Im} , and C_0 - C_3 , can be extracted from the manufacturers' datasheets or the modules' available databases. Besides, $V_t = N_s k T_c / q$ is the thermal voltage of the PV module as T_c is the P-N junction temperature in kelvin, $q = 1.60217646 \times 10^{-23}$ C is the charge of the electron, k is the Boltzmann constant, which is equal to $1.3806503 \times 10^{-23}$ J/K, and N_s is the number of solar cells connected in series. STC as subscript denotes the standard test condition. Moreover, G_{eff} is the effective irradiance ratio and is calculated based on the following equation [103]:

$$G_{eff} = f(AM)f(AOI)G_{sf} / G_{stc} \quad (3.9)$$

where K_{sf} accounts for factors related to module aging, G is the effective irradiance incident on the PV module surface, G_{stc} is the irradiance at the STC condition, and $f(AM)$ and $f(AOI)$ determine the impact of changes of the solar spectral distribution and

optical losses. In (3.9), three computable parameters must be determined in order to calculate the value of G_{eff} .

The available solar radiation (G) that a PV module can harvest that is known as plane of array (POA) irradiance, and is a combination of direct radiation that travels straight through the air to the PV module surface (G_{dir}), scattered sunlight caused by molecules and tiny particles in the air, which is known as diffused radiation (G_{dif}), and light that bounces off the ground or nearby surfaces and then reaches the PV surface, which is known as reflected radiation (G_{ref}). Since the current study is performed for the UAV application the latter component can be neglected. Therefore, the amount of available irradiance is derived by:

$$G = G_{dir} + G_{dif} \quad (3.10)$$

Direct beam radiation (G_{dir}) is given by [14]:

$$G_{dir} = DNI \times \cos(AOI) \quad (3.11)$$

where DNI refers to direct normal irradiance, and the angle of incident (AOI) is basically the angle between the direct sun ray and a line perpendicular to the surface of the PV module. It can be calculated as follows [104]:

$$AOI = \cos^{-1}(\cos\beta \cos(A - \varphi) \sin\theta_T + \sin\beta \cos\theta_T) \quad (3.12)$$

where β and A are the altitude and azimuth angles of sun, φ is the PV panel azimuth angle, and θ_T is the PV panel tilt angle. The altitude angle and azimuth angle of sun are shown in the Fig. 3.6 and are computed as [105]:

$$\beta = \sin^{-1}(\cos L \cos \delta \cos \omega + \sin L \sin \delta) \quad (3.13)$$

$$A = \sin^{-1}\left(\frac{\cos \delta \sin \omega}{\cos \beta}\right) \quad (3.14)$$

where L is the latitude of the flying UAV, $\omega = 15 \times (12 - ST)$ is the hour angle as ST is the solar time [13], and δ is the angle between the imaginary line passing through the center of the sun and the center of the earth, and the polar axis is changing over a year. As shown in Fig. 3.7, this angle changes between -23.45° in winter and $+23.45^\circ$ in summer and can be estimated by the following sinusoidal equation [105]:

$$\delta = 23.45 \sin \left[\frac{360}{365} (n - 81) \right] \quad (3.15)$$

where n represents the day number in a year.

The diffused radiation component of the solar irradiance can be calculated as follows [103]:

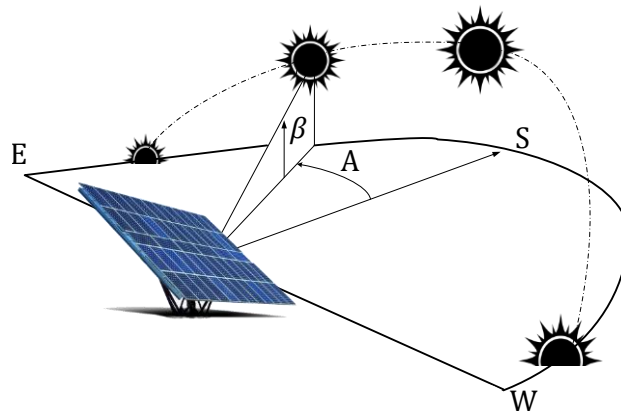


Figure 3.6. Sun's position changing during a day.

$$G_{dif} = DNI \times C \times \left[\frac{1 + \cos \theta_T}{2} \right] \quad (3.16)$$

where C is a sky diffuse factor and is calculated as:

$$C = 0.095 + 0.04 \sin \left[\frac{360}{365} (n - 100) \right] \quad (3.17)$$

The two other unknown parameters in (3.9) are $f(AM)$ and $f(AOI)$ are given by [103]:

$$f(AM) = a_0 + a_1(AM) + a_2(AM)^2 + a_3(AM)^3 + a_4(AM)^4 \quad (3.18)$$

$$f(AOI) = b_0 + b_1(AOI) + b_2(AOI)^2 + b_3(AOI)^3 + b_4(AOI)^4 + b_5(AOI)^5 \quad (3.19)$$

where a_0 - a_5 and b_0 - b_5 can be accessed through different module specifications which are prepared by the National Renewable Energy Laboratory (NREL) [46], and AM is the air mass, which is the amount of air within the atmosphere that the sun's rays pass to strike the PV panel. This is shown in Fig. 3.8 and it can be seen that its amount changes due to changing the position of earth to the sun. The amount of AM can be

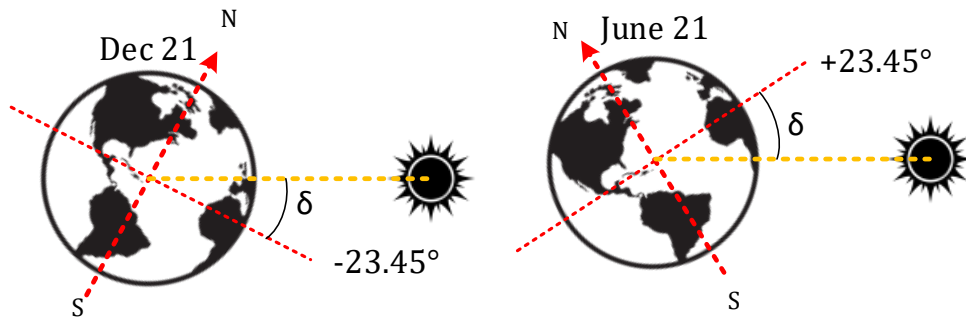


Figure 3.7. The position of the earth relative to the sun during the year.

calculated by:

$$AM = \sqrt{(r \cos \beta)^2 + 2r + 1} - r \cos \beta \quad (3.20)$$

where r is the ratio of the earth's radius to the thickness of the atmosphere and is approximately 708.

Incorporating the impact of UAV speed on the integrated PV module's performance involves calculating the module's temperature in relation to the UAV speed, and this calculation can be carried out as described in [106]:

$$T_c = T_{amb} + G \cdot e^{(d + b \cdot Speed)} \quad (3.21)$$

where $d = -3.58$ and $b = -0.113$ are the constants that depend on the module material and construction, T_{amb} is the ambient temperature, and $Speed$ is the UAV speed in m/s.

Another parameter that is still unknown in (3.7) is a , which is the ideality factor

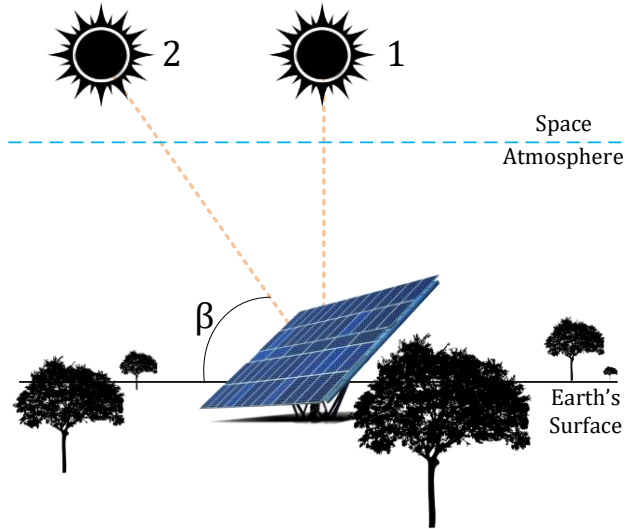


Figure 3.8. Change of sun's ray distance according to the elevation angle.

of the PV module diode. in general, the value of this parameter is between one and two and in numerous numbers of studies [107]-[110] is considered as a constant parameter. But in the real application the amount of ideality factor is changed in various module temperature and irradiance. Extracting this parameter for a specified condition of implementation is challenging enough and usually, is done by using the repetitive methods with considering the derivation of the calculated P_{mpp} and the measured P_{mpp} as its condition of convergence. In this work a new approach is used based on GWO to extract ideality factor of UAV integrated PV module.

3.2.4. Adaptive Computing PV Module Ideality Factor

As mentioned earlier following the interpretation of UAV movement in terms of PV module angles in the section 3.2.2, it is now possible to incorporate UAV movements into the analysis of its integrated PV module output power. In line with the power analysis, it becomes crucial to dynamically determine the diode ideality factor of the PV module in relation to each UAV movement. In this section, the GWO metaheuristic algorithm, as proposed in [111]-[113], is employed for this purpose. The parameters of the optimization algorithms used in this thesis were determined through trial and error to identify the most effective configuration. The fundamental concepts of GWO are presented in Appendix A1. The objective of the GWO is to minimize the disparity between the results of two sets of V_{mpp} equations by tuning the value of the PV module ideality factor (a). The first set was discussed in the section 3.2.3, while the second set is validated by [18] and is calculated as follows:

$$V_{Mo} = V_{M,STC} + V_T \ln\left(\frac{G}{G_{STC}} K_{sf}\right) + K_{Vm}(T_c - T_{STC}) \quad (3.22)$$

And the explained objective function can be formulated as follows:

$$OF = \sqrt{V_m^2 - V_{Mo}^2} \quad (3.23)$$

Throughout the optimization process, the ideality factor is constrained within the range of 1 to 1.25 [114]. The extracted ideality factors for different movement of UAV are illustrated in Fig. 3.9.

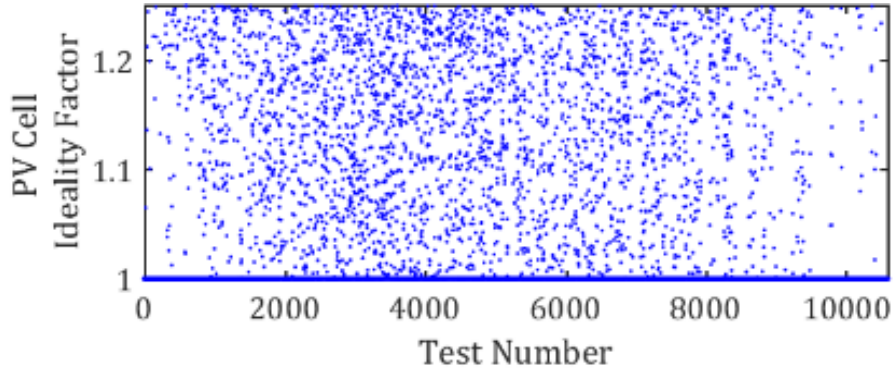


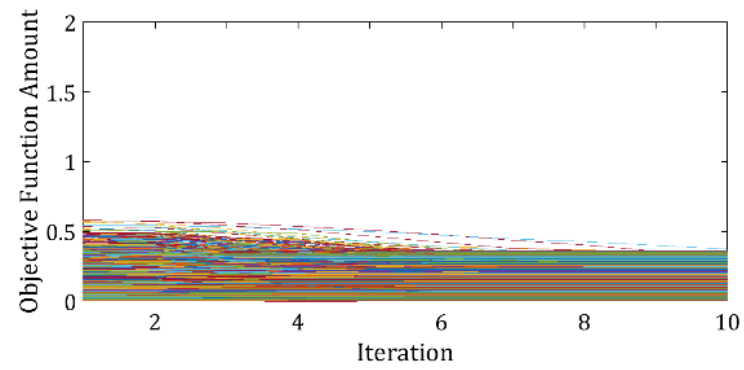
Figure 3.9. Diode ideality factor for various movement conditions.

To assess the performance of the GWO algorithm in extracting the depicted ideality factor and compare it with another metaheuristic algorithm, namely PSO, the convergence curves for 250 out of 10,656 curves are presented in Fig. 3.10. These curves reveal that in each execution of the GWO, the algorithm consistently reduces the value of the objective function by adjusting the parameter a . Moreover, one can notice that GWO converges to the objective function faster than the PSO. PSO yielded an average best score (convergence error) that was 3% higher than that of the GWO, demonstrating GWO's superior optimization performance. This demonstrates GWO's ability to achieve more precise parameter extraction.

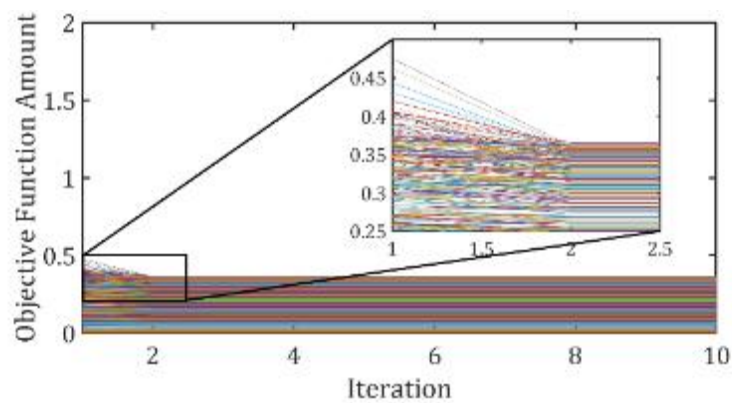
3.2.5. Computational Intelligence MPP Model

3.2.5.1. Input Dataset

The ML development related to the UAV-integrated PV module is carried out based on the historical environmental dataset of the Canadian Capital region which is accessible through the NREL website [46]. The dataset includes one-year data associated with the ambient temperature ($^{\circ}\text{C}$), DNI (W/m^2), and the time and date of data collection, which are time series datasets. Additionally, the height of the flight, the operational angles of the plane, and their operation speed are generated randomly in



(a)



(b)

Figure 3.10. Convergence curves of (a) PSO and (b) GWO algorithm.

acceptable ranges. Following the classifications provided by the North Atlantic Treaty Organization (NATO) and the National American Space Agency (NASA) as documented in [115] and [116], the maximum flight altitude for Class I aerial vehicles, characterized as small flying vehicles (weighing under 150 kg), is set at a threshold of 6000 meters. Additionally, the speed of the UAVs within Class I falls within the range encompassing their stall and top speeds, as defined by various models within this class according to [117]. This speed range is selected to be between 100 km/h and 200km/h.

Moreover, the pitch and roll angles, which are known as angle of attack and bank angle respectively, are considered -30 to 30 and between -30 to 30 respectively which is a reliable range [116]. Furthermore, the acceptable value of the yaw angle is considered between 0 and 360 degrees in order to cover the whole space of possible flight directions. The environmental temperature decreases by 6.5 °C for any 1000 m increase in the flying height [118] and consequently the temperature of the PV panel in the UAV's flight height is decreased.

3.2.5.2. Final Dataset Preparation

In order to achieve the final dataset, the whole process that is shown in Fig.3.1 has to be performed. It includes the concepts that are explained earlier in the previous sections. First of all, the flight and environmental datasets have to get processed with UAV movement to PV module operational angles interpreter, then they will get processed with the EDE and finally GWO is utilized to find out the PV module diode ideality factor for each datapoint. According to the explained procedure, important parameters of a UAV-integrated PV system, which are MPP properties are extracted for any available UAV movement and environmental condition. In this study, the MPP power is selected as the ML target feature. The aforementioned parameter is extracted

for the ET-M53695 commercial PV module. The resulting dataset, obtained after removing data points that lack logical or meaningful information using screening algorithms, includes instances when there is no irradiance or when the module placement results in absorbed irradiance falling below 100 W/m² (a threshold at which the module ceases power generation) [119], consists of 10,656 samples. This dataset includes various parameters such as temperature, day number in a year, time of day, irradiance, UAV flight altitude, UAV speed, roll angle, pitch angle, and yaw angle. This preprocessing step effectively reduces model complexity by eliminating a substantial number of data points where MPP control is not applicable. The scatter plots of the dataset features are shown in Fig. 3.11, except for the date and time.

3.2.5.3. Data Normalization

Data normalization is an important step in data preprocessing. The goal of data normalization is to scale all the parameters to a common range without distorting the data points' differences. The data is normalized between 0 and 1 according to the following equation [120]:

$$x_{norm} = \frac{x_{min} - x_i}{x_{min} - x_{max}} \quad (3.24)$$

where x_{norm} , x_{min} , x_{max} , and x_i are the normalized value of the sample, the minimum amount of observation in the dataset, the maximum amount in the dataset, and the current datapoint which is normalized respectively.

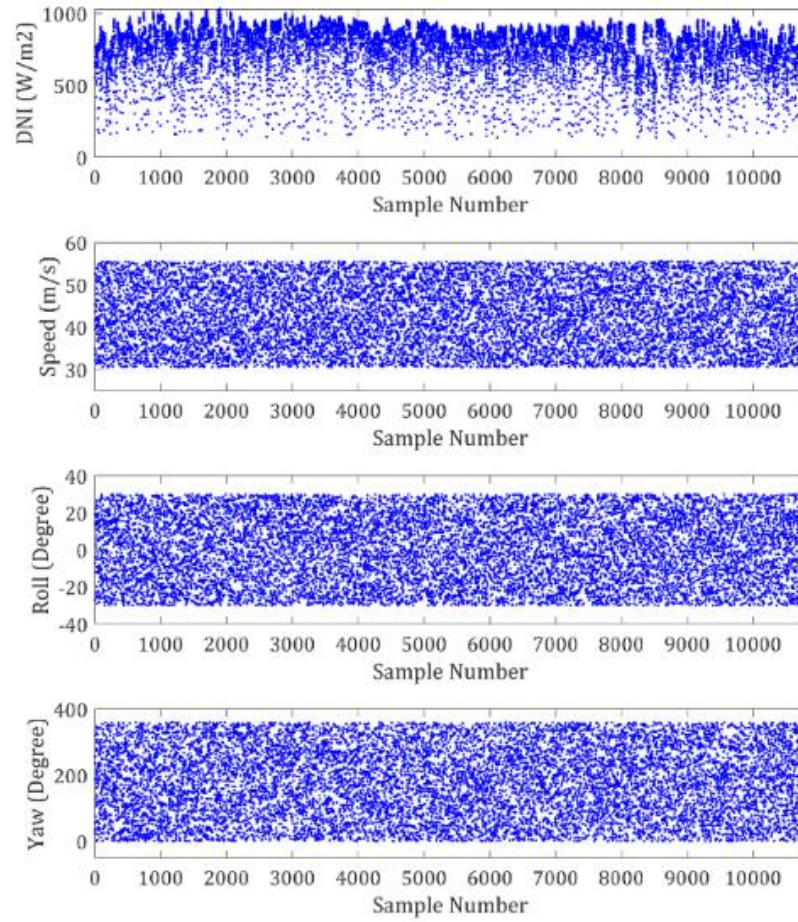


Figure 3.11. Utilized dataset for model training including input features and target feature (P_{mpp}).

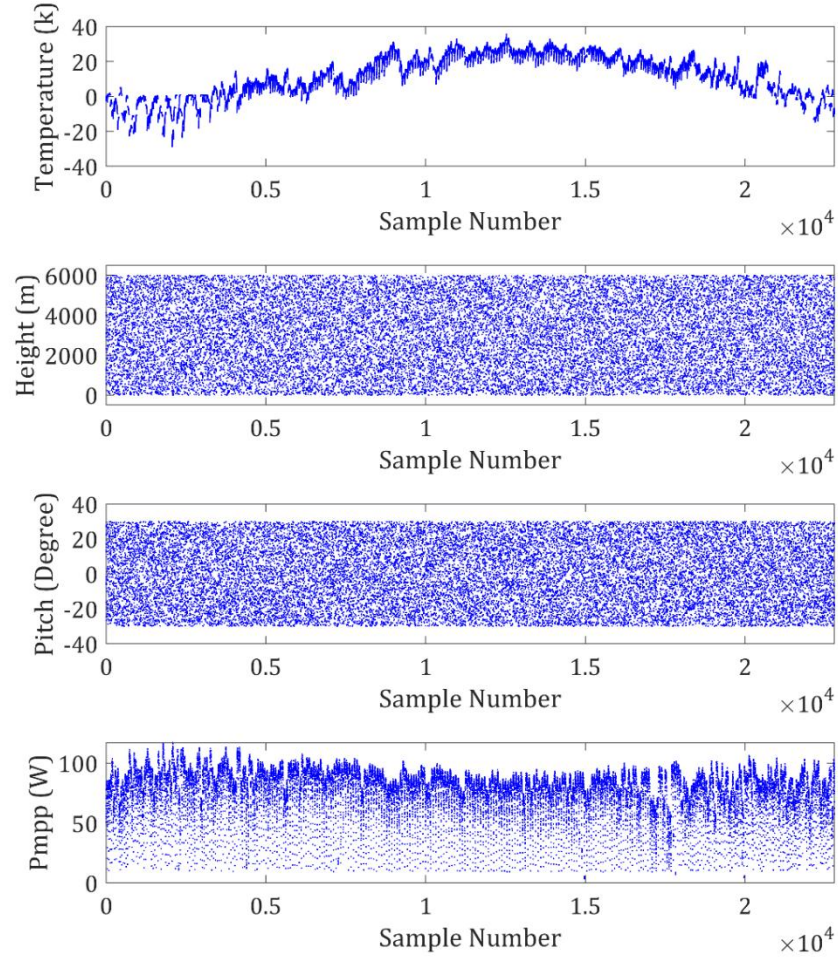


Figure 3.11 continued. Utilized dataset for model training including input features and target feature (P_{mpp}).

3.2.5.4. Maximum Power Point Prediction Models

In order to find the best possible ML model describing the system's MPP point performance in the most efficient way, various ML models are trained and evaluated for the previously mentioned PV module type. To perform validation on training a 10-fold cross validation is utilized, also, 20% is set aside as the test set. In total, twenty-three models using six different techniques, including Gaussian process regression (GPR), linear regression (LR), support vector machine (SVM), ensemble tree regression (ETR), and ANN, are trained and evaluated.

For stepwise linear regression, the maximum number of steps is set to 1000. The kernel scale for fine Gaussian SVM, medium Gaussian SVM and coarse Gaussian SVM is set to 0.75, 3, and wide neural networks, respectively. Moreover, the size of the first and second layers is set to 10 for both the bi-layered and tri-layered models, and the third layer size for the tri-layered model has been set to 10 as well.

3.2.5.5. Proposed MPP Model Computational Cost

All processes in this part of thesis were executed on a Dell Optiplex 9020 desktop equipped with an Intel Core i7-4790 CPU (3.6 GHz), Intel HD Graphics 4600, and 8 GB DDR3 RAM. The computational cost primarily lies in the training phase of the machine learning models and the optimization processes using GWO.

The training phase, which involves processing historical environmental and flight data, training ML models, and validating their performance, was performed on the same hardware and took approximately 1 hour.

3.3. Results

3.3.1. Machine Learning Models Performance

Various MISO machine learning algorithms are developed in order to find the best modeling algorithm for UAV-integrated PV modules. The values of test RMSE for each ML algorithm is presented in Table 3.1, which are shown in Fig. 3.12 for more clarification. As can be seen, the exponential Gaussian process regression (RQGPR) has the best performance among the other algorithms for the ET-M53695. This model can be applied in MPPT studies to guide the power converter toward the precise or

Table 3.1. ML Models RMSE Values

<i>Models</i>	<i>RMSE</i>
Gaussian Process Regression	
Rational Quadratic Gaussian Process Regression (RQGPR)	0.0062269
Squared Exponential Gaussian Process Regression (SEGPR)	0.0063406
Matern 5/2 Gaussian Process Regression (M5/2GPR)	0.0063058
Exponential Gaussian Process Regression (EGPR)	0.0066008
Linear Regression	
Linear Regression (LR)	0.012443
Interactions Linear (IL)	0.0070638
Robust Linear (RL)	0.012594
Stepwise Linear (SL)	0.0070628
Support Vector Machine Regression	
Linear SVM (LSVM)	0.01307
Quadratic SVM (QSVM)	0.01217
Cubic SVM (CSVM)	0.012598
Fine Gaussian SVM (FGSVM)	0.13121
Medium Gaussian SVM (MGSVM)	0.016856
Coarse Gaussian SVM (CGSVM)	0.012984
Kernel Regression	
SVM Kernel (SVMK)	0.016021
Least Squares Regression Kernel (LSRK)	0.021152
Ensemble Trees Regression	
Boosted Trees (BoT)	0.02659
Bagged Trees (BaT)	0.018657
Artificial Neural Network Regression	
Narrow Neural Network (NNN)	0.007114
Medium Neural Network (MNN)	0.007114
Wide Neural Network (WNN)	0.0066237
Bi-layered Neural Network (BNN)	0.0072531
Tri-layered Neural Network (TNN)	0.00723

nearly exact MPP. Consequently, this approach diminishes the response time of the converter in tracking the MPP point.

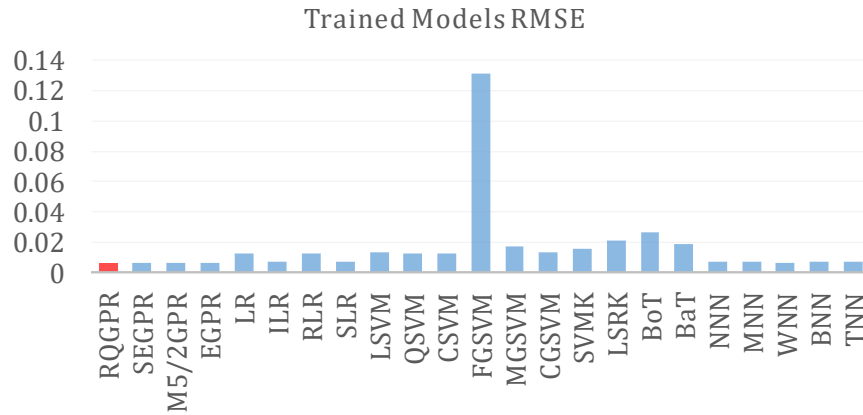


Figure. 3.12. RMSE for different trained models.

To evaluate the training procedure, a scatter plot comparing the actual and predicted data is presented in Fig. 3.13. This figure illustrates the proximity of the predicted data to the actual data points. To further emphasize this closeness, the associated errors of the predicted data points in comparison to the actual data is depicted in Fig. 3.14. (a). In this figure, the red lines represent the distances (i.e., errors) between the actual and predicted values. These lines are notably short for the majority of observations, often appearing as single dots due to the minimal disparities between

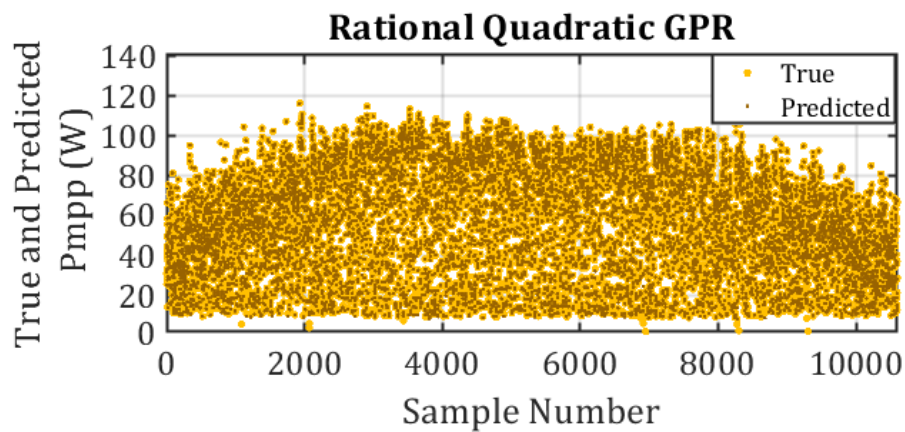
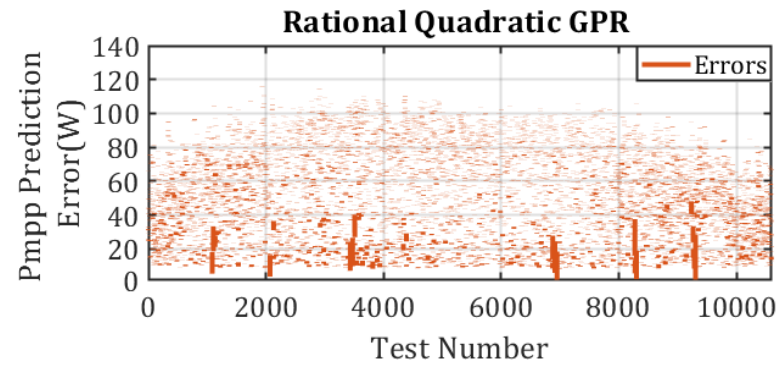
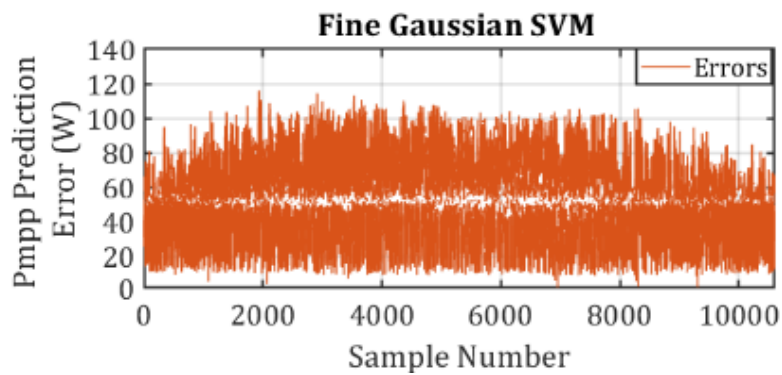


Figure 3.13. Predicted and actual datapoints of RQGPR model.

the actual and predicted values. This behavior confirms the model's high accuracy in predicting the UAV-integrated PV module's MPP. Conversely, Fig. 3.14.(b) shows the unacceptable performance of the fine Gaussian support vector machine (FGSVM) by featuring longer lines, indicative of higher error values, between the actual and predicted data. This behavior underscores the limitations of the FGSVM model in accurately predicting the UAV-integrated PV module's MPP properties. In contrary, Fig. 3.14(b) proves the poor performance of the FGSVM due to existence of extended



(a)



(b)

Figure 3.14. Error between actual and predicted datapoints for the best and worst performing trained models. (a) RQGPR, and (b) FGSVM.

lines, revealing a significant amount of error between the actual and predicted data.

3.3.2. Experimental Tests

To validate the effectiveness of the proposed model, a mobile structure capable of rotational movement along various axes, simulating the motion of the PV module when mounted on a UAV is prepared. This experimental setup, shown in Fig. 3.15, mainly consists of the ET-M 53695 PV panel, IV-400 PV analyzer, temperature and irradiance sensors, and a laptop for data collection from the analyzer. The PV panel analyzer extracts PV module characteristics under varying temperature and irradiance conditions. Total of 38 distinct experimental tests to determine the MPP of the ET-M53695 module are conducted. The resulting P-V curves from these tests are presented in Fig. 3.16. The power outputs at the MPP obtained from the experimental tests are



Figure 3.15. Experimental setup including ET-M53695 moving PV module, I-V 400 PV analyzer, irradiance and temperature sensors.

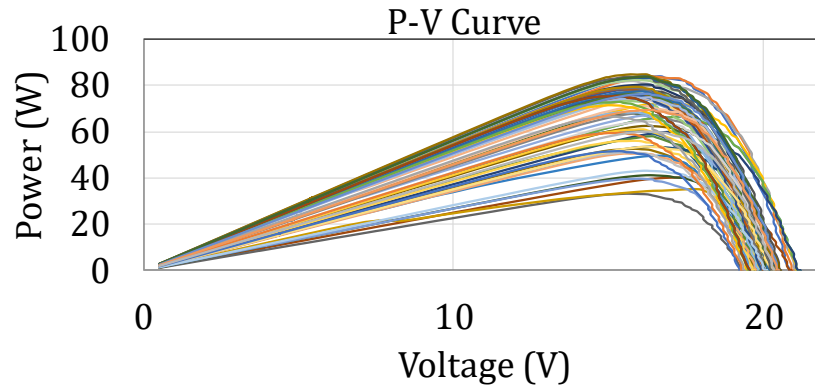


Figure 3.16. Experimental results of PV curves for different placement condition of Et-M53695 PV panel.

compared to the predictions of the trained RQGPR model under the same conditions. This comparison is illustrated in Fig. 3.17. In the majority of test cases, the experimental MPP closely aligns with or precisely matches the predictions of the computational intelligence model. This outcome serves as strong evidence of the computational intelligence model's effectiveness in identifying the MPP under various PV module conditions.

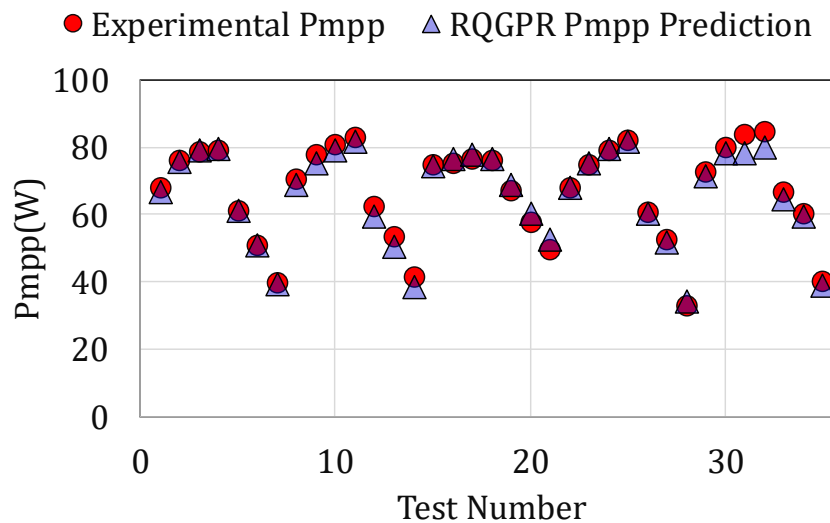


Figure 3.17. Experimental tests and trained model P_{mpp} .

3.3.3. Hardware Tests

To demonstrate an application of the proposed ML model, capable of predicting the MPP power, a hardware test was conducted. In this test, the movement of the UAV was simulated by varying the irradiance level on the TerraSAS PV simulator equipment. The diagram depicted in Fig. 3.18 illustrates the connection setup and hardware configuration. As shown in the figure, the UAV movement is translated into the irradiance level hitting the UAV-integrated PV panel using concepts introduced in previous sections. The PV simulator can be controlled by two input analog signals, with the appropriate signal associated with the interpreted irradiance level generated by dSpace. A designed interface circuit adjusts the generated analog signals to ensure they fall within the acceptable range of the PV simulator. This circuit not only regulates the analog signal level but also safeguards the signal from overvoltage to prevent any

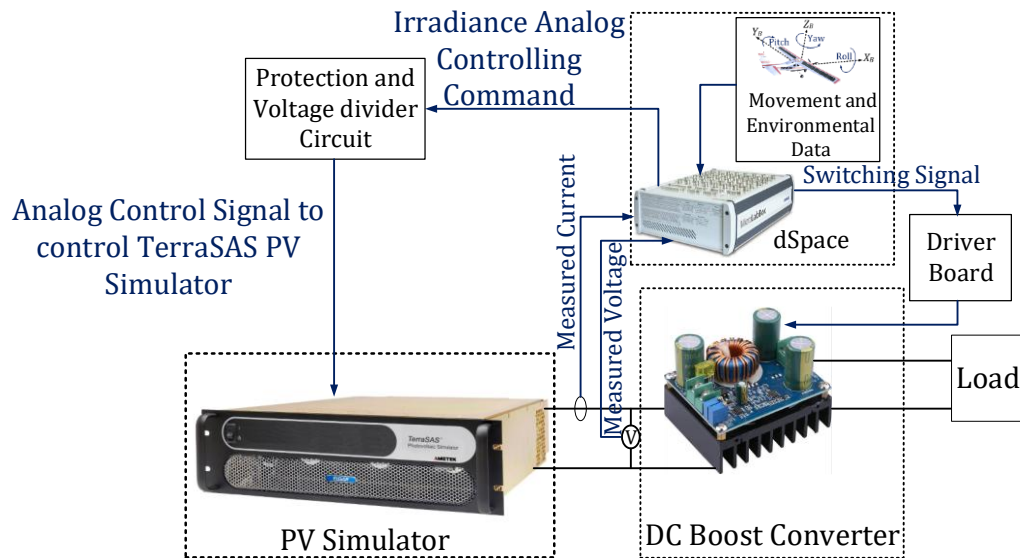


Figure 3.18. Connection between components of the hardware set up.

potential damage to the PV simulator input. By controlling the PV simulator and having access to the irradiance level and UAV movement parameters, essential for predicting the MPP level using the ML model, the experimental setup depicted in Fig. 3.19 was implemented.

The proposed MPPT method utilizes a combination of computational and conventional control methods. Initially, the MPPT controller's operational point is brought close to the MPP using the predicted MPP obtained from the ML model. Subsequently, a conventional MPPT control method manages the converter at the MPP operational point. This approach is based on the understanding that computational methods inherently contain errors and might not precisely predict the exact MPP, as discussed earlier. The control block diagram of the AI-based method is illustrated in Fig. 3.20. Following every change in irradiance, which simulates varying conditions during UAV flight, the MPPT AI method governs the MPPT converter for the initial

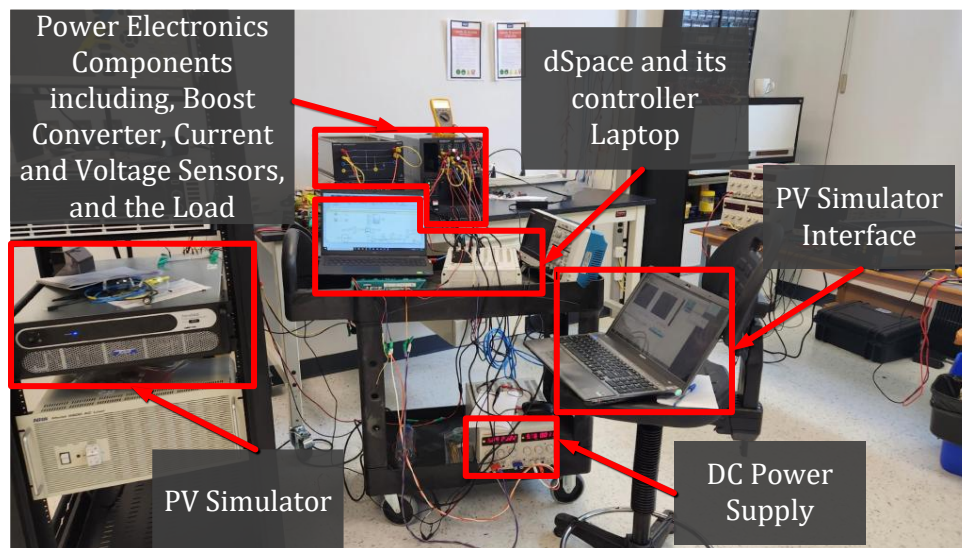


Figure 3.19. Experimental Setup.

set of processor unit sampling cycles after change in irradiance. This duration can be determined by observing the settling time of the waveform in the conventional method after any system change. This settling time indicates how long the conventional method takes to locate the MPP. This method ensures that the converter is controlled near the MPP. Subsequently, after several cycles, the control mechanism transitions to another method, such as IC, to precisely reach the MPP. The AI MPPT method diagram is depicted in Fig. 3.21.

The proposed hybrid method was implemented on the aforementioned hardware setup. This implementation showcases two key aspects: firstly, the capability of the hybrid method to regulate the PV module at its MPP, and secondly, its ability to enhance system control during significant changes in irradiance gradient. The power waveform that is shown in Fig. 3.21 confirms the mentioned facts. In order to have a

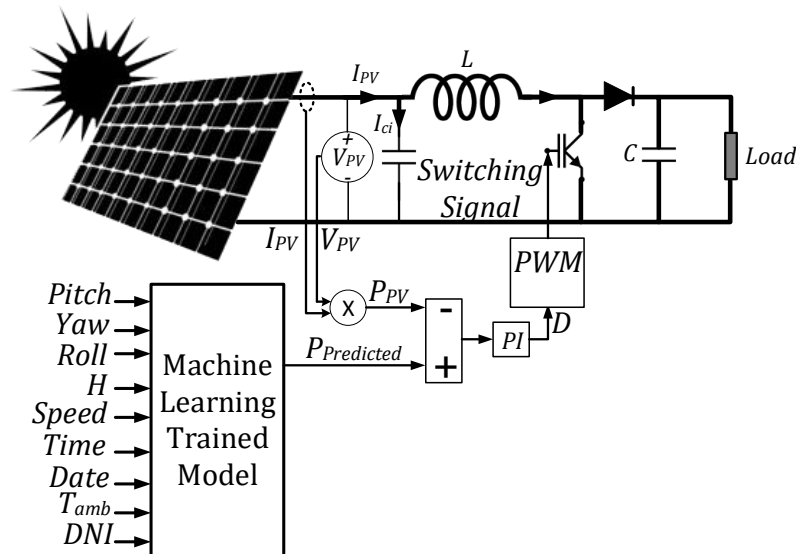


Figure 3.20. AI MPPT controller block diagram.

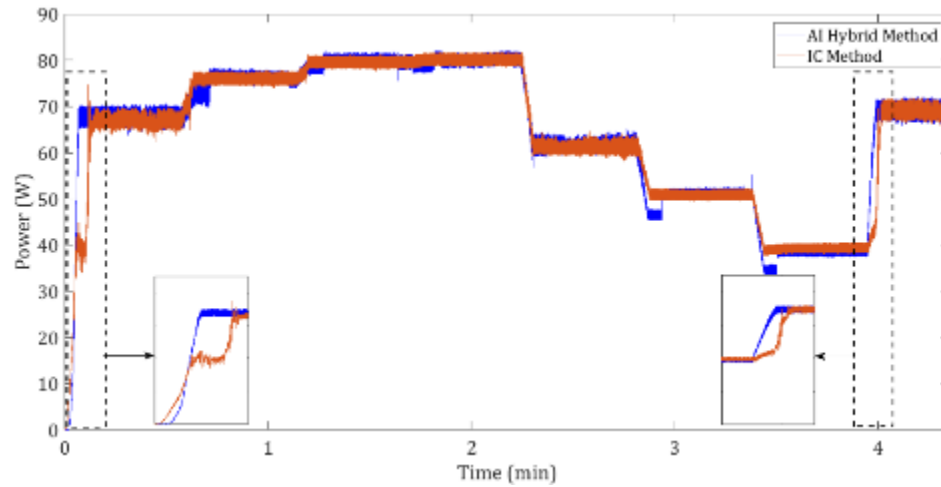


Figure 3.21. Waveform of controlled power on MPP with the hybrid MPPT and IC methods.

better understanding of the capabilities of the proposed method, Table 3.2 compares the proposed method properties and the ones of conventional methods. In terms of the speed of MPPT detection, the proposed hybrid method leverages ML models, allowing for near-instantaneous prediction, commonly referred to as the inference time of the trained model. In contrast, conventional algorithms typically operate on the scale of tens of milliseconds, which is relatively slow compared to the rapid inference time offered by ML-based predictions. To further clarify the presented table, the terms “moderate” and “simple” refer to the implementation complexity of the methods on a microcontroller. Conventional methods are straightforward to implement through basic coding, whereas the proposed method requires a more complex implementation.

Table 3.2. Comparison between the proposed and conventional methods.

<i>MPPT Prediction</i>				
	Finding MPPT speed for each instant change	Accuracy of the MPPT for each instant change	Ability of tracking MPPT after each instant change	Implementation complexity
<i>Proposed Method</i>	Immediate	Good	Excellent	Moderate
<i>Conventional methods</i>	Slow	Good	Poor	Simple

3.4. Conclusion

This chapter aims to provide a novel perspective to consider the dynamics of a moving panel, particularly in the context of a UAV application. First, an explanation of the angular parameters of the PV panel's equations in terms of the UAV-integrated PV module movement has been presented. Then, the empirical derived equations of the PV module, along with a novel solution based on the GWO, are introduced to adaptively determine the ideality factor of the PV module diode. A meteorological historical dataset related to the Canadian capital region together with a randomly generated UAV movement dataset have been processed through empirical derived equations alongside GWO in order to prepare the desired dataset for implementing the proposed analysis. According to the rapid changes in the UAV's location brought on by its unpredictable and fast mobility, there is a complex relationship between the UAV-integrated PV module MPP and the other input features in the obtained dataset. Considering the capability of the ML techniques, this limitation is expected to be handled by developing ML-based MPP prediction models. Consequently, twenty-three ML models are developed for a commercial PV panel, ET-M53695, and the optimal model representing the UAV-integrated PV modules' MPP conditions is extracted. A 10-fold cross-validation method is used for model validation, and 20% of the dataset was set aside for the model testing process. Among various ML-trained models, RQGPR exhibits the best performance with an RMSE value of 0.006. To validate the

proposed approach, a series of experimental tests are conducted on a PV module using an IV-400 photovoltaic analyzer, attached to a mobile mechanism capable of simulating UAV movements by rotating around its Yaw, Pitch, and Roll axes. Furthermore, a hardware setup is utilized to demonstrate the feasibility of implementing the proposed method for tracking MPP. This method combines an AI-based MPPT technique with a traditional MPPT method using IC, resulting in improved performance in tracking the MPP during rapid irradiance changes. This research strategy serves as an inspiration for future investigations concerning the integration of PV modules as primary or secondary energy sources in various vehicles, particularly UAVs. Moreover, this research achievements hold applicability beyond UAVs, offering valuable insights for any moving PV panel application.

4. Computational Intelligence-based Parameter Extraction of UAV-Integrated Photovoltaic System

4.1. Introduction

The precise modeling of UAV-integrated PV systems is central for their implementation on UAVs, especially due to their continuous movement. Accurate modeling is essential for developing control methods, conducting performance studies, and designing the whole system considering PV system parameters. This original study presents a novel modeling procedure for comprehensive modeling of UAV-integrated PV modules using MIMO and MISO machine learning models. These models are developed based on a historical environmental dataset and a randomly generated dataset representing flight conditions. Both datasets get processed during the preparation phase. In this phase, two sets of EDEs of the PV module are utilized. In addition, the WOA is employed to optimize one set of EDE containing PV system five unknown parameters. Moreover, the DTRA is used as an unconstrained problem solver in each loop of WOA to solve a system of equations consisting of the unknown parameters. Finally, the MIMO and MISO models will be trained with the processed dataset. The proposed approach in this chapter predicts UAV-integrated PV module behavior under diverse flight conditions, interprets panel movements, and is validated through experiments.

4.2. Methodology

4.2.1. Proposed Method Block Diagram

The proposed method employs a combination of analytical, metaheuristic, computational intelligence, and nonlinear optimization methods to extract the parameters of the PV module under any possible placement and environmental conditions of the UAV-integrated PV system.

First, historical meteorological data (including DNI), ambient temperature, and the date and time of the flight), combined with interpreted UAV flight data (including UAV air speed, flight height, and operational angles) using the method proposed in the section 3.2.2, is processed through a set of EDE. This analysis extracts a dataset pertaining to each placement of PV module, comprising its MPP voltage and current. Subsequently, these extracted MPP voltage and current values are integrated into the objective function of the WOA optimization algorithm and contrasted with data from the secondary set of EDE. This process allows the WOA to iteratively determine the unknown parameters, ultimately converging toward the optimal objective function.

The second set of equations includes an equation for voltage and one for current of MPP, which must be solved simultaneously to determine the unknown parameters. The simultaneous solving of these equations is performed by the DTRA due to its fast and accurate performance. This technique is run in every iteration of the WOA algorithm to solve two empirical PV module MPP equations simultaneously, aiming to find the MPP voltage and current while its unknown parameters are defined by WOA. The found MPP voltage and current are compared with another set of empirically precalculated MPP characteristics in the WOA algorithm objective function to detect

the best possible set of unknown parameters. The output of this process is a dataset of five unknown parameters of the PV module for data points within the input dataset, which consists of the historical meteorological data and the UAV movement data. This dataset serves as the target dataset for the computational intelligence model. The mentioned target dataset alongside the historical and UAV movement dataset are used to train the MIMO and MISO models after data normalization. The trained models are capable of predicting the parameters of the UAV-integrated PV module for any flight and environmental conditions. The block diagram in Fig. 4.1 demonstrates the entire concept of this work, including the aforementioned explanations. According to the presented procedure, the entire method consists of using the rotational matrices concept to interpret the UAV movement as the PV system's placement angles, the first empirical set of equations to derive the MPP properties of the PV system based on the meteorological conditions and placement of the PV module, the second set of equations to derive MPP properties based on the set of unknown PV module parameters, the WOA to compare two sets of empirical equations to extract the five unknown parameters of the PV module, and the DTRA to solve the current and voltage equations, simultaneously. Further details on these processes will be explained in the following sections.

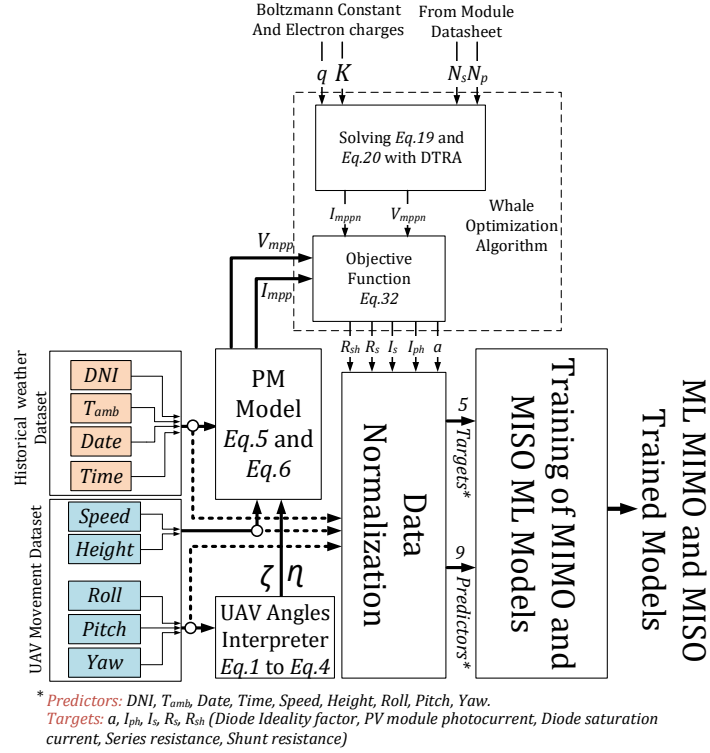


Figure 4.1. Block diagram of the proposed method.

4.2.2. Computing Five Unknown Parameters of UAV- integrated PV Module

In order to create a precise target dataset to train ML models, the five unknown parameters have to be computed first for a limited amount of datapoints (the available dataset). The procedure of computing the unknown parameters is discussed in the following sections.

4.2.2.1. Second Group of PV Module Empirical Derived Equations

As mentioned before, the first step of the whole proposed methodology consists in utilizing the PV module EDE. The first set of EDE is introduced and used in section

3.2.3. Another set of equations is proposed and empirically validated, which includes all unknown parameters of the single diode equivalent circuit model [121]. This model is developed to find out the voltage and current of MPP as follows [121]:

$$I_{mpp} = N_p I_{ph} - N_p I_s \left[\exp \left(\frac{q \left(V_{mpp} + I_{mpp} \frac{N_s}{N_p} R_s \right)}{N_s a k T_c} \right) - 1 \right] - \frac{V_{mpp} + I_{mpp} \frac{N_s}{N_p} R_s}{\frac{N_s}{N_p} R_p} \quad (4.1)$$

$$\frac{I_{mpp}}{V_{mpp}} = \frac{\frac{q N_p I_s}{N_s a k T_c} \exp \left(\frac{q \left(V_{mpp} + I_{mpp} \frac{N_s}{N_p} R_s \right)}{N_s a k T_c} \right) + \frac{1}{\frac{N_s}{N_p} R_p}}{1 + \frac{q I_s R_s}{a k T_c} \exp \left(\frac{q \left(V_{mpp} + I_{mpp} \frac{N_s}{N_p} R_s \right)}{N_s a k T_c} \right) + \frac{R_s}{R_p}} \quad (4.2)$$

where N_s and N_p are the number of cells in series and parallel connections, I_s is the PV cell diode reverse current, I_{ph} is the

4.2.2.2. Solving the Nonlinear System of Second Set of EDE by Trust Region Algorithm

In order to solve the two PV module EDEs simultaneously and utilize the results in the optimization algorithm process, a nonlinear solution should be performed. Some problems involve determining the maximum or minimum of a differentiable function of several variables over a set. These kinds of problems, known as unconstrained problems, can be solved by two types of methods, including inline search and Trust region. In inline search methods, the algorithms try to reach the answer by changing the value of the variable in a specified step size in an appropriate direction (such as Newton's method, gradient descent, quasi-newton, etc.).

Trust region approaches are a group of methods that attempt to decompose multidimensional functions into a series of smaller and easier tasks and a sequence of approximation steps [122].

In trust region approaches, achieving the next value of a variable involves considering a trustable model (m_k) within a trust region around the current value (x_k). This method aims to find a minimizer of m_k within a certain region around x_k . It simultaneously determines the direction and length of the variable step. If a step is deemed unacceptable, the algorithm reduces the size of the trust region to address the issue. The model function mentioned, which must be solved at every step of the trust region, can be represented as follows [123]:

$$m_k(x_k + p) = f_k(x_k) + g_k^T p + \frac{1}{2} p^T B_k p \quad (4.3)$$

$$f_k = f(x_k) \text{ and } g_k = \nabla f(x_k)$$

where p is the vector with the starting point x_k , used to minimize the model in the trust region, g_k^T is the gradient transpose of the $f(x_k)$, and B_k is a variable that can take different values according to the defined problem, including a constant, Hessian matrix of f at x_k , or a symmetric approximation to $\nabla_{xx} f(x_k)$ [123][124]. The problem that has to be solved in each step of the trust region algorithm is minimizing the model mentioned in (4.3), which is shown as follows [125]:

$$\min_{p \in R^n} m_k(x_k + p) = f_{xk} + g_k^T p + \frac{1}{2} p^T B_k p, \|p\| \leq \Delta_k \quad (4.4)$$

where Δ_k is trust region radius. Two main concepts should be clear in the trust region problem, namely the determination of the trust region radius and solving (4.4), which is the sub-optimization problem. The trust region radius is chosen according to the agreement between the model function m_k and the objective function f at previous iterations. To find out the amount of this conformity, an index could be determined as follows [124]:

$$\rho_k = \frac{f(x_k) - f(x_k + p_k)}{m_k(0) - m_k(p_k)} \quad (4.5)$$

The numerator of equation (4.5) determines the extent of reduction in the objective function across two consecutive executions of the algorithm, while the denominator represents the reduction in the model amount across two successive executions. In fact, the numerator and denominator of equation (4.5) signify the actual reduction and the predicted reduction of the trust region problem. When ρ_k is very close to zero or a negative value, the trust region radius should be decreased to enhance the consistency between the model and the function. A value of ρ_k close to 1 shows that the amounts of change in the model and function are similar, allowing for an increase in the trust region radius for the next iterations. Finally, for situations where ρ_k is positive not very close to 0 or 1, there is no need to adjust the trust region radius.

Because of the lack of a plausible solution to the subproblem presented by (4.4), the first thing that comes to mind is searching all over the trust zone for a real minimizer of the model function, but it is also possible to use an approximate minimizer. The Dogleg method is an approach introduced to be used as a reliable approximate minimizer [125]. This method works by minimizing the model function along a certain

path stretching from the origin to the boundary of the trust region and this path consists of a two-line segment. This path is piecewise linear and has the shape of a dog's leg, which explains the method's name [123].

The Dogleg method finds an approximate solution by replacing the curved trajectory for $p(\Delta)$ with a path consisting of two-line segments. The first line segment runs from the origin to the minimizer of m along the steepest descent direction [122], while the second line segment runs from p^U to p^B , which is shown in Fig. 4.2. Formally, we denote this trajectory by $p(\tau)$ for $\tau \in [0, 2]$. The Dogleg method finds the value of p that minimizes the model m along this path, subject to the trust-region bound. Three different situations can happen during the Dogleg minimizer calculation. According to the condition of the path and the trust region boundary, the trust region minimizer could be either the endpoint of the path or the intersection point of the path and trust region boundary. Three different situations can happen, including lying the trust region

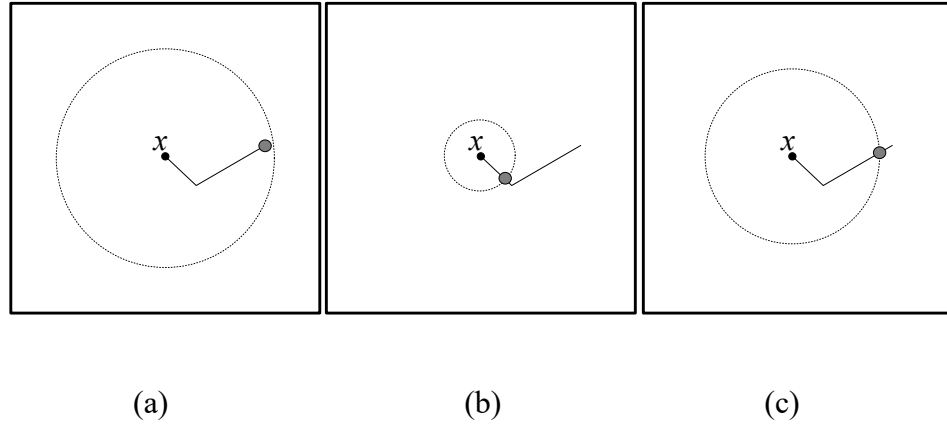


Figure 4.2. Location of dogleg path. (a) Dogleg path is completely within the trust region. (b) Intersection is occurred in the first leg of dogleg path. (c) Intersection is occurred in the second leg of dogleg path [123].

minimizer within the trust region, on the first line segment of the path, and on the second line segment of the path. These conditions are shown in Fig. 4.2.

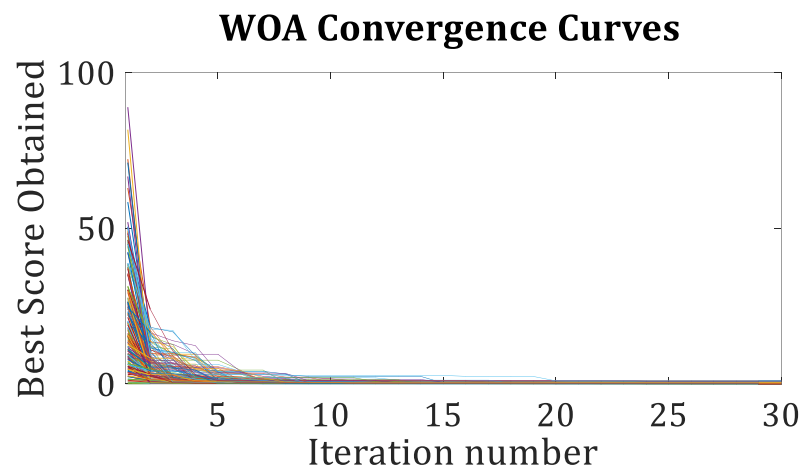
4.2.2.3. WOA to Extract the Unknown Parameters of the Integrated PV Module Independently

As mentioned in the previous section, the WOA, as discussed and proposed in [126]-[129], is utilized in this part of the research to identify the unknown parameters of the UAV-integrated PV module. This is achieved by employing two modified equations of the PV system, which are solved using the DTRA. The concept of this algorithm is discussed in detail in Appendix A2. The exploration of WOA for the unknown parameters is done according to an objective function, including the MPP properties of the moving module. The objective function that has been used to find out the moving PV system parameters is defined as follows:

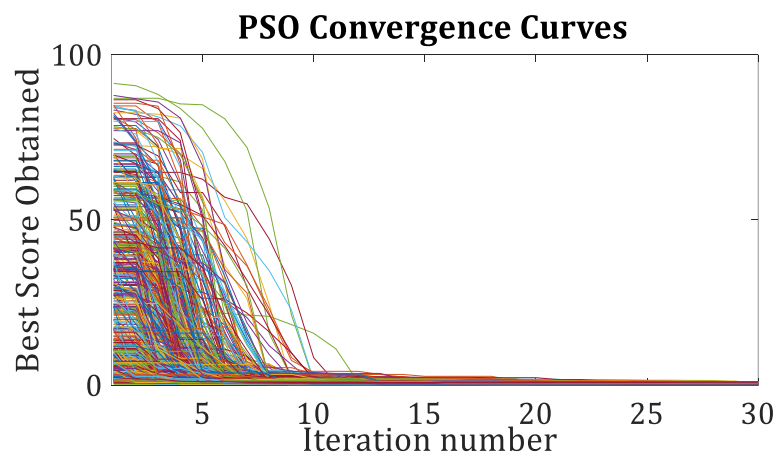
$$OF = \sqrt{\left|P_{mpp} - P_m\right|^2 + \left|I_{mpp} - I_m\right|^2 + \left|V_{mpp} - V_m\right|^2} \quad (4.6)$$

In this objective function, P_{mpp} , V_{mpp} , and I_{mpp} are calculated by (3.6) and (3.7). Moreover, P_m , V_m , and I_m are calculated by (4.1) and (4.2). This objective function aims to minimize the difference in MPP power, voltage, and current values of two sets of EDE by optimizing the values of five PV module's unknown parameters. Considering the amount of MPP power, which is the multiplication of MPP voltage and current, assists WOA in focusing its search efforts in a more targeted area while considering the effect of MPP voltage and current and their combination effect enhances the exploration process.

The convergence curve of the WOA for the objective function in (4.6) is shown in Fig. 4.3(a). According to the descent trend of the colored curves and converging of them to the amounts close to zero, it is obvious that the WOA can successfully optimize its objective function and reach the best values for the system parameters. To achieve



(a)



(b)

Figure 4.3. The best scores obtained by the (a) WOA, and (b) PSO method for randomly chosen datapoints.

a clearer illustration, only 150 curves out of the 10680 convergence curves are shown in this figure.

In order to approve the effectiveness of WOA compared to other optimization methods, an additional experiment is performed to compare the WOA with PSO, which is the most prominent optimization algorithm. The average best score obtained by PSO (the convergence error) was 2.36 times higher than that of WOA, indicating that WOA achieved better optimization results. This performance difference is attributed to WOA's ability to balance exploration and exploitation more effectively, leading to more accurate parameter extraction. Moreover, Fig. 4.3(a) confirms that WOA converges faster compared to PSO.

4.2.3. Machine Learning Models

4.2.3.1. Input Dataset Preprocessing

The dataset used in this research consists of two main components as mentioned in section 3.2.5.1: a historical environmental dataset from the Canadian Capital Region, and a randomly generated UAV flight properties dataset. Each parameter in the UAV flight dataset falls within acceptable and applicable ranges according to the references [115]-[118]. The meteorological dataset comprises one-year data associated with ambient temperature ($^{\circ}\text{C}$), DNI (W/m^2), and the time of data collection throughout the day. The parameters of the input datasets are depicted in Fig. 4.4. Fig. 4.5 illustrates the distribution of the dataset, providing insights into the spread and concentration of data points across different ranges, while the target dataset is shown in Fig. 4.6.

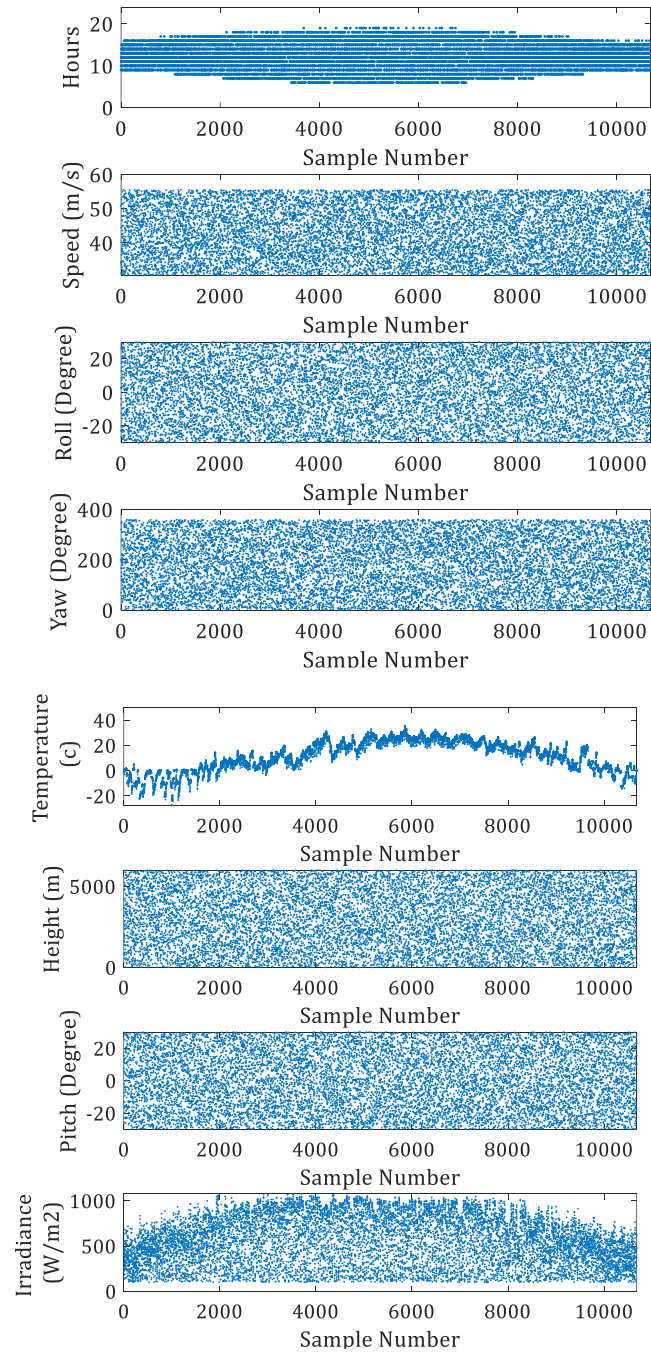


Figure 4.4. Predictors dataset

It also should be noted that processed data are normalized based on the concept

mentioned in section 3.2.5.3.

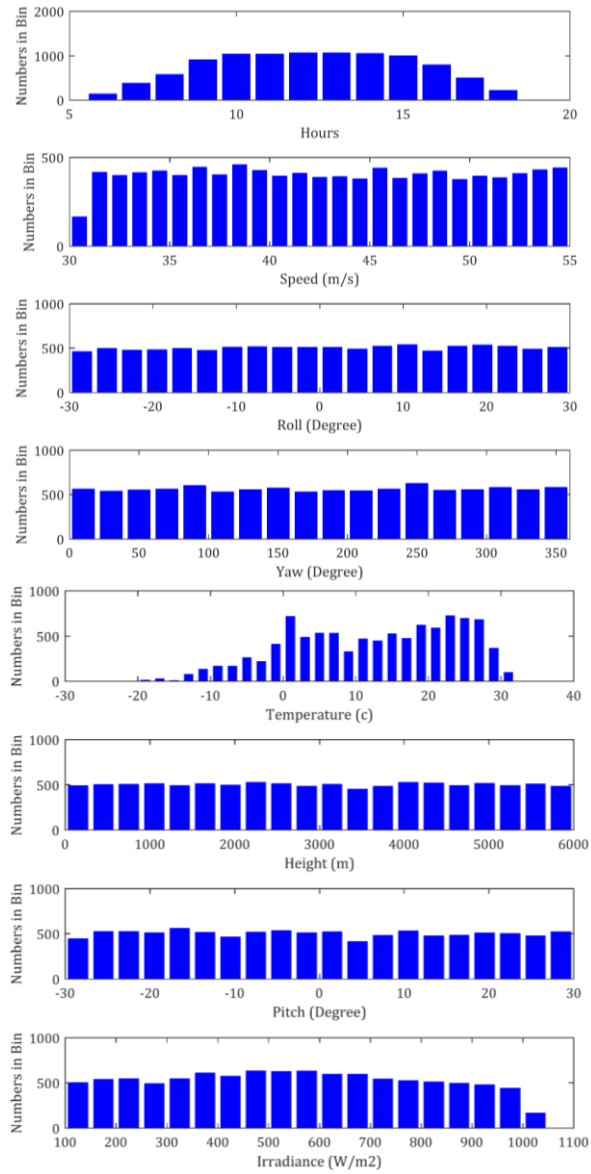


Figure 4.5. Distribution of predictor dataset features.

4.2.3.2. Trained Models

Due to the complexity of the problem of this chapter and to achieve optimal results, two different approaches are utilized for model training. This helps gain a better

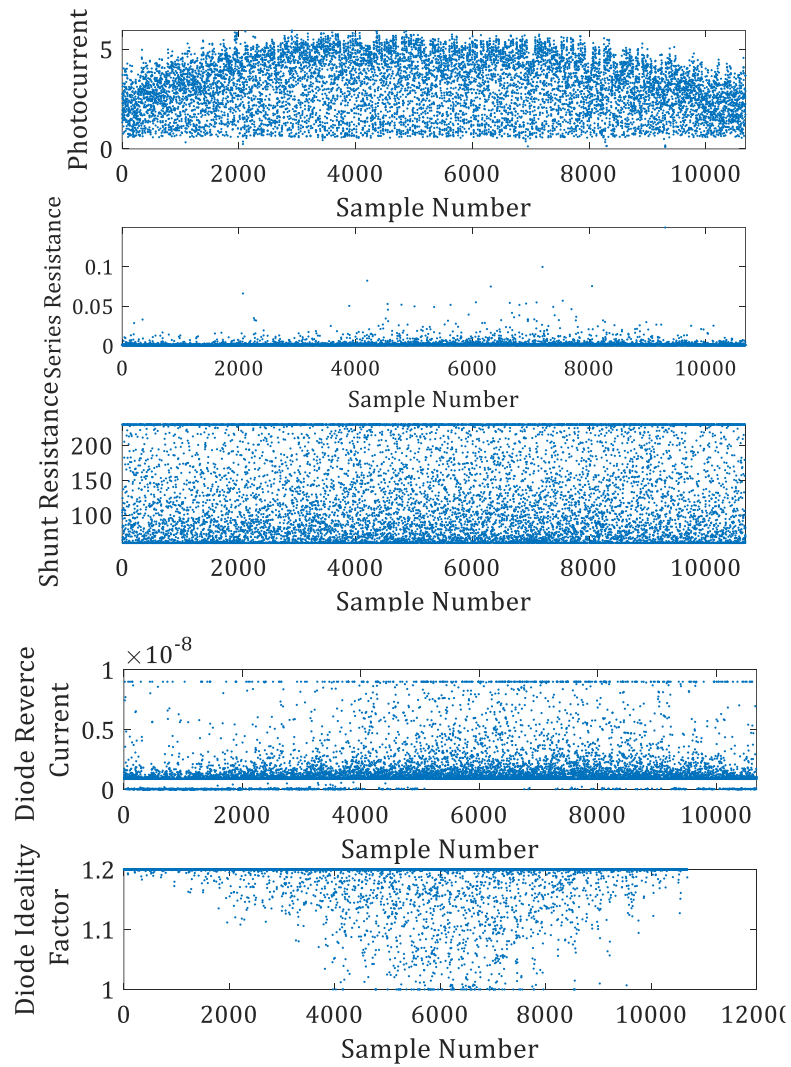


Figure 4.6. Processed target dataset.

understanding of which model type is more suitable for the current problem in terms of predictive performance and generalization to unseen data. First, a MIMO is trained based on nine predictors and five targets shown in Fig.4.4 and Fig.4.6. In the second approach, various MISO regression models are trained for each PV module's five unknown parameters, separately, using the same predictors. The performance of the trained model will be discussed in the section 4.3.

a) MIMO Regression Model

Artificial neural networks are comprised of simple components, typically called neurons, which operate in parallel and are inspired by the biological neurons of the human brain. In the structure of an ANN, these neurons are interconnected by weighted connections. The adjustment in an ANN is carried out by iteratively modifying these weights to align the output with the target values. In this paper, a multilayer feedforward architecture is employed. The ANN utilizes a backpropagation algorithm to adjust connection weights. The number of hidden layers is determined based on trying different numbers of hidden layers and hidden units and comparing the results to find an appropriate number. The input layer consists of nine input predictors. The Levenberg-Marquardt algorithm has been chosen as the ANN training algorithm.

The performance of the trained model across various phases of execution, including training, validation, and testing, for the predictor and target datasets is presented in Table 4.1. During the ANN training phase, 15% of the dataset is reserved for validation and another 15% is randomly separated for testing. The remaining 70% of the data is utilized for training. Mean squared error (MSE), the average squared difference between the predictions and the targets is used as a performance metric, with lower MSE indicating better model performance. Additionally, two other metrics are

Table 4.1. ANN performance

Artificial Neural Network				
Dataset	Observations	MSE	R	MAE
Training	7480	0.0381	0.8697	0.1139
Validation	1603	0.0389	0.8674	0.1151
Test	1603	0.0391	0.8668	0.1154

used: the regression coefficient (R) that measures the correlation between the predictions and the targets, and the mean absolute error (MAE) which is the amount of error between targets and predictions.

The plot presented in Fig. 4.7 illustrates the ANN predictions related to all five target variables. It demonstrates that a considerable portion of the data for different target variables is distributed around the ideal line, reflecting the overall accuracy of the trained model. However, given the inherent error in any trained model, certain data

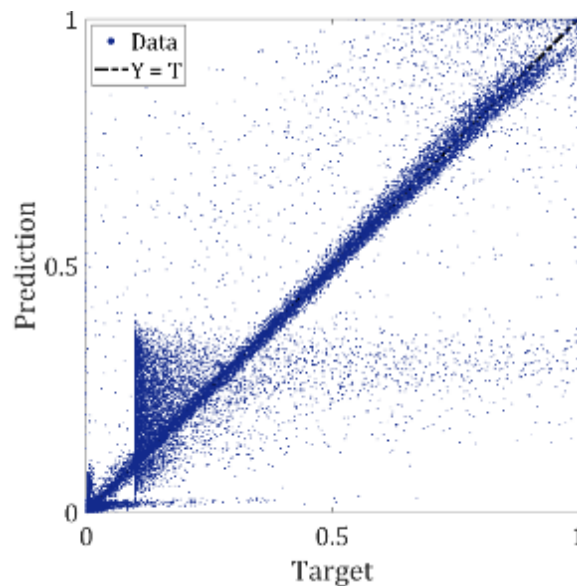


Figure 4.7. MIMO ANN target vs prediction

points exhibit discrepancies in predictions, indicating potential areas of interest for further studies.

The vertical line parallel to the Y-axis arises due to the model predicting a range of values for specific target variables. This behavior is likely caused by the weak or non-relevant relationship between the input features and the target features, which highlights the importance of methods like maximum relevance minimum redundancy, as utilized in the chapter 5.

b) MISO Regression Model

Various regression models, including linear regression, regression trees, support vector machine, ensemble of trees, Gaussian process regression, neural networks, and kernel approximation regression, are trained for each unknown parameter of the PV system in this work. The total number of the trained MISO models for all the parameters is 130 models (26 for each target parameter), where the best model for each parameter and its prediction errors (MSE) are shown in Table 4.2. As can be seen in this table, the best trained models for I_{ph} , a , I_0 , R_s , and R_{sh} are neural network, neural network, boosted tree, boosted tree, and stepwise linear, respectively. For both I_{ph} and a , the neural network consists of one fully connected layer with ReLU activation. The iteration limit is set to 1000, and lambda as 0. As for the boosted tree model, which shows the best performance for I_0 , R_s , the minimum leaf size is set to 8, the number of learners is set to 30, and the learning rate is set to 0.1.

4.2.3.3. Proposed Method's Computational Cost and Inference Time

To provide a comprehensive understanding of the efficiency and applicability of the proposed method, this section presents a detailed analysis of the computational

Table 4.2. Best MISO trained models' metrics for PV module unknown parameters

Parameter	I_{ph}	a	I_0	R_s	R_{sh}
Best Obtained Model	Neural Network	Neural Network	Boosted Tree	Boosted Tree	Stepwise Linear
RMSE (Validation/Test)	0.017667 / 0.016998	0.1216 / 0.12486	0.18069 / 0.19154	0.027214 / 0.021725	0.38175 / 0.38255
MSE (Validation/Test)	0.000312 / 0.000288	0.014786 / 0.015591	0.032647 / 0.036687	0.000740 / 0.000471	0.14576 / 0.14634
MAE (Validation/Test)	0.012013 / 0.011767	0.057008 / 0.05791	0.10237 / 0.11008	0.0090246 / 0.0088971	0.33482 / 0.33571

cost and inference time.

In this part of thesis, all processes were conducted on a Dell Optiplex 9020 Desktop computer with an Intel Core i7 4790 CPU (3.6 GHz), Intel HD Graphics 4600 (3592 MHz), and 8 GB DDR3 RAM. The computational cost of the proposed method primarily involves the training phase of the machine learning models and the optimization process using the WOA, DTRA, and data normalization phase. Performing training phase is a one-time cost that includes processing historical environmental and flight datasets, training the MIMO and MISO models, and validating their performance. This phase was conducted on the aforementioned hardware and took approximately 4 hours to complete.

Moreover, the inference time refers to the time taken by the trained models to predict the unknown parameters of the UAV-integrated PV system for a given set of input parameters. The experiments show that the inference time for a single prediction is approximately in the range of hundreds of microseconds on the same aforementioned hardware setup. This rapid inference time ensures that the model can provide real-time predictions during UAV flight operations regardless of the rate of change of mechanical parameter.

4.3. Experimental Results

In order to validate the proposed method's performance, at this stage of our work, experimental tests were conducted by simulating the movements of a UAV-integrated PV module using a moving PV module. This is achieved by utilizing a PV panel mounted on a moving structure, on a cart. Various tests (forty in total) were conducted to simulate different Yaw, Pitch, and Roll angles of the UAV by placing the PV panel in different positions. To extract the PV panel's I-V curve in the experimental phase, an IV-400 PV photovoltaic module analyzer is utilized. The experimental setup is shown in Fig. 3.16. Six measurements out of the forty tests were randomly selected to validate the predictions of the trained models. The experimental test parameters and their corresponding predicted values by the MIMO ANN model and the best obtained MISO models are presented in Table 4.3. Additionally, the extracted I-V curve of the PV system for the selected six measurements along with their corresponding I-V curves derived from the predicted parameters by the MIMO and best MISO models are shown

Table 4.3. Predictions of the MIMO model and the best MISO models for each parameter in the conducted experimental tests.

Test Number	Model Predictors								Predicted Parameters MIMO/MISO Models				
	Roll	Pitch	Yaw	Speed	Hour	Ambient Temperature	Height of Flight	Irradiance	Photocurrent	Series Resistant	Shunt Resistant	Diode Saturation Current	Diode Ideality Factor
1	10	20	45	13	14	24	2	881.3	5.46 / 5.44	0.210 / 0.207	151 / 149	3.53e-8 / 2.66e-8	1.086 / 1.085
2	10	-30	0	11	13	24	2	874.1	5.33 / 5.44	0.310 / 0.305	160 / 145	4.54e-8 / 2.79e-8	1.152 / 1.149
3	10	0	0	12	14	24	2	735.9	4.63 / 4.67	0.183 / 0.176	164 / 151	4.28e-8 / 3.07e-8	1.152 / 1.087
4	10	-20	0	12	13	24	2	867.6	5.31 / 5.39	0.110 / 0.105	162 / 146	4.51e-8 / 2.91e-8	1.104 / 1.082
5	10	-30	-45	12	14	24	2	903.2	5.65 / 5.91	0.359 / 0.355	153 / 145	3.89e-8 / 2.79e-8	1.090 / 1.082
6	10	10	45	12	14	24	2	834.2	5.21 / 5.20	0.359 / 0.354	155 / 149	3.85e-8 / 2.61e-8	1.092 / 1.087

in Fig. 4.8. According to the plotted curves, derived from the unknown five predicted parameters of the PV module and the PV module's basic regulating equations, both MIMO and MISO models exhibit proficiency in predicting the set of unknown

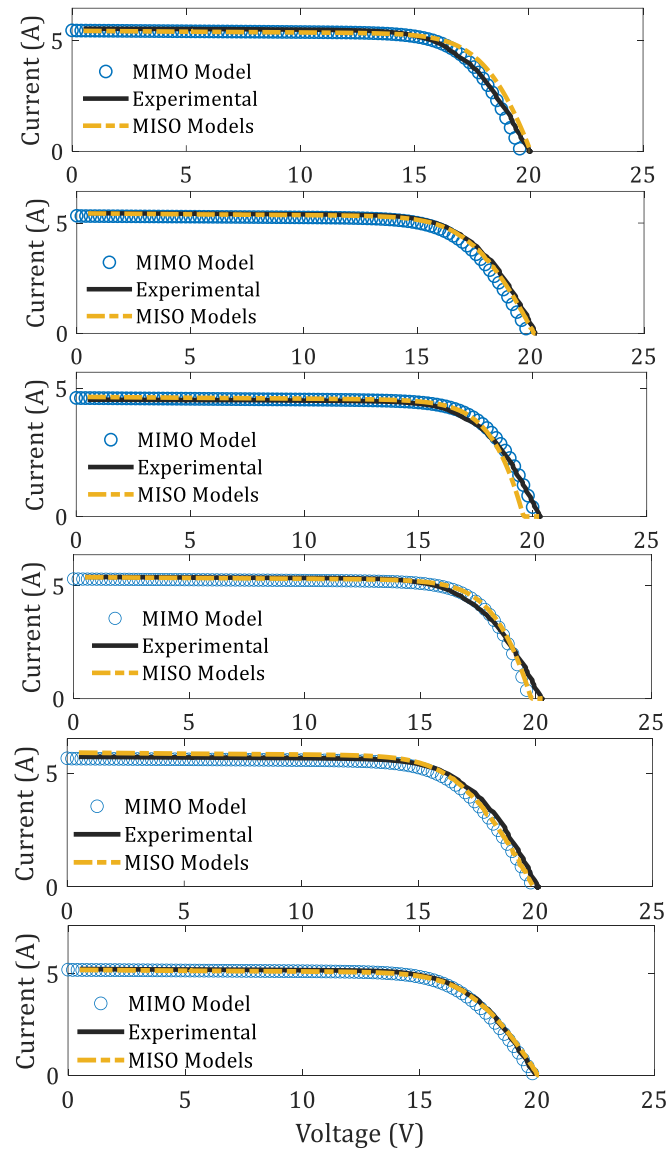


Figure 4.8. The I-V curve of the PV panel in the selected six experimental tests and by the predictions using the MIMO and MISO trained models.

parameters of the moving PV system. To provide further insight into the results, the Root Mean Squared Error (RMSE) of the curves derived from each method is listed in Table 4.4. This value indicates the error between the experimental test's extracted curve and its corresponding curve plotted based on the MIMO and MISO models' parameters predictions. As can be observed from the plotted curves and the provided table, the MIMO model exhibited smaller errors in most tests. However, in some tests, the MISO models demonstrated accurate predictions of the parameters, with errors significantly lower than those of the MIMO model in the same tests. The enhanced accuracy in predicting the values of photocurrent by the MISO models is the main reason for the lower errors observed in these tests.

4.4. Conclusion

This chapter presents a comprehensive method for extracting the unknown characteristics of a UAV-integrated PV system. The primary goal of this work is to propose a practical approach to extracting the unknown parameters of the UAV-mounted PV panel while considering various movements and environmental conditions. To achieve this objective, a computational intelligence-based modeling procedure is proposed, aiming to facilitate the identification of the moving PV system

Table 4.4. Metrics of the derived curves for MIMO and MISO Models

Test Number	RMSE MIMO	MAE MIMO	MSE MIMO	RMSE MISO	MAE MISO	MSE MISO
1	0.607	0.496	0.368	0.621	0.519	0.385
2	0.429	0.334	0.184	0.406	0.334	0.164
3	0.025	0.021	6.25e-4	0.053	0.044	0.002
4	0.375	0.279	0.140	0.350	0.263	0.122
5	0.765	0.550	0.585	0.680	0.473	0.462
6	0.420	0.321	0.176	0.424	0.333	0.179

characteristics. The approach utilizes different techniques, including rotational matrices theory to interpret the operational angles of the UAV as the angular parameters of the PV panel, a performance model of PV systems, WOA to optimize a system of empirical PV system equation parameters based on a second set of EDE, DTRA unconstrained problem solver to simultaneously solve a system of equations of EDE, and MIMO and MISO computational intelligence-based methods to predict the unknown parameters for any possible movement. The first step of the proposed modeling involves introducing a new scheme based on the concept of rotation matrices to interpret UAV movements as existing parameters in the PV panel equations. A historical environmental dataset related to the Canadian capital region, along with a randomly generated dataset of the UAV flight parameters within acceptable ranges, is employed to create the desired dataset for training the computational intelligence method. This dataset is initially used in the equivalent circuit-based model of the PV module to extract the system's MPP current and voltage. The MPP voltage and current are calculated based on another empirical set of equations that need to be solved simultaneously. A DTRA method is utilized to solve these empirical equations simultaneously, resulting in a new set of MPP voltage and current values, with this algorithm integrated into the whale optimization method. The objective of the whale optimization method is to minimize the error between two different sets of MPP current and voltage, with the second set optimized with a varying number of PV unknown parameters. Finally, the extracted PV unknown parameters, alongside the environmental and flight properties dataset, are used to train MIMO and MISO machine learning models. A comprehensive experimental measurement is conducted to validate the performance of the trained models. The experimental results confirm the effectiveness of the proposed method, with the MIMO trained model showing superior performance compared to the MISO trained models. This work proposes a novel

approach to creating a model for predicting the characteristics of UAV-integrated PV modules under various environmental and moving conditions. This approach can play a crucial role in further studies in the field of controlling, power and performance analyzing, and designing integrated PV modules in moving vehicles.

5. Computational Intelligence-Based Modeling of a UAV-Integrated PV Module in Icing Conditions

5.1. Introduction

Solar UAVs leverage the availability of solar energy, offering substantial advantages such as extended flight endurance, and lower maintenance requirements compared to traditional UAVs. However, atmospheric in-flight icing poses significant challenges to the performance and operational reliability of these UAVs. Ice accumulation on aerodynamic surfaces like wings and fuselage adversely impacts mechanical properties. Moreover, when integrated with PV systems, icing can obstruct sunlight from reaching the solar cells, drastically affecting the panels' parameters. The effects of partial shading caused by ice formation are more detrimental than uniform shading, complicating the PV module behavior analysis. This chapter presents a novel approach to model the behavior of UAV-integrated PV modules incorporating the impact of in-flight icing into irradiance calculations. By analyzing how ice formation acts as an obstacle and considering its effect on the PV module governing equations, this chapter develops a computational framework alongside with segmenting the PV module's operational curve into two zones: ice-covered and normal. The parameters for these zones are determined using advanced computational intelligence methods. The proposed method allows for predictions of PV module performance under dynamic and adverse conditions, such as movement-induced sunlight variations and partial shading. The research introduces a novel method to predict PV system behavior in cold regions,

making significant contributions to understanding and mitigating the effects of in-flight icing on solar-powered UAVs. This work serves as a reference for addressing challenges related to PV system performance under icing conditions, advancing the field of solar-powered UAV technologies.

5.2. Methodology

5.2.1. Overview of the Proposed Method

The objective of this chapter is to predict the unknown parameters of the UAV-integrated PV module while considering the in-flight icing phenomenon. To this aim the proposed method combines various statistical, mathematical, analytical, optimization, and computational intelligence-based approaches as shown in Fig.5.1. Initially, in-flight icing data for three different types of ice are extracted from specialized experimental research conducted to study the mechanical aspects of in-flight icing. To establish a relationship between in-flight icing properties (such as thickness and coverage) and flight speed, the curve fitting approach is employed. Four properties of the ice formed on the fuselage, including the ice thickness on the leading edge, the ice thickness at 1 cm from the leading edge, the ice thickness at 2 cm from the leading edge, and the coverage of ice on the fuselage are identified as key points. The fitted curves for these properties are extracted to incorporate in-flight icing effect in the PV module governing equations. Subsequently, the equations of the fitted curves are incorporated into the PV panel empirical equations to account for the effect of the formed ice on the sunlight reaching the moving PV panel. To calculate the MPP properties of the PV panel, environmental data, module placement parameters (such as tilt and azimuth angles), and the impact of ice cover on irradiance are essential. The module placement angles are determined through the approach proposed in section

3.2.2 which translates the operational angles of the UAV into the placement angles of the PV module. Subsequently, the calculated MPP properties serve as the reference for a metaheuristic optimization method, where an additional empirical set of equations containing the unknown parameters of the PV module aims to converge. A new-generation metaheuristic optimization method, WOA, is utilized in this phase to identify the unknown parameters of the UAV-integrated PV module for movements or in-flight icing conditions for any input data points. Finally, the five computed parameters of the UAV-integrated PV module, along with other input parameters, are used to train ML models. These models have the capability to predict the unknown parameters of the UAV-integrated PV module for various movements or in-flight icing conditions.

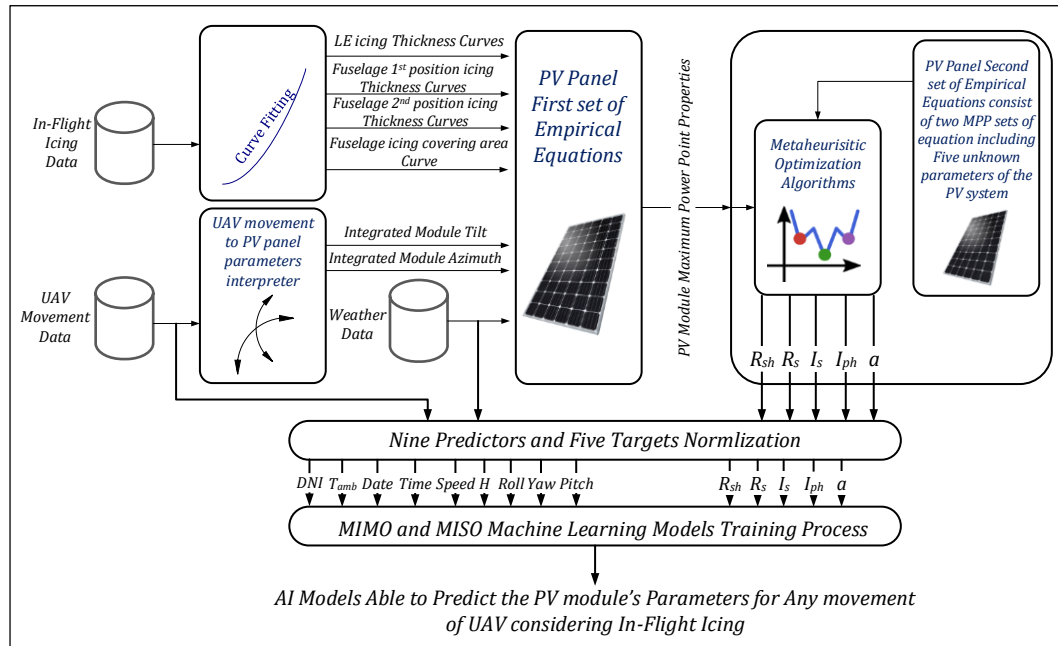


Figure 5.1. The whole block diagram of proposed method.

5.2.2. Consider In-flight Icing and UAV Movement on the PV Module Governing Equations

5.2.2.1. In-flight Icing Formulation

To consider the impact of ice on the UAV-integrated PV module, the first step is to determine the icing properties, which include type of ice, thickness and coverage in various parts of the wing, in relation to UAV movement and environmental conditions.

Ice formation on aircraft surfaces varies with the air temperature, resulting in different types, namely glaze, rime, and mixed ice as illustrated in Fig. 5.2. Glaze ice is formed just below freezing, where droplets freeze more slowly, leading to a smooth, transparent layer. Rime ice typically forms at very low temperatures, where droplets freeze instantly upon contact, trapping small air pockets and giving it a white appearance. Mixed ice combines characteristics of both rime and glaze ice, forming at temperatures between those required for rime and glaze formation [130].

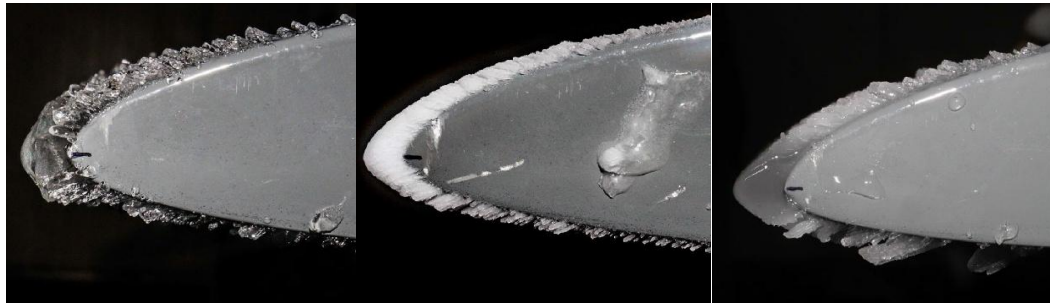


Figure 5.2. Various types of in-flight icing formed on the UAV wing from left glaze, rime and mix ice [36].

In this chapter of thesis, information on the properties of in-flight icing is derived from previous studies that specifically focused on this phenomenon and

conducted relevant tests for their mechanical analyses. In [10][40], Richard Hann and his colleagues conducted various tests in wind tunnels. The extracted data from [37] related to the pattern of icing for three main types of ice related to the speed which are used in this research are shown in Table. 5.1. Incorporating the icing properties into the calculation of the light that reaches the PV panel surface requires formulating the ice formation process. To achieve this, a curve fitting approach is employed to derive the formula for each type of ice. Curve fitting is a statistical technique used to determine the best-fitting curve that describes the relationship between two variables based on a dataset. Essentially, it involves adjusting a mathematical function to closely match the observed data points. The primary objective is to provide a smooth approximation of the data, which can be utilized for predictions, analysis, or understanding the

Table 5.1. Extracted data related to the icing properties on the wing of UAV based on experimental tests performed in [36].

UAV Speed (m/s)	Glaze thickness (cm)			Glaze Coverage from LE (cm)
	<i>1cm from LE</i>	<i>2 cm from LE</i>	<i>At LE</i>	
13	0.4	0.185	1.59	2.13
25	0.79	0.5	1.1	4.62
50	1.1	0.79	0.7	9.56
100	0	0	0	0
UAV Speed (m/s)	Rime thickness (cm)			Rime Coverage from LE (cm)
	<i>1cm from LE</i>	<i>2 cm from LE</i>	<i>at LE</i>	
13	0.38	0.08	1.23	1.84
25	0.56	0.18	1.48	3
50	0.64	0.43	1.58	5.07
100	0.82	0.69	1.74	6.58
UAV Speed (m/s)	Mixed thickness (cm)			Mixed Coverage from LE (cm)
	<i>1cm from LE</i>	<i>2 cm from LE</i>	<i>at LE</i>	
13	0.35	0.1	2.18	1.92
25	0.71	0.25	1.93	3.33
50	1.41	0.69	1.33	4.13
100	1.94	1.14	0.87	10.25

underlying relationship between variables. Measurements are taken at four points for each type of ice, including the ice thickness at the wing leading edge (LE), 1 cm after the leading edge, and 2 cm to the leading edge. Additionally, the ice coverage distance from the leading edge is measured for each ice type. The appropriate fitting function is chosen based on the R-squared metric, with the function demonstrating the highest R-squared value selected as the fitted curve.

The fitted curves equation for glaze ice is derived as follow:

$$Glaze_{LE} = -0.8539 \times Speed^{0.2997} + 3.409 \quad (5.1)$$

$$Glaze_{1st} = 0.562 - 0.492 \times \cos(Speed \times 0.05879) + 0.279 \times \sin(Speed \times 0.05879) \quad (5.2)$$

$$Glaze_{2nd} = 3.51 \times 10^{-7} \times Speed^3 - 0.0004269 \times Speed^2 + 0.04208 \times Speed - 0.2907 \quad (5.3)$$

$$Glaze_{Cov} = 0.2762 \times Speed^{0.9279} - 0.8539 \quad (5.4)$$

The equations of the fitted curves for the mixed ice are mentioned below:

$$Mix_{LE} = -0.9575 \times Speed^{0.2655} + 4.102 \quad (5.5)$$

$$Mix_{1st} = 0.6231 - 0.6399 \times \cos(Speed \times 0.02252) + 1.177 \times \sin(Speed \times 0.02252) \quad (5.6)$$

$$Mix_{2nd} = -2.902 \times 10^{-6} \times Speed^3 - 0.0003932 \times Speed^2 + 0.0008044 \times Speed + 0.02946 \quad (5.7)$$

$$Mix_{Cov} = 4.042 \times 10^{-5} \times Speed^3 - 0.005867 \times Speed^2 + 0.2952 \times Speed - 1.015 \quad (5.8)$$

And finally, the equations for the Rime ice are achieved as follow:

$$Rime_{LE} = 1.435 \times e^{0.001926 \times Speed} - 2.706 \times e^{-0.1858 \times Speed} \quad (5.9)$$

$$Rime_{1st} = 0.4995 \times e^{0.004957 \times Speed} - 5.69 \times e^{-0.2783 \times Speed} \quad (5.10)$$

$$Rime_{2nd} = 0.3341 - 0.3288 \times \cos(Speed \times 0.02858) + 0.1438 \times \sin(Speed \times 0.02858) \quad (5.11)$$

$$Rime_{Cov} = 2.149 \times e^{(-0.008353 \times Speed)} - 2.149 \times 10^5 \times e^{-(0.008354 \times Speed)} \quad (5.12)$$

where in the above group of equations *Speed* is the UAV speed. X_{LE} is the thickness of ice on the leading edge of UAV wing, X_{1st} is the thickness of ice on the 1cm after the LE, X_{2nd} is the thickness of ice on the 2cm after the LE, and X_{Cov} is the ice coverage distance from the LE, where X is the type of ice.

The curves related to the extracted equations are shown in Fig. 5.3 to illustrate and better understand the trend of ice thickness and coverage versus the speed of the UAV.

5.2.2.2. Incorporating the Icing Effect on Irradiance Calculation

In order to consider the effect of icing cover on the UAV-integrated PV module the following analysis is performed.

Based on the ice coverage equation derived earlier, the coverage of the accumulated ice on the UAV wing does not exceed the width of a cell in the studied PV module (Et-M53695), which has 36 cells in series and is divided into two strings by two bypass diodes. In this condition, the current of a string of the PV cells would be limited by the most covered cell, which is known as dominant cell in the PV panel research [131]. Therefore, the coverage of this cell can be derived through the coverage

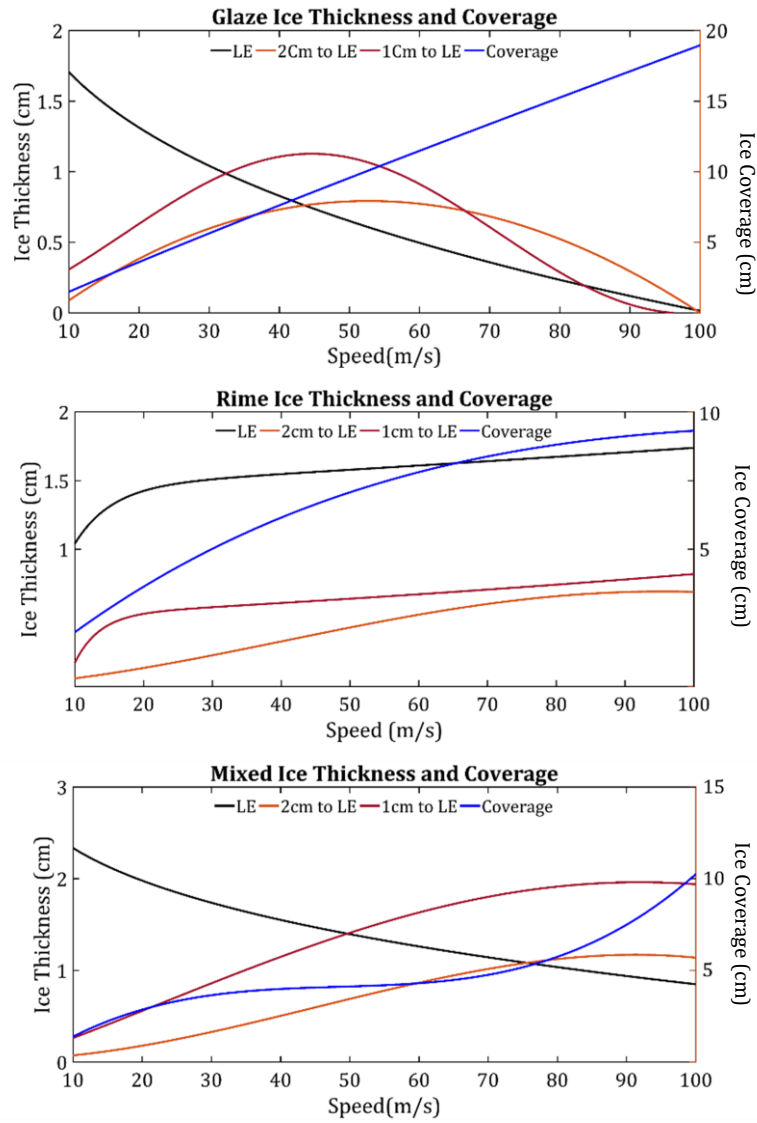


Figure 5.3. Coverage and thickness of various type of ice versus speed of UAV.

model that is proposed in the previous section. The dominant cell and a sample of expected icing coverage of UAV is shown in Fig. 5.4.

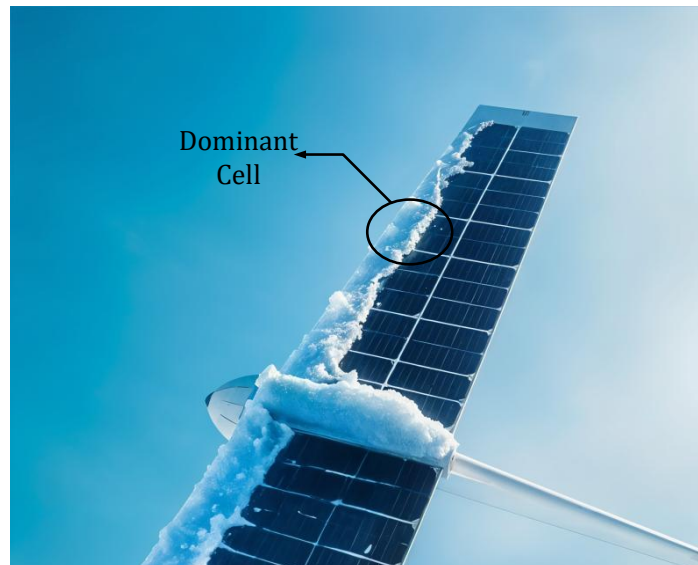


Figure 5.4. A sample of UAV icing and dominant cell [132].

In a PV cell, the current is generated by the movement of free electrons created when photons from sunlight impact the semiconductor material. The energy from these photons frees some electrons from their atomic bonds, leaving behind positively charged "holes." This creates electron-hole pairs. Due to the electric field at the p-n junction of the semiconductor, these electrons and holes are directed towards opposite sides of the cell, generating an electric current.

Since the generation of current depends on the number of photons absorbed, and therefore on the cell's surface area, the current is approximately proportional to the area of the PV cell exposed to sunlight. Thus, if a PV cell's active area is halved, the current generated will be roughly halved. This relationship holds because the current is proportional to the number of incident photons, which in turn is proportional to the cell area exposed to sunlight. Therefore, the following equation relation is expectable

$$I_{ph} \propto KG \quad (5.13)$$

where K is a constant related to the cell area and G is the irradiance on the free surface of the PV module. If the module is covered by ice or snow, the Bouguer-Lambert law can be utilized [18];

$$G_{\downarrow}(x) = G_0 e^{-k_{ext} x} \quad (5.14)$$

where $G_{\downarrow}(x)$ is the penetrated irradiance to the depth of x of the ice, G_0 is the irradiance on the surface of ice, K_{ext} is the ice extinction coefficient in cm^{-1} and x is the depth of ice in cm. Therefore, the current can be rewritten as follow:

$$I_{ph} \propto KG_0 e^{-k_{ext} x} \quad (5.15)$$

As mentioned earlier, to perform the analysis, four areas of icing are considered, as shown in Fig. 5.5. Each area represents a current source, and these sources are connected in parallel. From the leading edge to the 1 cm on the wing, from 1 cm to 2 cm, from 2 cm to the maximum ice coverage point, and from maximum ice coverage point to the end of the cell. Therefore, the following relation is established:

$$I_{ph} \propto KG_0 \left(e^{-k_{ext} x_1} \times \frac{1}{W} + e^{-k_{ext} x_2} \frac{1}{W} + e^{-k_{ext} x_3} \frac{Cov - 2}{W} + e^{-k_{ext} x_4} \frac{W - Cov}{W} \right) \quad (5.16)$$

where W is the width of the PV cell, and Cov is the maximum coverage of each type of ice in any speed which can be calculated with the formulas presented in the previous section. This derived current can be generated by another PV cell with the same properties, covered by a uniform ice layer known as $X_{eq.}$. This parameter can be calculated using the following formulas:

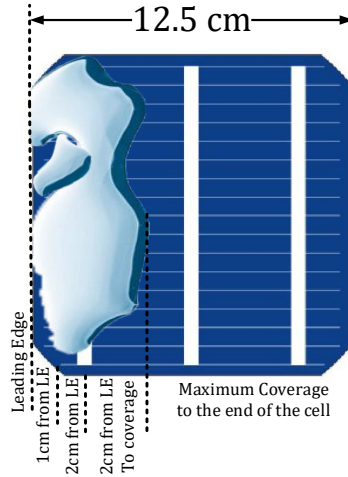


Figure 5.5. Four considered areas of a PV cell to consider icing effect.

$$I_{ph} = KG_0 e^{-k_{ext} x_{eq}} \quad (5.17)$$

Therefore

$$KG_0 e^{-k_{ext} x_{eq}} = KG_0 \left(e^{-k_{ext} x_1} \times \frac{1}{W} + e^{-k_{ext} x_2} \frac{1}{W} + e^{-k_{ext} x_3} \frac{Cov - 2}{W} + e^{-k_{ext} x_4} \frac{W - Cov}{W} \right) \quad (5.18)$$

And after simplification:

$$e^{-k_{ext} x_{eq}} = e^{-k_{ext} x_1} \times \frac{1}{W} + e^{-k_{ext} x_2} \frac{1}{W} + e^{-k_{ext} x_3} \frac{Cov - 2}{W} + e^{-k_{ext} x_4} \frac{W - Cov}{W} \quad (5.19)$$

And finally, the equivalent ice thickness can be derived as follows:

$$X_{eq} = \ln\left(e^{-k_{ext}x1} \times \frac{1}{W} + e^{-k_{ext}x2} \frac{1}{W} + e^{-k_{ext}x3} \frac{Cov-2}{W} + e^{-k_{ext}x4} \frac{W-Cov}{W}\right) / -k_{ext} \quad (5.20)$$

In this way the effect of various depth of ice in different area of UAV integrated PV module is considered as an equivalent ice depth on the wing of UAV which can be utilized in the governing equations of the UAV integrated PV module utilized in this research, which are two groups of empirical equations presented by [103] and [121]. These equations identified as the performance model proposed by [103] and includes two equations to calculate the MPP voltage (V_m) and current (I_m) as follows:

$$I_m = (C_0 G_{eff} + C_1 G_{eff}^2)(I_{m,STC} + k_{Im}(T_c - T_{STC})) \quad (5.21)$$

$$V_m = V_{m,STC} + C_2 a V_t \ln(G_{eff}) + \frac{C_3 (a V_t \ln(G_{eff}))^2}{N_s} + K_{Vm}(T_c - T_{STC}) \quad (5.22)$$

where a is the diode ideality factor, and the numerical parameters, including K_{vm} , K_{Im} , and C_0 - C_3 , can be extracted from the manufacturers' datasheets or the modules' available databases. Besides, $V_t = N_s k T_c / q$ is the thermal voltage of the PV module as T_c is the p-n junction temperature in kelvin, $q = 1.60217646 \times 10^{-23} C$ is the charge of the electron, k is the Boltzmann constant, which is equal to $1.3806503 \times 10^{-23} J/K$, and N_s is the number of solar cells connected in series. STC as subscript denotes the STC. Moreover, G_{eff} is the effective irradiance and the way of its calculation discussed in detail in section 3.2.3.

Another set of EDE, which includes all unknown parameters of the single diode

equivalent circuit model, is proposed and validated in [121]. This model is developed to find out the voltage and current of MPP as follows [121]:

$$I_{mpp} = N_p I_{ph} - N_p I_s \left[\exp \left(\frac{q \left(V_{mpp} + I_{mpp} \frac{N_s}{N_p} R_s \right)}{N_s a k T_c} \right) - 1 \right] - \frac{V_{mpp} + I_{mpp} \frac{N_s}{N_p} R_s}{\frac{N_s}{N_p} R_p} \quad (5.23)$$

$$\frac{I_{mpp}}{V_{mpp}} = \frac{\frac{q N_p I_s}{N_s a k T_c} \exp \left(\frac{q (V_{mpp} + I_{mpp} \frac{N_s}{N_p} R_s)}{N_s a k T_c} \right) + \frac{1}{\frac{N_s}{N_p} R_p}}{1 + \frac{q I_s R_s}{a k T_c} \exp \left(\frac{q (V_{mpp} + I_{mpp} \frac{N_s}{N_p} R_s)}{N_s a k T_c} \right) + \frac{R_s}{R_p}} \quad (5.24)$$

where N_s and N_p are the number of cells in series and parallel connections, I_s is the PV cell diode reverse current, I_{ph} is the PV cell photocurrent.

The two latter equations contain five unknown parameters of the PV module which can be solved by a nonlinear solver method simultaneously. By incorporating a nonlinear solver in an optimization method and optimizing the values of five parameters to make the calculated value of the second set converge to the calculated value of the first set of EDE, the five parameters can be extracted. This approach is done and validated in in section 4.2.2.

5.2.2.3. Considering In-flight Icing Effect on the Operational Curve of the UAV-Integrated PV Module

The curve shown in Fig. 5.6 is a sample curve of the studied module ET-M53695 partially covered by ice. The PV module has two bypass diodes, which means two series string of PV cells, and its curve consist of two parts. The first part which is called here “the non-covered zone” is actually the same as a curve of a whole non covered PV module and the covered zone is the same as a full covered module or a partially shaded module without bypass diode.

Considering this combination, the parameters of non-covered zone could be predicted with the discussed method in Chapter 4 and the covered zone will be predicted by the method presented in this chapter.

The break point of the curve and switching from non-covered zone prediction to covered zone prediction is achieved based on the following formulas [133]:

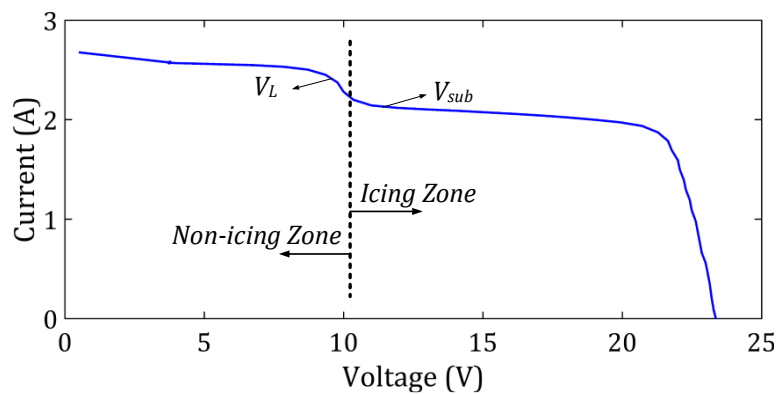


Figure 5.6. PV module curve under partial shading.

$$V_{sub} = [V_{oc} + \frac{1}{A} \ln(1 - \frac{G1}{G2})] \quad (5.25)$$

where $G1$ and $G2$ are the irradiances hitting the covered and noncovered sections, and A can be found as follows:

$$A = \frac{1}{(V_m - V_{oc})} \ln(1 - \frac{I_m}{I_{sc}}) \quad (5.26)$$

where V_m , V_{oc} , I_m , and I_{sc} are the module MPP voltage, open circuit voltage, MPP current, and short circuit current, respectively, where they can be found in the module datasheet. It should be noted that V_{oc} and V_m are the voltages related to a one string of the module that in this research case would be the half of the mentioned voltages in the datasheet. Moreover, the knee point of the curve (V_L) can be calculated by the 0.8 V_{oc} rule that is proposed in [134],[135]. In this way both parts of the curve and their important points can be computed.

5.2.3. Icing Condition UAV-integrated PV Module Parameters Extraction

As mentioned before, to find the unknown parameters of the moving PV panel under icing condition, two sets of EDEs are used. These two sets compute the same MPP properties in different ways and point to the same value. Therefore, a metaheuristic method must be utilized to adjust the unknown parameters of the second set so that the computed MPP properties match those calculated by the first set of EDE. Four nature-inspired metaheuristic optimization algorithms are employed for this purpose, with all four algorithms operating on the same objective function. The most effective algorithm is selected from the options mentioned, and the machine learning models are trained based on the output of the chosen algorithm. All the metaheuristic optimization algorithms are discussed in Appendix sections A1 to A4. The GWO and

WOA were already utilized in the previous sections. In addition to GWO and WOA, the MVO [136]-[138] and MFO [139]-[142] are employed to identify the best possible method by their comparison.

5.2.3.1 Assessing the Performance of utilized Metaheuristic Optimization Methods

The convergence curves of WOA, GWO, MVO, and MFO are depicted in Fig. 5.7(a) to Fig. 5.7(d). MFO exhibits the poorest optimization performance during the convergence phase among the utilized optimization methods. While there are variations among the other three optimization methods, a straightforward approach is implemented to determine the best performed optimization method. The best-performing algorithm is identified by averaging the best fitness value achieved by each algorithm at their final iteration for each run, indicating which algorithm converged most successfully to the objective function's closest value to zero. The average scores of the utilized algorithms are detailed in Table 5.2. The mentioned average in Table 5.2 confirms that WOA achieves a better performance among the other optimization methods.

Table 5.2. Average of obtained score of optimization methods at their last iteration

Optimization algorithm	WOA	GWO	MVO	MFO
Convergence score(fitness) average	0.06239	0.28321	0.287244	0.223152

5.2.4. Development of Machine Learning Models to Extract Unknown Parameters of UAV-Integrated PV Modules under In-Flight Icing Conditions

Various ML models are trained in this work to find the best model for predicting each unknown parameter of the moving PV panel considering in-flight icing. The procedure, the quality of trained models, and the method to enhance the model's performance are discussed in this section. It should be noted that the utilized dataset is

presented in section 3.2.5.1. Moreover, data normalization is performed according to

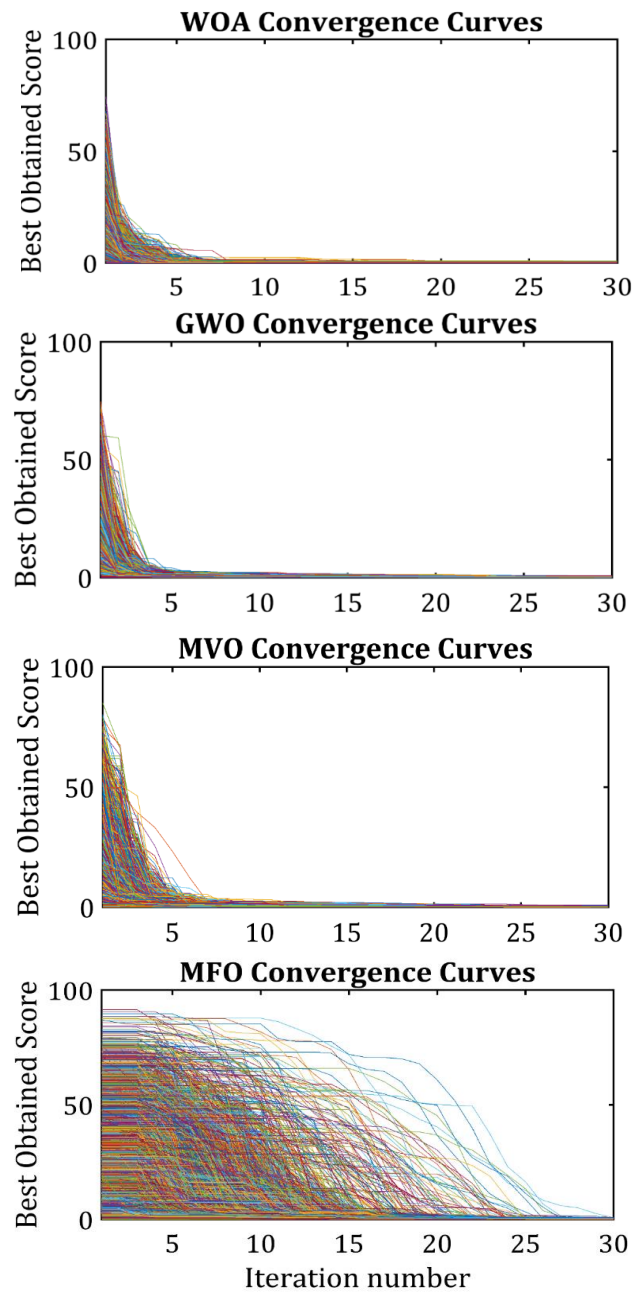


Figure 5.7. Meta heuristic optimization methods convergence curves. (a) WOA, (b) GWO, (c) MVO, (d) MFO.

the section 3.2.5.3.

5.2.4.1. Trained ML Models and Their Performance

This study employed a variety of regression models, including linear regression, regression trees, SVM, ensemble methods, Gaussian Process Regression, neural networks, and kernel approximation regression, to estimate the unknown parameters of the PV system. In total, 140 models were developed, 28 models for each target parameter. According to the performance of the models, the best models for estimating I_{ph} , a , I_0 , R_s , and R_{sh} are GPR Matern 5/2, neural network, Quadratic GPR, Least Square Kernel, and stepwise linear, respectively.

5.2.4.2. Minimum Redundancy Maximum Relevance (MRMR)

The MRMR algorithm is a feature selection technique designed to identify a subset of features that are highly relevant to the target variable while minimizing redundancy among selected features. This method is particularly valuable in high-dimensional datasets, for improving model performance by selecting the most informative features [143].

The algorithm measures the amount of information a feature shares with the target variable, which is known as relevance, using mutual information [143]. It also evaluates redundancy by assessing similarity between features, with highly correlated ones marked as redundant [143]. The MRMR process involves calculating the mutual information between each feature and the target variable to assess relevance [144], then measuring redundancy by computing mutual information between pairs of features [144]. Features are ranked according to both their relevance to the target and their redundancy with other features [145]. Finally, the top-ranked features, combining high

relevance and low redundancy, are selected for the model [146]. This algorithm enables the possibility of decreasing the complexity of the ML models while increase the performance of the model. After applying this algorithm, the best obtained models are trained again with the new set of features. The selected features, identified as the most relevant predictors for each target feature, along with their respective MRMR scores, are presented in Table 5.3. Additionally, the error metrics of the best ML models derived for each parameter alongside with the models trained after feature selection are shown in Table 5.4. Applying this approach will decrease the complexity of system and increase the performance of the processing unit to extract the parameters of the UAV integrated PV systems.

5.2.5. Experimental Tests

To validate the proposed method, various icing scenarios were experimentally conducted on a PV panel to simulate ice formation on the UAV wing. To ensure a clear

Table. 5.3. MRMR of the most important predictor features for different target features

<i>I_{ph}</i> most relevant features and their scores					
Feature name	Irradiance	Flight Height	Hour in a day	Temperature	Day in a year
MRMR	2.3	0.38	0.37	0.35	0.29
<i>I₀</i> most relevant features and their scores					
Feature name	Temperature	Flight height	Pitch	Roll	Speed
MRMR	0.156	0.112	0.0186	0.018	0.017
<i>R_s</i> most relevant features and their scores					
Feature name	Temperature	Day in a year	Yaw	Speed	Roll
MRMR	0.0630	0.0510	0.045	0.041	0.0201
<i>a</i> most relevant features and their scores					
Feature name	Temperature	Flight height	Roll	Speed	Pitch
MRMR	0.13	0.0906	0.0454	0.0418	0.0402
<i>R_{sh}</i> most relevant features and their scores					
Feature name	Temperature	Flight height	Roll	Speed	Pitch
MRMR	0.059	0.049	0.0407	0.038	0.035

Table. 5.4. Best trained models' metrics for each parameter in the icing zone

Parameter		I_{ph}	a	I_0	R_s	R_{sh}
Before Feature selection	Best Obtained Model	GPR Matern5/2	Neural Network	QGPR	Least Square Kernel	Stepwise Linear
	RMSE (Validation/Test)	0.025/0.023	0.364/0.363	0.1901/0.1874	0.0324/0.0332	0.3193/0.3127
	MSE (Validation/Test)	0.00062/0.00056	0.1326/0.1323	0.0361/0.0351	0.0010/0.0011	0.101/0.097
	MAE (Validation/Test)	0.0187/0.0185	0.304/0.305	0.1034/0.1008	0.0121/0.0118	0.252/0.247
After Feature selection	RMSE (Validation/Test)	0.024/0.023	0.363/0.364	0.1900/0.1871	0.0333/0.0337	0.318/0.311
	MSE (Validation/Test)	0.00062/0.00055	0.1322/0.1325	0.0361/0.0350	0.00111/0.00114	0.1014/0.0971
	MAE (Validation/Test)	0.0185/0.0180	0.3051/0.3059	0.1016/0.0988	0.0119/0.0115	0.2513/0.2466

procedure that meets the requirements for representing UAV icing conditions, the test design is first presented, followed by a discussion of the test results.

5.2.5.1. Experimental Tests Design

Three tests were conducted to represent three types of ice. According to the fitted curve in the first section, the maximum amounts of equivalent ice that could accumulate in the UAV-integrated PV system are shown in Fig. 5.8 for the entire dataset. The figure shows that the maximum amounts are approximately 0.34 cm for

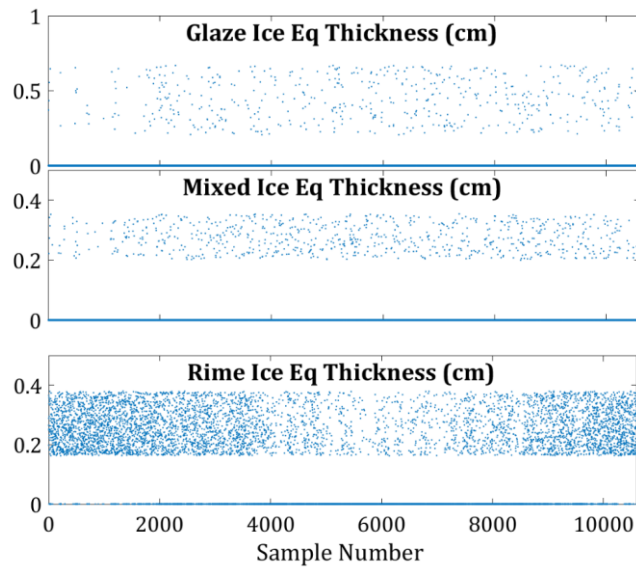


Figure 5.8. Equivalent thickness of different types of ice.

rime ice, 0.42 cm for mixed ice, and 0.65 cm for glaze ice. The experimental tests are conducted based on the specified ice types and their respective thicknesses. For glaze ice, water is gradually dripped onto the PV panel, which is then placed in freezing early morning temperatures until the ice forms. For rime ice, pre-prepared ice plates from the refrigerator are placed on the PV panel surface. Lastly, for mixed ice, crushed ice from accumulated snow is used. Fig. 5.9 shows the experimental performed tests. To accurately simulate UAV icing, ice is placed on a single string of the PV panel. The ice thickness represents the UAV's speed, crucial for predicting parameters with trained ML models. After applying different types of ice, the PV panel is tested using the I-V 400 PV panel analyzer. The resulting PV panel curve from the analyzer is then compared with the curves derived from the predicted parameters by the ML models.



Figure 5.9. Experimental tests by simulating of various kind of ice from top: glaze, mixed and rime.

5.2.5.2. Results

A series of tests were conducted under icing conditions, with their properties detailed in Table 5.5. Fig. 5.10 shows the curves related to the predicted parameters and their comparison with the experimentally extracted curves. The error metrics for the predicted curves versus the actual experimental curves are listed in Table 5.6. This table indicates that the models achieve more accurate performance after feature selection with the MRMR method in most of the tests. Moreover, Table 5.7 provides a comparison between the parameter extraction method proposed in this work and conventional methods. The comparison in this table highlights the advantages of the proposed parameter extraction method over conventional techniques. Specifically, the proposed method demonstrates the ability to extract PV module parameters under any movement condition and partial coverage without requiring prior experimental testing. Moreover, it delivers results immediately, whereas conventional methods are limited in adaptability and are comparatively slower. This suggests that the proposed approach is significantly more flexible, efficient, and suitable for dynamic environments like UAV-integrated PV systems.

Table 5.5. Predictions of the ML models for each parameter in the conducted experimental tests for each region of the PV curve (zone1/zone2).

Test Number (Ice type)	Ice thickness (cm)	Associate Speed with ice thickness (m/s)	Day Number	Hour	Ambient Temperature	Height of Flight	Irradiance	Photocurrent (A)	Series Resistant (m Ω)	Shunt Resistant (Ω)	Diode Saturation Current (A)	Diode Ideality Factor
1 (Glaze)	0.32	30	44	13	-2	2	535	3.11 / 2.90	3.51/4.15	78.19 / 82.6	8.87e-10/7.65e-11	1.07/1.08
2 (Glaze)	0.16	10	44	13	-2	2	551	2.95/ 2.81	3.58/6.44	78.19 / 82.6	8.87e-10/6.74e-11	1.07/1.10
3 (Mixed)	0.33	50	35	11	-6	2	280	1.47/ 1.37	3.49/2.30	92.6 / 83.1	5.97e-10 /5.37e-11	1.06/1.05
4 (Mixed)	0.26	40	35	11	-5	2	320	1.71/1.59	3.38/2.32	91.9 / 83.1	5.97e-10 /5.37e-11	1.06/1.05
5 (Rime)	0.31	47	45	12	-10	2	450	2.50/2.31	3.38/10.8	119/ 118	7.17e-10 /1.57e-10	1.14/1.12

Table 5.6. Error metrics between curves derived by trained model and the actual experimental curves

	Tests	<i>Test1</i>	<i>Test2</i>	<i>Test3</i>	<i>Test4</i>	<i>Test5</i>	<i>Test6</i>
Before Feature selection	RMSE	0.092	0.0504	0.0139	0.0143	0.0498	0.0577
	MAE	0.071	0.0439	0.0097	0.0105	0.0419	0.0479
After Feature selection	RMSE	0.089	0.0399	0.0129	0.0133	0.0498	0.0582
	MAE	0.069	0.0347	0.008	0.009	0.0414	0.0500

5.3. Conclusion

This chapter investigated the impact of in-flight icing on the performance of UAV-integrated PV modules. To achieve this, first ice formation patterns and coverage data were extracted from prior experimental studies on the effect of in-flight icing on UAV mechanical performance. This data was used to develop a mathematical model of ice formation using a curve fitting approach. Next, a new analytical method was proposed to model non-uniform ice accumulation on the UAV wing as an equivalent ice layer thickness, based on the icing coverage and thickness ranges observed during flight. This approach allows for incorporating the effects of in-flight icing into empirical equations for the PV module. The ice layer on the PV module acts as a barrier, creating a partial shading effect and altering the module's operating curve according to its structure. To address this, the PV module's operating curve was divided into two sections: ice-covered and non-covered. Separate analyses and calculations were performed for each section to predict unknown parameters. A one-year dataset, including meteorological conditions and UAV movement data, was processed through two sets of empirical equations that account for the PV module icing effect. These equations were combined with WOA metaheuristic optimization method to extract the unknown parameters for the ice-covered UAV-integrated PV module. In total, 140 ML models were trained on the processed data, with the top-performing model selected for experimental testing. The MRMR method further refined the models, and the final best model was retrained for optimal results. Finally, the predicted parameter curves were

validated against experimental test results, confirming the effectiveness of the proposed method.

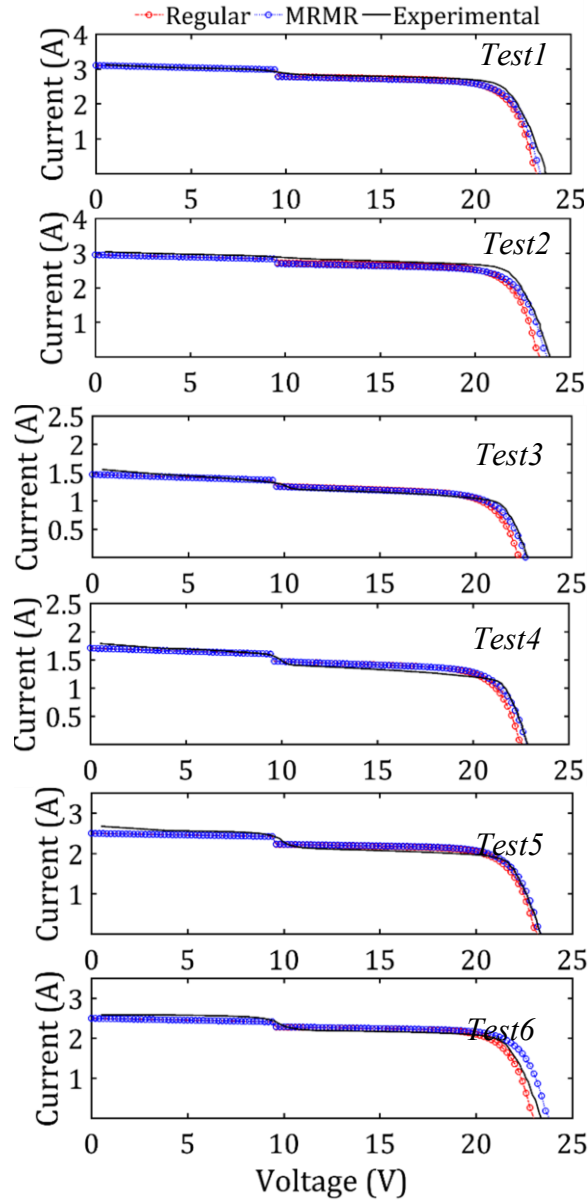


Fig. 5.10. The I-V curve of PV panel related to the performed experimental tests, comparing the experimental curve, and the curves predicted by ML methods before (Regular, in red) and after of feature selection by MRMR (MRMR, in blue).

Table 5.7 Comparison of the proposed parameter extraction method with conventional methods.

<i>Parameter Extraction</i>				
	Ability to extract parameters under any movement condition	Need to any prior experimental tests	Ability to extract parameters under PV panel partial coverage	Speed of parameter extraction process
<i>Proposed Method</i>	Yes	No	Yes	Immediate
<i>Conventional Methods</i>	No	Yes	No	Slow

6. Conclusion and Future Work

6.1. Concluding Remarks

The use of renewable energy is steadily increasing as a reliable and clean power source in electrical networks, microgrids, and even as the primary or auxiliary power source for vehicles. While there are some limitations in integrating PV systems with vehicles due to the PV panel performance, and its power density constraints, ongoing research will advance this field, especially with improvements in semiconductor technologies. The mentioned prospective makes the integration of PV panel with various vehicles more and more promising.

Among various types of vehicles, the flying vehicles have the most complex movement patterns. UAVs, cutting-edge technology, have drawn significant attention for their wide range of applications, from military to surveillance. Integrating PV technology into UAVs presents an exciting opportunity to extend flight times and endurance, making it an attractive area of research. The synergy between these two technologies offers potential advancements in optimal PV module energy harvesting utilization, UAV endurance, and the behavior of UAV-integrated PV modules during continuous movement.

Analyzing the performance of a moving PV module introduces new challenges that require an innovative analytical and technical perspective. This becomes even

more complex when considering the effect of in-flight icing on the PV module. In-flight icing occurs when airborne water droplets collide with the UAV body, potentially covering parts of the PV module and creating additional challenges.

The primary goal of this thesis was to investigate the performance of UAV-integrated PV systems under in-flight icing conditions. This study employed a comprehensive approach involving analytical, mathematical, optimization, and machine learning methods to assess system performance. To achieve this goal, a range of methods and analyses were employed and validated through experimental measurements and hardware testing. The key findings of this research are as follows:

The first part of this thesis presents a new approach to explaining the angular parameters of the PV panel equation, tilt and azimuth angles, in terms of the UAV-integrated PV module's movement parameters, specifically the Yaw, Roll, and Pitch angles, through detailed mathematical analysis. Furthermore, a novel method utilizing the EDE of the PV module and the GWO algorithm simultaneously is developed to adaptively compute the PV module's diode ideality factor for any placement condition of the UAV-integrated PV module.

The performance of GWO was compared with PSO, demonstrating GWO's superiority, with PSO's convergence error being 3% higher. After processing a dataset of 10,800 data points through the EDE of the PV module to determine the MPP current and voltage properties and adaptively derive the diode ideality factor, twenty-three ML models were developed for the ET-M53695 commercial PV panel. A 10-fold cross-validation method is used for model validation, and 20% of the dataset was set aside for the model testing process. Among the various trained ML models, the RQGPR model demonstrated the best performance, achieving a RMSE of 0.006.

To validate the proposed approach, a series of experimental tests were conducted on a PV module using an IV-400 photovoltaic analyzer attached to a mobile mechanism capable of simulating UAV movements by rotating around its Yaw, Pitch, and Roll axes. The predictions made by the RQGPR-trained model under the experimental conditions closely matched the actual measurements. Moreover, to evaluate the prediction performance in a power electronics context, a hybrid MPPT method combining AI-based techniques with traditional IC methods was implemented, showing improved performance in tracking the MPP during high variation irradiance changes.

This proposed method not only provides inspiration for future investigations into integrating PV modules as primary or secondary energy sources in various vehicles, particularly UAVs, but also enhances the performance of MPPT methods by offering an initial MPP estimate that is either exact or very close to the actual MPP during UAV movement. Additionally, the insights and methodologies developed in this thesis have broader applicability, offering valuable solutions for any application involving moving PV panels.

The second part of this thesis presents a practical approach to extracting the unknown parameters of a UAV-mounted PV module while considering various movements and environmental conditions. To this aim a computational intelligence-based modeling procedure is proposed. The approach incorporates several techniques, including rotational matrix theory to interpret the operational angles of the UAV as the angular parameters of the PV module. Additionally, two sets of EDE of PV modules are employed, along with the WOA to optimize empirical PV system equation parameters based on a second set of EDE. The DTRA is also utilized to simultaneously

solve a system of equations in the second set of EDE, and developed MIMO and MISO computational intelligence-based methods to predict unknown parameters under various movement conditions.

A historical environmental dataset related to the Canadian capital region, along with a randomly generated dataset of UAV flight parameters within acceptable ranges, is employed to create the desired dataset for training the computational intelligence models. After translating the UAV-integrated PV module movement datapoints into the PV module's basic placement parameters, the entire dataset is processed through the primary set of EDE of the PV module to extract the system's MPP current and voltage. A DTRA method is employed to solve the system of equations in the second set of EDE, resulting in a new set of MPP voltage and current values. This algorithm is integrated into the WOA, which minimizes the error between two sets of MPP current and voltage values, with the second set optimized by varying the PV module's unknown parameters. The performance of WOA is compared to PSO, a well-known optimization algorithm. Results show that the average best score (convergence error) obtained by PSO was 2.36 times higher than that of WOA, confirming the superior optimization performance of WOA.

The computed PV parameters, alongside the environmental and flight dataset, are used to train MIMO and MISO models. An ANN is employed as the MIMO model, while a total of 130 MISO models are trained to predict each unknown parameter of the PV module under various flight and environmental conditions. Among the MISO models, neural networks demonstrate the best performance in predicting photocurrent and the diode ideality factor. Boosted trees show superior performance in predicting series resistance and diode reverse saturation current, while stepwise linear models

perform best for other prediction tasks.

Comprehensive experimental measurements were conducted to validate the performance of the trained models. The extracted operational curves for six different experimental tests were compared with the curves derived from the predicted parameters of the MISO and MIMO trained models. The results confirm the effectiveness of the proposed method, with the MIMO-trained model demonstrating superior performance compared to the MISO-trained models.

This research introduces a novel approach for predicting the characteristics of UAV-integrated PV modules under varying environmental and movement conditions. It holds significant potential for future studies in the fields of control, power and performance analysis, and the design of integrated PV modules in moving vehicles.

In the third part of the project, extracting the unknown parameters of UAV integrated PV module considering in-flight icing is investigated. To address this, the thesis incorporates ice formation patterns and coverage derived from prior extensive experimental studies on the effects of in-flight icing on UAV mechanical performance. This data is utilized to formulate a mathematical model of ice formation using a curve-fitting approach for three various kinds of ice, which is subsequently integrated into the calculation of effective irradiance hitting the PV module. Additionally, an analytical approach is proposed to model the non-uniform ice coverage of a UAV-integrated PV module as its uniform equivalent ice coverage.

Depending on the type of ice, the ice covering the PV module acts as an obstacle, resulting in a partial shading effect. This introduces local and global optimization challenges on the PV module's operating curve. The PV operating curve is divided into

ice-covered and non-ice-covered regions, with separate analyses and calculations performed for each region. Once the effects of ice on the PV module are accounted for, the behavior of the UAV-integrated PV module is analyzed using a dataset of meteorological and UAV movement data. During the data processing stage, several metaheuristic optimization methods, including WOA, GWO, MFO, and MVO are employed to compute the unknown parameters of the UAV-integrated PV module, taking the impact of in-flight icing into consideration. Among these optimization methods, WOA demonstrates the best performance, achieving the lowest convergence average score of 0.06239.

The processed data points are then used to train machine learning models capable of predicting the parameters of the moving PV module under icing conditions. A total of 140 machine learning models are trained, with 26 models dedicated to predicting each parameter. According to the error metrics of these models, the most accurate models for estimating the parameters I_{ph} , a , I_0 , R_s , and R_{sh} are the GPR, Matern 5/2 kernel, neural networks, Quadratic GPR, Least Square Kernel, and stepwise linear models, respectively.

Following the model training, the MRMR approach is employed to identify a subset of features that are highly relevant to the target variable. This feature selection results in simpler models by reducing the number of input features to the five most relevant ones for each target parameter. The resulting curves from both the regular models and the simplified MRMR models are then compared with experimentally extracted curves of the PV module under various ice and placement conditions. The results indicate that, in most cases, the models demonstrate improved accuracy after applying the MRMR-based feature selection method.

The overall contribution of this thesis can be summarized as follows:

- Proposing a new approach to interpret the three-dimensional movements of a moving PV panel in terms of its fundamental operational angles.
- Proposing a new solution based on GWO to compute the PV module diode ideality factor for different placement condition of the PV module.
- Validating a series of machine learning algorithms designed to predict the MPP parameters of UAV-integrated photovoltaic modules based on environmental and positioning conditions, enabling real-time adaptation to the rapid fluctuations in panel output throughout UAV flight.
- Proposing a hybrid MPPT technique that integrates the proposed machine learning-based model into an IC MPPT algorithm, enabling faster tracking of the MPP, particularly during rapid irradiance fluctuations.
- Utilizing MIMO and MISO machine learning models to develop a comprehensive predictive model for unknown parameters of the moving PV panel.
- Introducing a novel method for parameter extraction of PV modules based on the WOA using two sets of empirical equations.
- Extracting the parameters of the UAV-integrated PV module model under various UAV flight and environmental conditions
- Mathematical modeling of the UAV in-flight icing phenomenon for various type of ice.
- Proposing an innovative method to model the nonuniform ice coverage of a UAV-integrated PV module using an equivalent ice layer.
- Considering the effect of in-flight icing on the governing equations and operational curve of the UAV-integrated PV module.

- Predicting the unknown parameters of UAV-integrated PV modules under in-flight icing conditions.

6.2. Research Perspectives

According to the research work in this study, several recommendations for the future studies beyond the scope of this research are presented here:

- Propose a virtual model of the UAV integrated PV system to collect performance data under regular and icing conditions to develop and train predictive models that accurately reflect PV module behavior based on more accurate data.
- Develop optimization strategies for UAV movement and path planning that account for PV system parameters, such as power loss and efficiency, to maximize energy harvesting and overall flight endurance.
- Investigate the feasibility of combining PV systems with RF energy harvesting on UAVs to create a hybrid energy source and conduct performance analysis on this integrated system.
- Propose comprehensive models that include both electrical and mechanical parameters including battery parameters, and variable load of the PV system to enhance the overall performance of solar UAVs, with a focus on efficiency and energy sustainability.
- Develop advanced computational intelligence models to simulate in-flight icing,

taking into account all effective parameters, for improved prediction and mitigation of icing impacts on PV systems.

Appendix

In this section the theoretical concepts of four utilized metaheuristic optimization algorithms are provided.

A1. Grey Wolf Optimization Algorithm

Grey wolf optimization algorithm, which is a metaheuristic optimization algorithm inspired by the social structure of grey wolves is proposed by [111]. This metaheuristic algorithm has several advantages, including fewer parameters, easy implementation, and a simple principle, as compared to conventional optimization methods like PSO and GA [112]. These mentioned advantages align perfectly with the objectives of this research, which prioritize simplicity and straightforward understanding. In this optimization method, wolves are classified into four groups including alpha, beta, delta, and omega based on their performance. These groups collaborate in a structured manner to reach their goal. Alpha wolves are leader of the group and making decisions about different activities that influence the entire pack. Beta wolves act as alternatives to alphas. Delta pairs have a hierarchical position between omega wolves and the alpha and beta leaders, while omega wolves follow orders and are the last to feed on prey. In the optimization problem alpha, beta, and delta wolves are the optimal individual, second optimal individual, and third optimal ones.

Grey wolves hunt their prey through three main steps including pursuit, tracking, and approaching the prey, chasing, encircling, and harassing the prey until it stops, and finally attacking the prey [113].

Mathematical modeling of prey encirclement includes considering the distance between the prey and the wolves (D) using the following formula [111]:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \quad (\text{A.1})$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (\text{A.2})$$

where t indicates the iteration number, $\vec{X}_p$ denotes the position vector of the prey, X is the position of a grey wolf, and $\vec{A}$ and $\vec{C}$ stand for coefficient vectors and can be calculated as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (\text{A.3})$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (\text{A.4})$$

where $\vec{r}_1$ and $\vec{r}_2$ are two random vectors between 0 to 1, and components of $\vec{a}$ linearly decrease from 2 to 0 as the iterations progress.

As mentioned earlier about the properties of different types of wolves, alphas lead hunting, and wolves of type beta and delta might be cooperating in hunting. The idea is that these three types of wolves have the best knowledge about the possible location of the prey. So, only three best solutions are considered while the wolves'

position updating can be considered as follows [111]:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|, \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \quad (\text{A.5})$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \quad (\text{A.6})$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$$

Using the equations provided above, the wolves adjust their positions relative to the prey. The algorithm operates iteratively until a specified stopping condition is met, wherein the search agents (wolves) converge on the objective function (prey). This process involves updating the position of omega wolves based on the movements of the other three main wolves that are exploring the search environment and are closest to the prey. This behavior is exhibited by omega wolves during the exploration phase and is determined by parameter A . Essentially, the next position of a search agent can be anywhere between its current position and the prey. When $|A|$ is less than 1, the search agent is directed to approach the prey, while $|A|$ greater than 1 leads the search agent to adjust its position in response to the movements of the three best-performing wolves. These concepts regarding the updating position procedure, as well as the hunting or searching behavior for a prey, are illustrated in Fig. A.1.

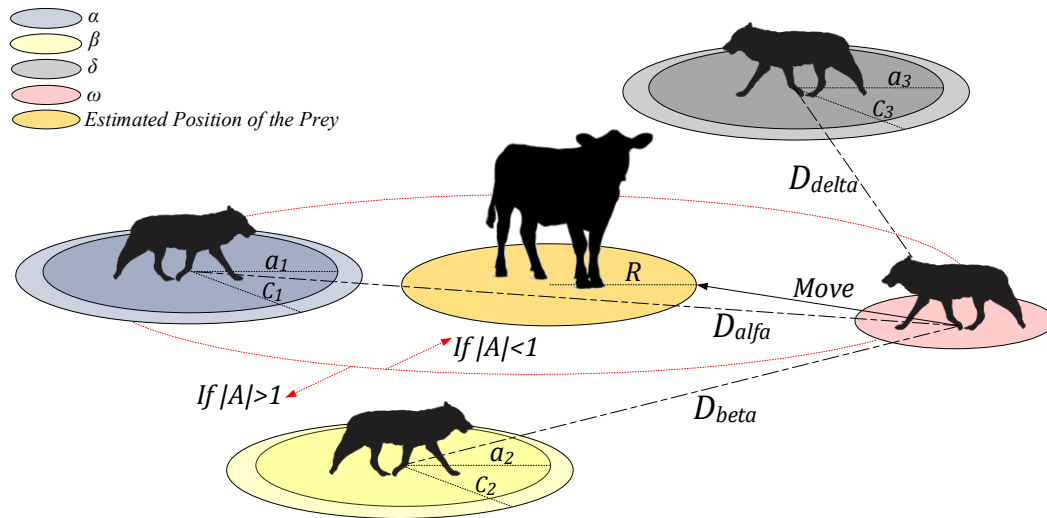


Figure A.1. Grey wolves updating position, and attacking prey versus searching for prey.

A2. Whale Optimization Algorithm

The main idea of this algorithm is inspired by whales' hunting behavior. This is a population-based algorithm inspired by nature. It has been proposed in [126] and has garnered attention from researchers in recent years due to its fast-tracking behavior compared to other prevalent methods [127]. For hunting, whales dive down and then ascend in a conical spiral path toward the water surface while creating bubbles, which is known as the bubble net and illustrated in Fig. A.2. This feeding behavior is mathematically modeled to form the basis of the algorithm.

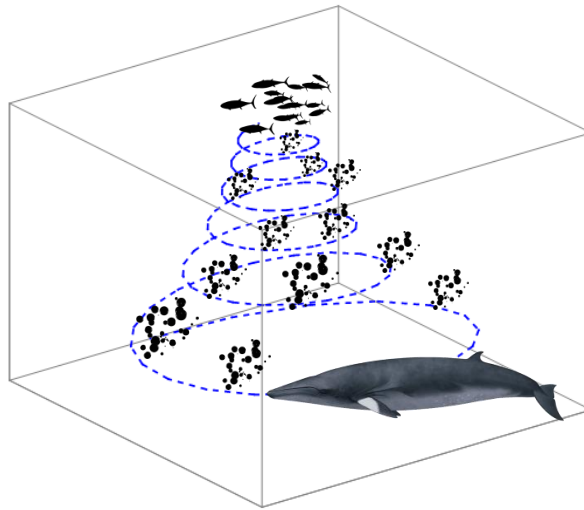


Figure A.2. Whales' bubble net hunting behavior to reach their prey [128].

In this algorithm, the prey that the whales aim to hunt is assumed to represent the optimal solution. The decision variables in this context are the locations of the whales. Once the best agent (whale) is identified, the others update their locations accordingly. In this algorithm, the agents try to reach their prey, which in this study are

each unknown parameter of the PV module for various flying and environmental conditions of the UAV. This process involves iteratively updating the locations of the agents based on the best agent's position. The described procedure can be mathematically formulated as follows, initially by considering the encircling of the prey [126]:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_{(t)}^* - \vec{X}_{(t)} \right| \quad (\text{A.7})$$

$$\vec{X}(t+1) = \vec{X}_{(t)}^* - \vec{A} \cdot \vec{D} \quad (\text{A.8})$$

where t represents the current iteration number, and X^* and X are the obtained optimal position and the current position of the whale, respectively. D is the distance between the current optimal solution and the search agents, and A and C coefficients are derived as follows [129]:

$$\vec{A} = 2\vec{n} \cdot \vec{r} - \vec{n} \quad (\text{A.9})$$

$$\vec{C} = 2 \cdot \vec{r} \quad (\text{A.10})$$

where n is a value between 2 and 0 and is decreased linearly during the iterations (in the extraction and exploration phases). r_0 is a random value between 0 and 1.

The next mathematical modeling step involves capturing the bubble-net attacking behavior of whales. This process encompasses two distinct modeling approaches: shrinkage encircling mechanisms and spiral position updating.

The shrinkage behavior is represented by a gradual decrease in the value of

parameter a from 2 to over successive iterations. To depict the spiral movement of a whale around its prey, as illustrated in Fig. A.3, the following equation is employed. This equation quantifies the distance between the whale located at coordinates (X, Y) and its prey located at (X^*, Y^*) [126].

$$\vec{X}(t+l) = \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) \quad (\text{A.11})$$

where D' represents the distance between the searching agent and the target prey. b denotes the spiral shape constant parameter, and l is a random value in the range of -1 to 1.

Considering the humpback whale's tendency to move along both possible shrinking circular and spiral-shaped paths, the probability of occurrence of each movement is considered as 50 percent during the optimization process. Therefore, the selection between these two conditions is modeled mathematically as follows [126]:

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A} \cdot \vec{D} & \text{if } p < 0.5 \\ \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) & \text{if } p \geq 0.5 \end{cases} \quad (\text{A.12})$$

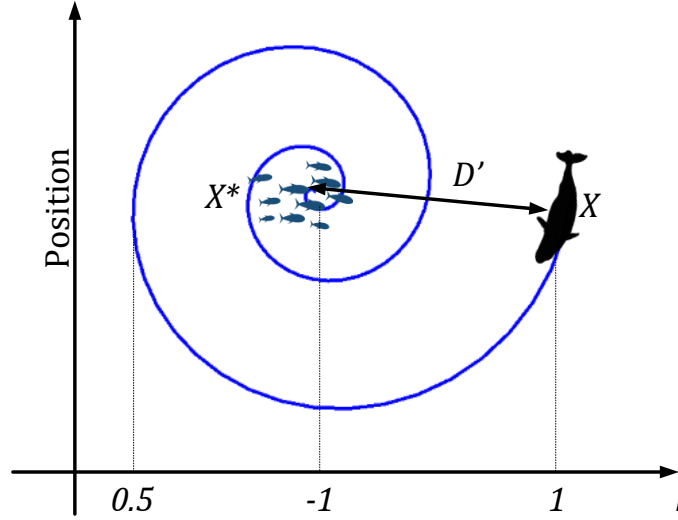


Figure A.3. Whales spiral updating position [128].

In order to avoid trapping in local optimum points, the search range has to be expanded. So, the value of A is chosen randomly to be greater than 1 or smaller than -1 to force humpback whales to search far away from the reference whale. The model of this search is as follows [126]:

$$\vec{D} = \left| \vec{C} \cdot \overrightarrow{X_{rand}} - \vec{X} \right| \quad (\text{A.13})$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A} \cdot \vec{D} \quad (\text{A.14})$$

where X_{rand} is the random position of a random whale, and D is the distance between the random agent and X .

A3. Multiverse Optimization Algorithm

MVO is a nature-inspired optimization technique proposed in [136]. The key idea of MVO is inspired from the theory of multiverses. Since its invention, it is applied to solve several real-world problems. In [136], it is shown that MVO obtained very competitive results compared with other metaheuristic optimization algorithms.

The MVO is a recent population-based algorithm inspired by the multiverse theory, which suggests the existence of multiple universes created by numerous big bangs. These universes interact with one another through different types of "holes," such as white holes, black holes, and wormholes. A schematic of this fact is shown in Fig. A.4. MVO uses these concepts to guide its search for the global solution to an optimization problem. The primary objective of MVO is to find the optimal solution by modeling how objects (or variables) travel between universes, leveraging both exploration and exploitation processes.

The big bang theory proposes that the universe started with a massive explosion, but the multiverse theory goes further by suggesting that there are multiple big bangs, each leading to the creation of different universes [136][137]. The algorithm utilizes three key elements of this theory: white holes, which allow objects to exit a universe; black holes, which attract objects into a universe; and wormholes, which act as shortcuts connecting different parts of the universe or even different universes [138].

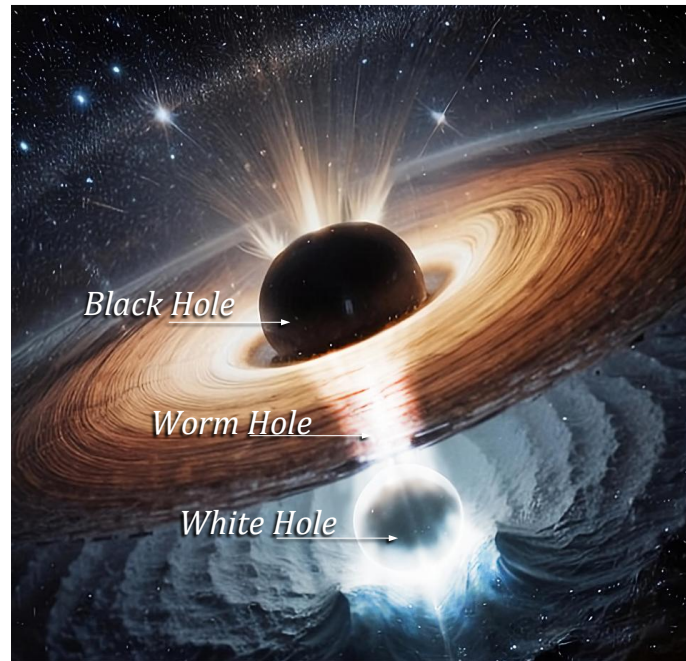


Figure A.4. Multiverse theory schematic.

In the MVO algorithm, each solution in the search space is considered a universe, and each variable within that solution represents an object. These universes expand at different rates, referred to as the inflation rate, which is proportional to the quality of the solution [138]. Universes with a higher inflation rate (better solutions) tend to send objects through white holes, while universes with a lower inflation rate (poorer solutions) receive objects through black holes [137][138]. This exchange of objects between universes helps improve the quality of solutions over iterations.

In addition to the white and black hole mechanics, wormholes provide a mechanism for objects to move randomly between different universes, independent of their inflation rate. This allows for further exploration of the search space and prevents the algorithm from getting stuck in local optima. The combination of white holes for

exploration and wormholes for exploitation helps maintain a balance between searching broadly across the solution space and refining the best solutions found [138].

The algorithm starts by initializing a population of solutions (universes) and updates these solutions over a set number of iterations, constantly moving objects between universes based on their inflation rates. This process continues until the best solution is identified [136]-[138].

The main mathematical model of MVO algorithm depends on (A.15) and (A.16) which are described as follows:

$$X_i^j = \begin{cases} X_k^j, r_1 < NI(U_i) \\ X_i^j, r_1 > NI(U_i) \end{cases} \quad (A.15)$$

where X_i^j is the j th object of the i th universe, r_1 is a random number in the range (0,1), $NI(U_i)$ shows the normalized inflation rate of the i th universe and X_k^j represents the j th object of the k th universe.

In MVO, the worm hole tunnels are always established between a universe and the best universe provided so far. This mechanism can mathematically define as follows:

$$X_i^j = \begin{cases} \begin{cases} (X_j + TDR \times (ub - lb) \times r_4 + lb), r_3 < 0.5 \\ (X_j - TDR \times (ub - lb) \times r_4 + lb), r_3 \geq 0.5 \end{cases}, r_2 < WEP \\ X_i^j, r_2 \geq WEP \end{cases} \quad (A.16)$$

where X_j is the j -th parameter of the best obtained universe, ub and lb are upper and lower bounds, traveling distance rate (TDR) and Wormhole Existence Probability (WEP) are coefficients, and r_2 , r_3 , and r_4 are random numbers in the range of (0,1). WEP and TDR are variables which are changed in any iterations. The former coefficient is for defining the probability of wormhole's existence in universes. It is required to increase linearly over the iterations in order to emphasize exploitation as the progress of optimization process. Travelling distance rate is also a factor to define the distance rate (variation) that an object can be teleported by a wormhole around the best universe obtained so far. In contrast to WEP, TDR is increased over the iterations to have more precise exploitation/local search around the best obtained universe. These two coefficients can be calculated based on the following formulas:

$$WEP = \min + l \times \left(\frac{\max - \min}{L} \right) \quad (A.17)$$

$$TDR = 1 - \frac{L^{1/p}}{L^{1/p}} \quad (A.18)$$

where p represents the exploitation factor, l is the current iteration, and L shows the maximum iteration.

A4. Moth Flame Optimization Algorithm

The MFO algorithm, introduced by Mirjalili in 2015, is a population-based optimization technique inspired by the unique nocturnal navigation behavior of moths [139]. Moths are fascinating insects, closely related to butterflies, with over 160,000 species documented in nature. Their life cycle consists of two main stages: larva and

adult, with the transformation into moths occurring within cocoons [139][140].

One of the most intriguing characteristics of moths is their transverse orientation mechanism, which they use for night navigation. This method allows moths to travel in a straight path by maintaining a constant angle relative to the moon. Since the moon is a distant celestial body, this technique is highly effective for long-distance travel, ensuring that moths fly in a straight line. This same principle can be applied to humans; for example, if a person keeps the moon on their left side while walking, they can maintain a straight course eastward [139][140].

However, when moths encounter artificial light sources, such as street lamps, they are tricked. Artificial lights are much closer than the moon, and the transverse orientation method becomes ineffective. As a result, moths fly in spirals around the light source, as they try to maintain the same angle relative to it, resulting in erratic flight patterns [139][140]. A schematic of this fact is shown in Fig. A.5.

Mirjalili modeled this behavior mathematically and proposed the MFO algorithm, which simulates the spiral motion of moths as they search for optimal solutions in a defined search space [141]. In the MFO algorithm, moths represent candidate solutions, and flames represent the best solutions found so far. Moths are attracted to the flames and move toward them in a spiral trajectory, which is a key feature of the optimization

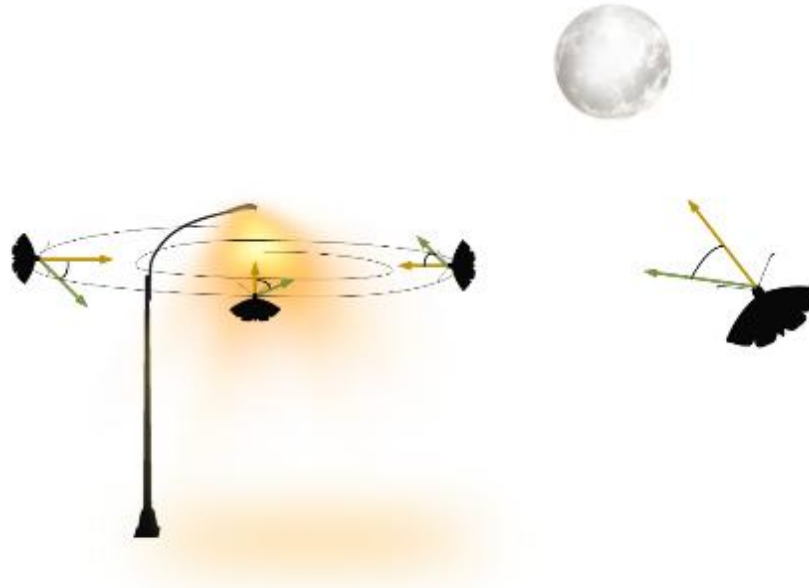


Figure A.5. Moth-flame theory schematic.

process. The flames guide the moths toward better solutions by continuously updating their positions in the search space [141][142].

The MFO algorithm has gained popularity due to its simplicity, robustness, and ease of implementation, and has been successfully applied in a variety of fields [141][142]. The interaction between moths and flames, mathematically modeled to mimic real-life behavior, allows the algorithm to effectively explore and exploit the search space, making it a powerful tool for solving complex optimization problems [141][142].

This algorithm initializes the population position by the following equation.

$$M = R(n, d) \times (ub - lb) + lb \quad (\text{A.19})$$

where n is the population size, d is the dimension number, R is a random number generating which generate number between 0 to 1. Moreover, ub and lb are the upper and lower bounds. According to the fact that this algorithm is based on the population, the moths can be presented in the form of matrix.

$$M = \begin{pmatrix} m_{11} & \dots & m_{1d} \\ \vdots & \ddots & \vdots \\ m_{n1} & \dots & m_{nd} \end{pmatrix} \quad (\text{A.20})$$

where n is number of solutions (moths) and d is the dimension of the problem that defines the position of moth in search space. Moreover, the fitness values of moths are stored in another matrix as follows:

$$OM = \begin{pmatrix} OM_1 \\ \vdots \\ OM_n \end{pmatrix} \quad (\text{A.21})$$

It is notable that another variable is introduced here, i.e., flame. The moths and flames are actually candidate solutions. The flame can be seen as the flag of the moth in the search space. The moth is responsible for moving in the search space and finding the best position, and the flame represents the best position that has been found so far. The position of the flames and the corresponding fitness values are stored in the matrices F and OF , respectively.

$$F = \begin{pmatrix} F_{11} & \cdots & F_{1d} \\ \vdots & \ddots & \vdots \\ F_{n1} & \cdots & F_{nd} \end{pmatrix} \quad (\text{A.22})$$

$$OF = \begin{pmatrix} OF_1 \\ \vdots \\ OF_n \end{pmatrix} \quad (\text{A.23})$$

This mechanism mimics the fire-fighting behavior of moths in real life. According to the sorted flames, the moths fly around the flames in a spiral motion. This phenomenon is described as [141]:

$$M_i = S(M_i, F_j) \quad (\text{A.24})$$

$$S(M_i, F_j) = D_i \times e^{bt} \times \cos(2\pi t) + F_j \quad (\text{A.25})$$

$$D_i = |F_j - M_i| \quad (\text{A.26})$$

where, M_i is the updated position of the i -th moth, S represents a logarithmic spiral curve, F_j represents the j -th flame, b is a constant, t represents a random number between $[a, 1]$, where a decreases linearly from 1 to -2 as the number of iterations increases, and D_i is the distance from the i -th moth to the j -th flame.

References

- [1] A. Diab-Marzouk and O. Trescases, "SIC-based bidirectional buck converter with differential power processing and MPPT for a solar powered aircraft," *IEEE Transactions on Transportation Electrification*, vol. 1, no. 4, pp. 369–381, 2015. doi:10.1109/tte.2015.2505302.
- [2] R. M. Bhatt, *Solar power unmanned aerial vehicle: High altitude long endurance applications (HALE-SPUAV)*, Master of Science thesis, San Jose State University, 2012. [Online]. Available: <https://www.sjsu.edu/>
- [3] L. Girlevicius, *Evaluation of solar-powered systems in small-scale UAV designs*, KTH Thesis Report, Degree Project in Technology, Second Cycle, Stockholm, Sweden, 2022.
- [4] A. Bakar, L. Ke, H. Liu, Z. Xu, and D. Wen, "Design of Low Altitude Long Endurance Solar-Powered UAV Using Genetic Algorithm," *Aerospace*, vol. 8, no. 8, p. 228, Aug. 2021.
- [5] Y. Chu, C. Ho, Y. Lee, and B. Li, "Development of a solar-powered unmanned aerial vehicle for extended flight endurance," *Drones*, vol. 5, no. 2, p. 44, May 2021, doi: 10.3390/drones5020044.
- [6] Boucher, Robert J. "Sunrise, the world's first solar-powered airplane". eng. In: *Journal of aircraft* 22.10 (1985), pp. 840–846. ISSN: 0021-8669.
- [7] B. D. Safyanu, M. N. Abdullah, and Z. Omar, "Review of Power Device for Solar-Powered Aircraft Applications," *Journal of Aerospace Technology and Management*, Oct. 2019.
- [8] Siquig, A., "Impact of Icing on Unmanned Aerial Vehicle (UAV) Operations," *Naval Environmental Prediction Research Facility*, 1990
- [9] C. Deiler and T. Kilian, "Dynamic aircraft simulation model covering local icing effects," *CEAS Aeronautical Journal*, vol. 9, no. 3, pp. 429–444, Mar. 2018.
- [10] R. Hann, "UAV Icing: Ice Accretion Experiments and Validation," *SAE Technical Papers on CD-ROM/SAE Technical Paper Series*, Jun. 2019.
- [11] A. Sharma, A. Dasgotra, S. K. Tiwari, A. Sharma, V. Jatly, and B. Azzopardi, "Parameter

- extraction of photovoltaic module using tunicate swarm algorithm,” *Electronics*, vol. 10, no. 8, p. 878, Apr. 2021, doi: 10.3390/electronics10080878.
- [12] DSH. Chan and JCH. Phang, “Analytical methods for the extraction of solar-cell single- and double-diode model parameters from I–V characteristics,” *Electron Dev IEEE Trans*, vol. 34, pp. 286–93, 1987.
- [13] C. Nemes and F. Munteanu, “An analysis of a photovoltaic panel model: Comparison between measurements and analytical models,” in *International Conference and Exposition on Electrical and Power Engineering*, Iasi, Romania, 2012, pp. 939-944.
- [14] E. I. Batzelis, G. E. Kampitsis, S. A. Papathanassiou, and S. N. Manias, “Direct MPP Calculation in Terms of the Single-Diode PV Model Parameters,” *IEEE Transactions on Energy Conversion*, vol. 30, no. 1, pp. 226–236, Mar. 2015, doi: 10.1109/tec.2014.2356017.
- [15] K. Ding, X. Bian, H. Liu, and T. Peng, “A MATLAB-Simulink-Based PV Module Model and Its Application Under Conditions of Nonuniform Irradiance,” *IEEE Transactions on Energy Conversion*, vol. 27, no. 4, pp. 864–872, Dec. 2012, doi: 10.1109/tec.2012.2216529.
- [16] A. Molina-Garcia, J. Guerrero-Perez, M. C. Bueso, M. Kessler, and E. Gomez-Lazaro, “A New Solar Module Modeling for PV Applications Based on a Symmetrized and Shifted Gompertz Model,” *IEEE Transactions on Energy Conversion*, vol. 30, no. 1, pp. 51–59, Mar. 2015, doi: 10.1109/tec.2014.2330741.
- [17] S. Hosseini, S. Taheri, M. Farzaneh and H. Taheri, “Modeling of snow- covered photovoltaic modules,” *IEEE Transactions on Industrial Electronics*, vol. 65, no. 10, pp. 7975-7983, Oct. 2018, doi: 10.1109/TIE.2018.2803725.
- [18] M. Khenar, S. Taheri, A. -M. Cretu, S. Hosseini and E. Pouresmaeil, "PSO-based modeling and analysis of electrical characteristics of photovoltaic module under nonuniform snow patterns," *IEEE Access*, vol. 8, pp. 197484-197498, 2020, doi: 10.1109/ACCESS.2020.3034748.
- [19] J.F. Gaviria, G. Narv'aez, C. Guillen, L.F. Giraldo, and M. Bressan, “Machine learning in photovoltaic systems: a review,” *Renew. Energy*, vol. 196, pp. 298–318, 2022.
- [20] Hashemi, A. -M. Cretu and S. Taheri, “Computational intelligence-based snow cover prediction for photovoltaic systems,” in *IEEE Electrical Power and Energy Conference (EPEC)*, Toronto, ON, Canada, 2021, pp. 1-6, doi: 10.1109/EPEC52095.2021.9621702.
- [21] Hashemi, S. Taheri and A. -M. Cretu, “Systematic analysis and computational intelligence-based modeling of photovoltaic power generation in snow conditions,” *IEEE Journal of Photovoltaics*,

vol. 12, no. 1, pp. 406-420, Jan. 2022, doi: 10.1109/JPHOTOV.2021.3123198.

- [22] B.Hashemi, S.Taheri, A.M.Cretu, E.Pouresmaeil, "Computational intelligence based PEVs aggregator scheduling with support for photovoltaic power penetrated distribution grid under snow conditions," *Electric Power Systems Research*, Volume 214, Part A, 2023,
- [23] F. Ghani, G. Rosengarten, M. Duke, and J. K. Carson, "The numerical calculation of single-diode solar-cell modelling parameters," *Renew. Energy*, vol. 72, pp. 105–112, Dec. 2014.
- [24] A.M. Humada, M. Hojabri, M.B. Mohamed, B. Sulaiman, M. Herwan, and T.H. Dakheel, "A proposed method of photovoltaic solar array configuration under different partial shadow conditions," *Adv. Mater. Res. Trans. Tech. Publ.*, pp. 307–311, 2014.
- [25] A.M. Humada, F.B. Samsuri, M. Hojabria, M.B. Mohamed, M.H.B. Sulaiman, and T.H. Dakheel, "Modeling of photovoltaic solar array under different levels of partial shadow conditions," in *Power Electronics and Motion Control Conference and Exposition (PEMC)*, 2014, pp. 461–465.
- [26] P. Lin, S. Cheng, W. Yeh, Z. Chen, and L. Wu, "Parameter's extraction of solar cell models using a modified simplified swarm optimization algorithm," *Sol. Energy*, vol. 144, pp. 594–603, 2017.
- [27] H. Saleem and S. Karmalkar, "An analytical method to extract the physical parameters of a solar cell from four points on the illuminated J-V curve," *IEEE Electron Device Lett*, vol. 30, pp. 349–352, 2009.
- [28] M. Khenar, S. Hosseini, S. Taheri, A. Cretu, E. Pouresmaeil, and H. Taheri, "Particle swarm optimisation-based model and analysis of photovoltaic module characteristics in snowy conditions," *IET Renewable Power Gener.*, vol. 13, no. 11, pp. 1950–7, Aug. 2019.
- [29] M. S. Ismail, M. Moghavvemi, and T. M. I. Mahlia, "Characterization of PV panel and global optimization of its model parameters using genetic algorithm," *Energy Conversion and Management*, vol. 73, pp. 10–25, 2013.
- [30] R. B. Messaoud, "Extraction of uncertain parameters of double-diode model of a photovoltaic panel using ant lion optimization," *Social Netw. Appl. Sci.*, vol. 2, no. 2, pp. 367–372, Feb. 2020.
- [31] S. Xu and Y. Wang, "Parameter estimation of photovoltaic modules using a hybrid flower pollination algorithm," *Energy Convers. Manage.*, vol. 144, pp. 53–68, Jul. 2017.
- [32] X. Chen, S. Wang, and K. He, "Parameter estimation of various PV cells and modules using an improved simultaneous heat transfer search algorithm," *J. Comput. Electron.*, no. 23, pp. 584–599, 2024.

- [33] X. Chen, Q. Lu, Y. Yuan, and K. He, “A novel derivative search political optimization algorithm for multi-area economic dispatch incorporating renewable energy,” *Energy*, pp. 131510, May 2024.
- [34] Bernstein, B. C., Wolff, C. A. & McDonough, F. An Inferred Climatology of Icing Conditions Aloft, Including Supercooled Large Drops. Part I: Canada and the Continental United States. *Journal of Applied Meteorology and Climatology* 46, 1857–1878. ISSN: 1558-8432, 1558-8424. [https://journals.ametsoc.org/doi/10.1175/2007JAMC1607.1\(2022\) \(Nov. 1, 2007\).](https://journals.ametsoc.org/doi/10.1175/2007JAMC1607.1(2022) (Nov. 1, 2007).)
- [35] Bernstein, B. C. & Le Bot, C. An Inferred Climatology of Icing Conditions Aloft, Including Supercooled Large Drops. Part II: Europe, Asia, and the Globe. *Journal of Applied Meteorology and Climatology* 48, 1503–1526. ISSN: 1558-8432, 1558-8424. [http://journals.ametsoc.org/doi/10.1175/2009JAMC2073.1 \(2022\) \(Aug. 1, 2009\)](http://journals.ametsoc.org/doi/10.1175/2009JAMC2073.1 (2022) (Aug. 1, 2009))
- [36] Hann, R., and Johansen, T., *Unsettled Topics in UAV Icing*, SAE International, SAE EDGE Research Report EPR2020008, 2020.
- [37] Hann, R., *Atmospheric Ice Accretions, Aerodynamic Icing Penalties, and Ice Protection Systems on Unmanned Aerial Vehicles*, PhD Thesis NTNU2020:200, Norwegian University of Science and Technology, 2020.
- [38] Gao, M., Hugenholtz, C. H., Fox, T. A., Kucharczyk, M., Barchyn, T. E., and Nesbit, P. R., “Weather constraints on global drone flyability,” *Scientific Reports*, 2021, pp. 1–13. <https://doi.org/10.1038/s41598-021-91325-w>
- [39] Goyal, R., *Urban Air Mobility (UAM) Market Study*, NASA
- [40] R. Hann, N. Müller, M. Lindner, and J. Wallisch, “UAV Icing: Experimental Validation Data for Predicting ice Shapes at Low Reynolds Numbers,” *SAE Technical Papers on CD-ROM/SAE Technical Paper Series*, Jun. 2023.
- [41] C. Deline,” *Partially shaded operation of a grid-tied system*”, *Proceedings of 34th IEEE Photovoltaic Specialists Conference*, Philadelphia, Pennsylvania, June 7-12, 2009.
- [42] P. Grunow, S. Lust, D. Sauter, V. Hoffmann, C. Beneking, B. Litzenburger and L. Podlowski,” *Weak light performance and annual yields of PV modules and systems as a result 22 of the basic paramter set of industrial solar cells*”, *Proceedings of 19th European Photovoltaic Solar Energy Conference*, Paris, France, June 7-11, 2004.
- [43] N.H. Reich, W.G.J.H.M. van Sark, E.A. Alsema, S.Y. Kan, S. Silverster, A.S.H. van der Heide, R.W. Lof and R.E.I. Schropp,” *Weak light performance and spectral response of different solar cell types*”, *Proceedings of the 20th European Photovoltaic Solar Energy Conference*, Barcelona,

Spain, June 6-10, 2005.

- [44] A. Woyte, J. Nijs and R. Belmans, "Partial shadowing of photovoltaic arrays with different system configurations: literature review and field test results", *Solar Energy*, 74, 217-233, 2003.
- [45] E. Andenæs, B. P. Jelle, K. Ramlo, T. Kolås, J. Selj, and S. E. Foss, "The influence of snow and ice coverage on the energy generation from photovoltaic solar cells," *Solar Energy*, vol. 159, pp. 318–328, Nov. 2017.
- [46] National Solar Radiation Database, National Renewable Energy Laboratory. [Online]. Available: <https://nsrdb.nrel.gov/>.
- [47] M. Yang, L. Zhang, Z. Zhao, and L. Wang, "Comprehensive benefits analysis of electric vehicle charging station integrated photovoltaic and energy storage," *Journal of Cleaner Production*, vol. 302, p. 126967, Apr. 2021.
- [48] A. S. Rodriguez, T. De Santana, I. MacGill, N. J. Ekins-Daukes, and A. Reinders, "A feasibility study of solar PV-powered electric cars using an interdisciplinary modeling approach for the electricity balance, CO2 emissions, and economic aspects: The cases of The Netherlands, Norway, Brazil, and Australia," *Progress in Photovoltaics Research and Applications*, vol. 28, no. 6, pp. 517–532, Nov. 2019.
- [49] S. Hisoglu, A. Tuominen, and A. Huovila, "An approach for selecting optimal locations for electric vehicle solar charging stations," *IET Smart Cities*, vol. 5, no. 2, pp. 123–134, May 2023.
- [50] H. Wirth, D. H. Neuhaus, T. Kroyer, C. Reise, A. Schmid, D. Eberlein, L. E. Alanis, M. Mittag, F. Basler, C. Kutter, and M. Heinrich, "Potential and Challenges of Vehicle Integrated Photovoltaics for Passenger Cars," *37th European Photovoltaic Solar Energy Conference and Exhibition*, pp. 1695–1700, Oct. 2020.
- [51] M. C. Brito, T. Santos, F. Moura, D. Pera, and J. Rocha, "Urban solar potential for vehicle integrated photovoltaics," *Transportation Research Part D Transport and Environment*, vol. 94, p. 102810, Mar. 2021.
- [52] D. Ghose, S. Pradhan, P. Tamuli, and N. Shabbiruddin, "Optimal material for solar electric vehicle application using an integrated Fuzzy-COPRAS model," *Energy Sources Part a Recovery Utilization and Environmental Effects*, vol. 45, no. 2, pp. 3859–3878, Sep. 2019.
- [53] G.R. Chandra Mouli, P. Bauer and M. Zeman, "System design for a solar powered electric vehicle charging station for workplaces" *Applied Energy*, Vol 168, pp 434-443, 2016.

- [54] A. Inba Remy and R. Seyezhai, "A comparative study of active power factor correction ac-dc converters for electric vehicle applications" *ARNP Journal of Engineering and Applied Sciences*, Vol. 8, No. 9, Sep2013.
- [55] Z. Zhou, C. Zhang, C. Xu, F. Xiong, Y. Zhang and T. Umer, "Energy-Efficient Industrial Internet of UAVs for Power Line Inspection in Smart Grid," in *IEEE Transactions on Industrial Informatics*, vol. 14, no. 6, pp. 2705-2714, June 2018.
- [56] B. Yang, H. Shi and X. Xia, "Federated Imitation Learning for UAV Swarm Coordination in Urban Traffic Monitoring," in *IEEE Transactions on Industrial Informatics*, vol. 19, no. 4, pp. 6037-6046, April 2023
- [57] H. Fang, Z. Liao, X. Wang, Y. Chang and L. Yan, "Differentiated Attention Guided Network Over Hierarchical and Aggregated Features for Intelligent UAV Surveillance," in *IEEE Transactions on Industrial Informatics*, vol. 19, no. 9, pp. 9909-9920, Sept. 2023
- [58] P. Manoharan et al., "Improved Perturb and Observation Maximum Power Point Tracking Technique for Solar Photovoltaic Power Generation Systems," *IEEE Systems Journal*, vol. 15, no. 2, pp. 3024-3035, June 2021.
- [59] M. Shashati et al., "Design and fabrication of a solar powered unmanned aerial vehicle (UAV)," in *Advances in Science and Engineering Technology International Conferences (ASET)*, Dubai, United Arab Emirates, 2023, pp. 1-10.
- [60] H. Suryatmojo et al., "Design of MPPT based fuzzy logic for solar-powered unmanned aerial vehicle application," in *International Conference on Engineering, Applied Sciences, and Technology (ICEAST)*, Phuket, Thailand, 2018, pp. 1-4.
- [61] S.-H. Ko and R.-M. Chao, "Photovoltaic dynamic MPPT on a moving vehicle," *Solar Energy*, vol. 86, no. 6, pp. 1750–1760, Apr. 2012.
- [62] Messai A, Mellit A, Guessoum A, Kalogirou SA. Maximum power point tracking using GA optimized FLC and its FPGA implementation. *Sol Energy*. 2011;85(2):265-277
- [63] S. Prasad, M. Ulaganathan, D. Durairaj, M. J. Aljaafreh and M. AlSalhi, "Implementation of MPPT for Flexible Solar Cells embedded on unmanned aerial vehicles," in *IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS)*, Tamilnadu, India, 2019, pp. 1-6.
- [64] L. Shang, H. Guo, and W. Zhu, "An improved MPPT control strategy based on incremental conductance algorithm," *Protection and Control of Modern Power Systems*, vol. 5, no. 1, Jun. 2020.
- [65] A. Saberi, M. Niroomand, and B. M. Dehkordi, "An Improved P&O Based MPPT for PV Systems with Reduced Steady-State Oscillation," *International Journal of Energy Research*, vol. 2023, pp. 1–

15, Jul. 2023.

- [66] Kulaksiz AA, Akkaya R. A genetic algorithm optimized ANN based MPPT algorithm for a stand-alone PV system with induction motordrive. *Sol Energy*. 2012;86(9):2366-2375
- [67] Salah C, Ouali M. Comparison of fuzzy logic and neural network in maximum power point tracker for PV systems. *Electr Power Syst Res*.2011;81(1):43-50.
- [68] N. Kumar, B. Singh, and B. K. Panigrahi, "Grid synchronisation framework for partially shaded solar PV-based microgrid using intelligent control strategy," *IET Generation Transmission & Distribution*, vol. 13, no. 6, pp. 829–837, Oct. 2018.
- [69] N. Ncir and N. E. Akchioui, "An advanced intelligent MPPT control strategy based on the imperialist competitive algorithm and artificial neural networks," *Evolutionary Intelligence*, vol. 17, no. 3, pp. 1437–1461, Feb. 2023.
- [70] M. Q. Raza, N. Mithulanathan, J. Li, K. Y. Lee and H. B. Gooi, "An Ensemble Framework for Day-Ahead Forecast of PV Output Power in Smart Grids," in *IEEE Transactions on Industrial Informatics*, vol. 15, no. 8, pp. 4624-4634, Aug. 2019.
- [71] F. J. Toledo, J. M. Blanes and V. Galiano, "Two-Step Linear Least-Squares Method For Photovoltaic Single-Diode Model Parameters Extraction," in *IEEE Transactions on Industrial Electronics*, vol. 65, no. 8, pp. 6301-6308, Aug. 2018, doi: 10.1109/TIE.2018.2793216.
- [72] J. Xu, "Separable Nonlinear Least Squares Search of Parameter Values in Photovoltaic Models," in *IEEE Journal of Photovoltaics*, vol. 12, no. 1, pp. 372-380, Jan. 2022, doi: 10.1109/JPHOTOV.2021.3126105.
- [73] J. Tang, Q. Pan, Z. Chen, G. Liu, G. Yang, F. Zhu, and S. Lao, "An Improved Artificial Electric Field Algorithm for Robot Path Planning," *IEEE Transactions on Aerospace and Electronic Systems*, pp. 1–14, Jan. 2024.
- [74] B. Ma, Z. Liu, W. Zhao, J. Yuan, H. Long, X. Wang, and Z. Yuan, "Target tracking control of UAV through deep reinforcement learning," *IEEE Trans. Intell. Transp. Syst.*, 2023.
- [75] B. Ma, Z. Liu, F. Jiang, W. Zhao, Q. Dang, X. Wang, J. Zhang, and L. Wang, "Reinforcement learning based UAV formation control in GPS-denied environment," *Chinese Journal of Aeronautics/Chinese Journal of Aeronautics*, vol. 36, no. 11, pp. 281–296, Nov. 2023
- [76] AC Propulsion, "AC Propulsion's Solar Electric Powered SoLong UAV", 2004, http://www.acpropulsion.com/ACP_PDFs/ACP_SoLong_UAV_48hr_Flight_2005-06-05.pdf

- [77] L. S. Al Dhafari, A. Afzal, O. K. Al Abri and A. Khan, "Solar-Powered UAVs: A systematic Literature Review," 2024 2nd International Conference on Unmanned Vehicle Systems-Oman (UVS), Muscat, Oman, 2024, pp. 1-8, doi: 0.1109/UVS59630.2024.10467158.
- [78] A. Noth, "Designing solar airplanes for continuous flight," SPIE Newsroom, 2009. doi:10.1117/2.1200906.1649
- [79] P. B. MacCready, P. B. S. Lissaman, W. R. Morgan, and J. D. Burke, "Sun-powered aircraft designs," *Journal of Aircraft*, vol. 20, no. 6, pp. 487–493, Jun. 1983.
- [80] X. Zhu, Z. Guo, and Z. Hou, "Solar-powered airplanes: A historical perspective and future challenges," *Progress in Aerospace Sciences*, vol. 71, pp. 36–53, 2014. doi:10.1016/j.paerosci.2014.06.003
- [81] Hann, R., and Johansen, T. A., "UAV icing: the influence of airspeed and chord length on performance degradation," *Aircraft Engineering and Aerospace Technology*, Vol. 93, 2021. <https://doi.org/10.1108/AEAT-06-2020-0127>.
- [82] Hann, R., Enache, A., Nielsen, M. C., Stovner, B. N., van Beeck, J., Johansen, T. A., and Borup, K. T., "Experimental heat loads for electrothermal anti-icing and de-icing on UAVs," *Aerospace*, Vol. 8, 2021. <https://doi.org/10.3390/aerospace8030083>
- [83] Oswald, J.; Enache, A.; Hann, R.; Glabeke, G.; Lutz, T. UAV Icing: Experimental and Numerical Study of Glaze Ice Performance Penalties on an RG-15 Airfoil. In Proceedings of the AIAA Scitech 2022 Forum, San Diego, CA, USA, 3–7 January 2022. [CrossRef]
- [84] Lynch, F.T.; Khodadoust, A. Effects of ice accretions on aircraft aerodynamics. *Prog. Aerosp. Sci.* 2001, 37, 669–767.
- [85] Müller, N.; Hann, R. UAV Icing: A Performance Model for a UAV Propeller in Icing Conditions. In Proceedings of the AIAA Aviation 2022 Forum, Chicago, IL, USA, 27 June–1 July 2022.
- [86] Yamauchi, G.K. A Summary of NASA Rotary Wing Research: Circa 2008–2018. NASA/TP—2019–220459; NASA Ames Research Center Moffett Field: Mountain View, CA, USA, 2019.
- [87] Liu, Y.; Li, L.; Chen, W.; Tian, W.; Hu, H. An experimental study on the aerodynamic performance degradation of a UAS propeller model induced by ice accretion process. *Exp. Therm. Fluid Sci.* **2019**, 102, 101–112.
- [88] Mason, J.; Chow, P.; Riley, J. Engine Ice Crystal Icing Technology Plan with Research Needs; DOT/FAA/TC-20/34; Federal Aviation Administration, William J. Hughes Technical Center,

Atlantic City International Airport: Egg Harbor Township, NJ, USA, 2020.

- [89] Struk, P.; Broeren, A.; Potapczuk, M.; Kreeger, R.; Blankenship, K.; Chen, R.-C.; Flege Al Porter, C.; Ratvasky, T.; Van Zante, D.; Van Zante, J.; et al. NASA Analysis of Alternatives Study for Icing Research; NASA/TM-20220006956; NASA Glenn Research Center: Cleveland, OH, USA, 2022.
- [90] Yugulis, K.; Chase, D.; McCrink, M. Ice Accretion Analysis for the Development of the HeatCoat Electrothermal Ice Protection System. In Proceedings of the AIAA Aviation 2020 Forum, Online Event, 15–19 June 2020.
- [91] R. W. Andrews, A. Pollard, and J. M. Pearce, “The effects of snowfall on solar photovoltaic performance,” *Solar Energy*, vol. 92, pp. 84–97, Mar. 2013.
- [92] M. Taylor, Statistical Relationship Between Photovoltaic Generation and Electric Utility Demand in Minnesota (1996–2002), in Proceedings of the Solar Conference, American Solar Energy Society, American Institute of Architects, 2003, pp. 213–218.
- [93] T. Sugiura, T. Yamada, H. Nakamura, M. Umeiya, K. Sakuta and K. Kurokawa, Measurements, analyses and evaluation of residential PV systems by Japanese monitoring program, *Sol. Energy Mater. Sol. Cells*, 2003, 75(3–4), 767–779.
- [94] L. Powers, J. Newmiller and T. Townsend, Measuring and modeling the effect of snow on photovoltaic system performance, in 2010 35th IEEE Photovoltaic Specialists Conference, IEEE, 2010 Jun 20, pp. 000973–000978.
- [95] R. W. Andrews and J. M. Pearce, Prediction of energy effects on photovoltaic systems due to snowfall events, in 2012 38th IEEE Photovoltaic Specialists Conference, Austin, TX, USA, IEEE, 2012, pp. 003386–003391.
- [96] Ross, M M.D. Photovoltaic array icing and snow accumulation: A study of a passive melting technology. Canada: N. p., 1995. Web. pp. 423–428, <https://doi.org/10.1016/j.egypro.2017.09.650>.
- [97] M. He, J. Wang, H. Li, Y. Song, Super-hydrophobic surfaces to condensed microdroplets at temperatures below the freezing point retard ice/frost formation, *Soft Matter* 7 (2011) 3993, <https://doi.org/10.1039/c0sm01504k>.
- [98] T. Kako, A. Nakajima, H. Irie, Z. Kato, K. Uematsu, T. Watanabe, K. Hashimoto, Adhesion and sliding of wet snow on a super-hydrophobic surface with hydrophilic channels, *J. Mater. Sci.* 39 (2004) 547–555, <https://doi.org/10.1023/B:JMSC.0000011510.92644.3f>.
- [99] K. Ramlo, B.P. Jelle, E. Andenæs, T. Kolås and P.M. Stenstad, ”The robustness and durability of photovoltaic cell surfaces attempting to avoid snow and ice formation”, To be submitted, 2015.
- [100] S. Hosseini, S. Taheri, M. Farzaneh and H. Taheri, "Modeling of Snow-Covered Photovoltaic Modules," in *IEEE Transactions on Industrial Electronics*, vol. 65, no. 10, pp. 7975-7983, Oct.

2018, doi: 10.1109/TIE.2018.2803725

- [101] E. Mohammadi and G. Moschopoulos, "Performance Investigation of Roof-Mounted PV Systems in Snowy Conditions Considering Snow Coverage and Snow Removal Process," 2020 IEEE Power & Energy Society General Meeting (PESGM), Montreal, QC, Canada, 2020, pp. 1-5, doi: 10.1109/PESGM41954.2020.9282029.
- [102] J. A. Mendoza-Mendoza, V. J. Gonzalez-Villela, C. F. Aguilar-Ibañez, and L. Fonseca-Ruiz, *Drones to Go*. 2021.
- [103] D. L. King, W. E. Boyson, and J. A. Kratochvil, "Photovoltaic array performance model," Sandia National Laboratories, Albuquerque, New Mexico, 2004.
- [104] S. Hosseini, S. Taheri, M. Farzaneh, H. Taheri and M. Narimani, "Determination of Photovoltaic Characteristics in Real Field Conditions," IEEE Journal of Photovoltaics, vol. 8, no. 2, pp. 572-580, March 2018, doi: 10.1109/JPHOTOV.2018.2797974.
- [105] G. M. Masters, "The solar resources," in *Renewable and Efficient Electric Power Systems* in John Wiley & Sons, 2013.
- [106] Sandia Module Temperature Model," PV Performance Modeling Collaborative (PVPMC). <https://pvpmc.sandia.gov/modeling-steps/2-dc-module-iv/module-temperature/sandia-module-temperature-model/>.
- [107] Siddique, H.A.B.; Xu, P.; De Doncker, R.W. "Parameter extraction algorithm for one-diode model of PV panels based on datasheet values," In International Conference on Clean Electrical Power (ICCEP), Alghero, Italy, 11–13 June 2013; pp. 7–13.
- [108] M. G. Villalva, J. R. Gazoli, and E. R. Filho, "Comprehensive approach to modeling and simulation of photovoltaic arrays," IEEE Transactions on Power Electronics, vol. 24, no. 5, pp. 1198–1208, May 2009, doi: 10.1109/tpel.2009.2013862.
- [109] N. Anani and H. Ibrahim, "Adjusting the single-diode model parameters of a photovoltaic module with irradiance and temperature," Energies, vol. 13, no. 12, p. 3226, Jun. 2020, doi: 10.3390/en13123226.
- [110] A. Chatterjee, A. Keyhani, and D. Kapoor, "Identification of photovoltaic source models," IEEE Transactions on Energy Conversion, vol. 26, no. 3, pp. 883–889, Sep. 2011, doi: 10.1109/tec.2011.2159268.
- [111] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in Engineering*

- Software, vol. 69, pp. 46–61, Mar. 2014, doi: 10.1016/j.advengsoft.2013.12.007
- [112] Y. Hou, H. Gao, Z. Wang, and C. Du, “Improved grey wolf optimization algorithm and application,” *Sensors*, vol. 22, no. 10, p. 3810, May 2022, doi: 10.3390/s22103810.
- [113] C. Muro, R. Escobedo, L. Spector, and R. P. Coppinger, “Wolf-pack (*Canis lupus*) hunting strategies emerge from simple rules in computational simulations,” *Behavioural Processes*, vol. 88, no. 3, pp. 192–197, Nov. 2011, doi: 10.1016/j.beproc.2011.09.006.
- [114] D. R. Ahmed, H. M. Abdullah, and F. F. Muhammadsharif, “Utilization of device parameters to assess the performance of a monocrystalline solar module under varied temperature and irradiance,” *Energy Systems*, vol. 14, no. 1, pp. 229–241, Aug. 2021, doi: 10.1007/s12667-021-00472-6.
- [115] V. U. Castrillo, A. Manco, D. Pascarella, and G. Gigante, “A review of counter-UAS technologies for cooperative defensive teams of drones,” *Drones*, vol. 6, no. 3, p. 65, Mar. 2022.
- [116] G. Lykou, D. Moustakas, and D. Gritzalis, “Defending airports from uas: a survey on cyber-attacks and counter-drone sensing technologies,” *Sensors*, vol. 20, no. 12, p. 3537, Jun. 2020, doi: 10.3390/s20123537.
- [117] J. Gundlach, *Designing Unmanned Aircraft Systems*. AIAA (American Institute of Aeronautics & Astronautics), 2014.
- [118] US Standard Atmosphere, National Oceanic and Atmospheric Administration, National Aeronautics and space Administration, US Air Force, Washington, D.C., USA, Oct. 1976.
- [119] ET Solar, “ET module monocrystalline,” ET-M53695 95W datasheet.
- [120] B. Hashemi, A. -M. Cretu and S. Taheri, “Snow loss prediction for photovoltaic farms using computational intelligence techniques,” *IEEE Journal of Photovoltaics*, vol. 10, no. 4, pp. 1044–1052, July 2020, doi: 10.1109/JPHOTOV.2020.2987158.
- [121] H. Tian, F. Mancilla-david, K. Ellis, P. Jenkins, and E. Muljadi, “A detailed performance model for photovoltaic systems preprint,” *Sol. Energy J.*, no. July.2012.
- [122] S. Bellavia, M. Macconi, and S. Pieraccini, “Constrained Dogleg methods for nonlinear systems with simple bounds - Computational Optimization and Applications,” *SpringerLink*, Mar. 2012.
- [123] “Trust Region Algorithm,” Birgham Young University. [Online]. Available: <https://acme.byu.edu/>.

- [124] A. R. Conn, N. I. M. Gould, and Ph. L. Toint, "Trust Region Methods," in SIAM, 2000.
- [125] J. Nocedal and S. J. Wright, "Numerical Optimization" in Springer, 2006.
- [126] S. Mirjalili, A. Lewis, "The Whale Optimization Algorithm," *Adv. Eng. Softw.*, vol. 95, pp. 51–67, 2016.
- [127] N. Rana, M. S. A. Latiff, S. M. Abdulhamid, and H. Chiroma, "Whale optimization algorithm: a systematic review of contemporary applications, modifications and developments," *Neural Computing and Applications*, vol. 32, no. 20, pp. 16245–16277, Mar. 2020.
- [128] M. H. Nadimi-Shahraki, H. Zamani, Z. Asghari Varzaneh, and S. Mirjalili, "A systematic review of the whale optimization algorithm: theoretical foundation, improvements, and hybridizations," *Archives of Computational Methods in Engineering*, vol. 30, no. 7, pp. 4113–4159, May 2023.
- [129] J. O. Adoghe, Control of unmanned aerial vehicle with wing shape identification using vision system and sensor fusion, Ph.D. dissertation, Department of Mechanical and Aerospace Engineering, Carleton University, Ottawa, Canada, 2022. [130] M. Lindner, J. Wallisch, and R. Hann, "UAV Icing: Numerical Simulation of Icing Effects on Wing and Empennage," *SAE Technical Papers on CD-ROM/SAE Technical Paper Series*, Jun. 2023.
- [131] R. Sangrody, S. Taheri, A.-M. Cretu, and E. Pouresmaeil, "An Improved PSO-Based MPPT Technique Using Stability and Steady State Analyses Under Partial Shading Conditions," *IEEE Transactions on Sustainable Energy*, vol. 15, no. 1, pp. 136–145, May 2023.
- [132] Created by: www.PromeAI.pro
- [133] J. Ahmed and Z. Salam, "An Improved Method to Predict the Position of maximum Power Point During Partial Shading for PV Arrays," *IEEE Transactions on Industrial Informatics*, vol. 11, no. 6, pp. 1378–1387, Dec. 2015.
- [134] H. Patel and V. Agarwal, "Maximum power point tracking scheme for PV systems operating under partially shaded conditions," *IEEE Trans. Ind. Electron.*, vol. 55, no. 4, pp. 1689–1698, Apr. 2008.
- [135] A. Kouchaki, H. Iman-Eini, and B. Asaei, "A new maximum power point tracking strategy for PV arrays under uniform and non-uniform insolation conditions," *Solar Energy*, vol. 91, pp. 1–12, May 2013, doi: 10.1016/j.solener.2013.01.030.
- [136] S. Mirjalili, S. M. Mirjalili, and A. Hatamlou, "Multi-Verse Optimizer: a nature-inspired algorithm for global optimization," *Neural Computing and Applications*, vol. 27, no. 2, pp. 495–513, Mar. 2015.
- [137] I. Aljarah, M. Mafarja, A. A. Heidari, H. Faris, and S. Mirjalili, "Multi-verse Optimizer: Theory,

- Literature Review, and Application in Data Clustering,” in *Studies in computational intelligence*, 2019, pp. 123–141.
- [138] G. I. Sayed, A. Darwish, and A. E. Hassanien, “Quantum multiverse optimization algorithm for optimization problems,” *Neural Computing and Applications*, vol. 31, no. 7, pp. 2763–2780, Nov. 2017.
- [139] M. Shehab, L. Abualigah, H. A. Hamad, H. Alabool, M. Alshinwan, and A. M. Khasawneh, “Moth-flame optimization algorithm: variants and applications,” *Neural Computing and Applications*, vol. 32, no. 14, pp. 9859–9884, Oct. 2019.
- [140] S. Mirjalili, “Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm,” *Knowledge-Based Systems*, vol. 89, pp. 228–249, Jul. 2015.
- [141] L. Ma, C. Wang, N.-G. Xie, M. Shi, Y. Ye, and L. Wang, “Moth-flame optimization algorithm based on diversity and mutation strategy,” *Applied Intelligence*, vol. 51, no. 8, pp. 5836–5872, Jan. 2021.
- [142] M. Qaraad, S. Amjad, N. K. Hussein, M. Badawy, S. Mirjalili, and M. A. Elhosseini, “Photovoltaic parameter estimation using improved moth flame algorithms with local escape operators,” *Computers & Electrical Engineering*, vol. 106, p. 108603, Jan. 2023.
- [143] Pino Angulo, A., & Shin, K. (2019). Mrmr+ and Cfs+ feature selection algorithms for high-dimensional data. *Applied Intelligence*, 49(3), 1954-1967. This paper discusses MRMR and its enhanced version, MRMR+, which addresses redundancy issues.
- [144] Xie, S., Zhang, Y., Lv, D., Chen, X., Lu, J., & Liu, J. (2022). A new improved maximal relevance and minimal redundancy method based on feature subset. *The Journal of Supercomputing*, 79(3), 3157-3180. This study combines mutual information and Pearson correlation to measure feature relevance.
- [145] De Jay, N., Papillon-Cavanagh, S., Olsen, C., El-Hachem, N., Bontempi, G., & Haïbe-Kains, B. (2013). mRMRe: an R package for parallelized mRMR ensemble feature selection. *Bioinformatics*, 29(18), 2365-2368. This paper introduces an ensemble approach to MRMR.
- [146] Erolu, C., et al. (2019). Maximum Relevance and Minimum Redundancy Feature Selection Methods for High-Dimensional Data. *arXiv preprint arXiv:1908.05376*. This study extends MRMR methods with non-linear redundancy and model-based relevance measures.