Comparative analysis of Grey Wolf Optimization algorithm and Ant Colony Optimization algorithm for PV panel under extreme conditions

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Supervisor: Dr. Ashraf Yahya

Co-Supervisor: Dr. M. Farhan Khan

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LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS

I	Load’s current.
Il	Photovoltaic current.
Id	Junction’s current of the diode.
Io	Reverse saturation’s current.
q	Boltzmann constant.
V.oc	Open circuit voltage.
T	Temperature.
A	Diode quality factor.
Rs	Resistance
Rsh	Resistance in parallel
EA	is the power output from the module
HA	is the sun’s solar irradiation
PAS	is the output of the module at STC
GS	is the solar irradiance at STC
MPPT	Maximum power point tracking
GWO	Grey wolf optimization
ACO	Ant colony optimization

ABSTRACT

Under ideal circumstances, every energy generating systems created by mankind gives near perfect result. However, we hardly ever get the chance to work under such impeccable conditions. The same will always be true for any solar system. With varying temperature and solar irradiation, we may mistake the local peak power as the true potential of our systems. This may lead us to add additional panels to meet our demand, thus increasing the overall price of the system. To offset this predicament, we use various MPPT optimization. algorithm. Two of these optimization techniques are grey wolf and ant colony optimization. Both techniques have remarkable performance, yet we must still pick one MPPT as efficiency is paramount. Even if we do manage to select one, considering the escalating impact of global climate change leading to heightened temperature extremes and an alarming increase in rainfall in certain regions, the need for a robust comparative analysis of these optimization techniques becomes more pronounced. This research conducts a comprehensive comparative analysis of the grey wolf and ant colony optimization techniques under diverse climate conditions. The simulation, conducted in Simulink, meticulously presents each technique independently, culminating in a detailed evaluation and comparison of their performance under the dynamic scenarios posed by varying temperatures and near-total shading conditions, yielding nigh on kindred results.

Keywords: Grey wolf algorithm, ant colony algorithm, maximum power point tracking, PV system

CHAPTER 1: INTRODUCTION

When a design engineer constructs any system, no matter to which field they belong, they always start from the system's exemplar conditions. After working in these conditions, they intentionally degrade the system's state and observe its performance. For a solar system, these ideal conditions are an abundance of solar irradiance and a temperature range which is neither too low nor too high. Naturally, in the complete lifetime of a solar system, these outstanding operating conditions do not last for a long time.

The distribution of sunshine across Earth's surface is a dynamic phenomenon shaped by a myriad of intricate factors. Geographical location, Earth's axial tilt, and atmospheric conditions all contribute to the varying amounts of sunlight received by different regions. Colombia has a city by the name of Totoró, and this unfortunate city has approximately 637.0 hours of sunshine annually. Tórshavn in the Faroe Island and Chongqing in China also share a similar fate with receiving only 840.0 and 954.8 hours of sunshine annually respectively. On the opposite end we have the city of Yuma in the United States receiving an astonishing 4015.3 hours of sunshine on a annual bases. And similarly, we have the city of Marsa Alam and Dakhla Oasis in Egypt receiving 3958.0 and 3943.4 hours of sunshine respectively.

As for solar irradiance, it too is also distributed unequally just like sunshine hours. Solar irradiation's distribution across the Earth's surface is a phenomenon of paramount importance, driving a plethora of natural processes and shaping the planet's climate and ecosystems. The main factor which determines how much solar irradiance will an area receive is the angle at which the sun rays hit the surface. The closer the rays are to 90 degrees, the more irradiance that surface will receive. Under this fact, the two poles, north and south, are regions which receive the least amount of irradiance with the values remaining in the range of 500-0 W/m2, depending on the month [1]. Now, if we take the atmospheric conditions into account then it's a competition between the area between Spitzbergen and Iceland in the north and the areas just off the cost off the Antarctica in the south.

The other element which alters the output of a solar systems is temperature. The temperature distribution on Earth is influenced by a complex interplay of various factors, including geographical location, altitude, ocean currents, and atmospheric circulation. Understanding these temperature patterns are crucial for comprehending the global climate system and its impact on various ecosystems. As of today, the hottest place know to us on the surface is the Lout desert of Iran with temperatures reaching more than 70 degrees Celsius [2]. Followed by Death Valley in the USA with a maximum temperature recorded of 56.7 degrees Celsius. As for the coldest regions, it is found in east Antarctica, the temperatures dipping to -98 degrees Celsius [3]. Followed by Denali in Alaska with a record of -73.8 degrees Celsius.

Undoubtedly, with an average increment of 1.5 °C in global temperature and in climate change stand as formidable global predicaments woven into the fabric of this world. As the world warms due to human activities like deforestation and combustion of fossil fuels, the equilibrium of our climate system falters, setting off a chain reaction of profound consequences. This phenomenon, a consequence of global warming, manifests as climate change, a sweeping transformation that encompasses altered weather patterns, rising sea levels, extreme climatic events, and disruptions to ecosystems. These changes reverberate across the globe, jeopardizing biodiversity, food security, water resources, and human well-being. The disintegration of polar ice caps accelerate as temperatures climb, imperiling coastal settlements through escalating sea levels. Concurrently, precipitation shifts intensify droughts, floods, and storms, amplifying agricultural challenges and exacerbating water scarcity [4].

The repercussions of climate change and global warming are starkly evident in the surge of frequent and intensified extreme weather conditions experienced worldwide. As temperatures rise, the delicate balance of atmospheric dynamics is disrupted, culminating in more frequent and severe weather events. Heatwaves have become more frequent and intense, subjecting regions to sweltering temperatures that threaten public health, strain energy resources, and pose formidable challenges [6]. Moreover, the frequency and intensity of heavy rainfall and flash floods have surged, endangering communities, infrastructure, and livelihoods. What this means is that we will be witnessing weather conditions which we do not desire for our systems more frequently [7].

In terms of peak summer monthly temperatures, a substantial 79% of the climate model presents a significant trend statistically. The implications of this trend are particularly pronounced, as it has led to an escalation in the graveness and likelihood of achieving the summer’s maximum peak value across 97% of the climate model. Notably, this phenomenon is especially conspicuous in a significant portion of the tropics, where the trend's contribution reaches a minimum of 50% of the magnitude.

Redirecting our attention to the highest daily temperature experienced throughout the year., only 41% of the climate model demonstrates a statistically significant trend. However, despite the modest prevalence of this trend, its impact has been substantial. The trend has notably intensified both the severity and the likelihood of attaining the highest recorded value in over 82% of the model. This effect is notably evident across Europe and eastern Asia, where the trend's influence is particularly notable, contributing to at least 30% of the magnitude [8].

In a separate climate model, the same trend of declination can be seen for the cold end of the temperature scale. In the mid-winter of 2020/21, Successive episodes of extremely wintry weather took place across the continents of the Northern Hemisphere. Remarkably, there were two instances of wintry air outbreaks that traveled from Siberia to East Asia from December 2020 to January 2021. These occurrences resulted in the establishment of record-shattering wintry surface air temperatures, coupled with powerful winds across extensive regions. In Beijing and Tianjin, China, temperatures dropped to –19.6°C and –19.9°C on the 7th of January 2021, respectively, setting new records for that date. After this period, Deep South of North America and Great Plains experienced impactful snow and ice storms, accompanied by the intrusion of cold airmasses, in February 2021. Unprecedentedly low temperatures and prolonged duration were observed in the South of United States, such as Oklahoma and Texas. Like on 15 February, Austin and Houston experienced temperatures of –13.3°C and –8.3°C, respectively, breaking previous records. The gravity and socioeconomic consequences of these chilling events are rarely seen on the same dates or within a single winter season in the past century. Nevertheless, an rise in the occurrence of extreme chilly weather events has been noted in North America and Eurasia over not long past decades [5, 9].

Regarding annual precipitation patterns, a discernible trend has emerged, indicating an escalation in both graveness and likelihood of the min annual precipitation across 42% of the observed area. Remarkably, the dominance of this trend is predominantly observed in the tropics. Examining the most damp 5-day duration of the year, a historical trend is by stats significantly over just 18%. This trend has significantly escalated the graveness and likelihood of experiencing the maximum event in more than 58%. This influence is notably apparent in regions encompassing the United States and Europe [8].

1.1 Problem Statement

Issues: Inefficient MPPT- Maximum power point technique techniques pose a significant challenge to optimal solar panel performance and, consequently, diminish energy output. Traditional MPPT algorithms, designed for relatively stable conditions, often struggle to adapt to the dynamic environmental factors inherent in real-world solar energy systems. This limitation can result in substantial power loss and decreased overall power efficiency.

Resolutions: To address these challenges, a comprehensive comparative analysis of different MPPT algorithms is crucial. Such an analysis offers a nuanced understanding of the pros and cons of each algorithm. By identifying the most suitable MPPT technique for specific environmental conditions, solar energy systems can be equipped to navigate dynamic scenarios more effectively. This, in turn, facilitates informed decision-making for implementing the most appropriate MPPT technique in solar energy systems.

Outcomes: The outcomes of a well-informed choice in MPPT technique are substantial. Precise MPPT algorithms, tailored to environmental dynamics, contribute to increased power generation and enhanced energy efficiency. This, in turn, translates into higher overall system performance, optimizing the utilization of available solar energy. Additionally, the implementation of a well-suited MPPT technique holds the potential for cost savings in solar installations, ensuring a more sustainable and economically viable approach to harnessing solar power.

1.2 Research Aims and Objectives

1. To implement Ant Colony and Grey Wolf optimization algorithms in a simulated environment.

2. To investigate the performance characteristic of Grey Wolf and Ant Colony optimization algorithms for MPPT for PV panels.

3. To quantify and differentiate the efficiency of Grey Wolf and Ant Colony in regard to power extraction and speed of convergence.

4. To assess the stability and sensitivity of the algorithms to changes in parameters during extreme weather conditions.

5. To assess the robustness and adaptability of the algorithms under various environmental conditions.

1.3 Research Significance

The investigation into the comparative performance of Grey Wolf and Ant Colony optimization algorithms for PV panels under extreme weather conditions holds paramount significance within the realm of renewable energy and sustainable technology. The global drive to transition towards clean and efficient energy sources underscore the need for highly effective MPPT techniques. As solar energy systems become increasingly integral to power generation, ensuring their optimal performance under diverse climatic conditions becomes imperative.

This study addresses a critical knowledge gap in the existing literature by examining the effectiveness of two prominent optimization algorithms, Grey Wolf and Ant Colony, in the context of extreme weather conditions. Extreme weather events, including both severe cold and scorching heat, have gained significant attention due to their increasing frequency and implications for renewable energy systems. Understanding how these algorithms respond to such conditions is vital for enhancing the resilience and adaptability of photovoltaic systems.

Furthermore, the outcomes of this research have direct implications for practical applications in various sectors. Solar energy installations are deployed across a wide range of geographical locations, each with its unique climate and weather patterns. By comparing the performance of Grey Wolf and Ant Colony algorithms, this study contributes valuable insights for designing and deploying efficient MPPT techniques tailored to specific environmental conditions. This knowledge is instrumental in enhancing the reliability and efficiency of solar energy systems, reducing operational costs, and ensuring consistent power generation, even in challenging weather scenarios.

Moreover, the study's findings hold relevance for policy makers, energy planners, and industry stakeholders who seek to optimize the employment of renewable sources. The identification of superior optimization algorithms for extreme weather conditions can guide the development of standardized practices, regulations, and recommendations for PV system integration, maintenance, and performance assessment.

This research extends beyond algorithmic comparison and emerges as a crucial endeavor with implications for sustainable energy adoption, technological advancement, and climate resilience. By shedding light on the performance of Grey Wolf (GW) and Ant Colony (AC) algorithms in extreme climate conditions, this study contributes to the broader goals of achieving a greener and more sustainable energy landscape.

1.4 Thesis Structure

1. Chapter 1: This chapter contains the necessary context required to understand the content of this thesis. It also contains the thesis significance along with the aims and objectives.

2. Chapter 2: This chapter contains the literature review, which contains the information acquired from different sources used as a foundation of this thesis. The content within it includes information on grey wolf and ant colony algorithms used for MPPT.

3. Chapter 3: This chapter is reserved for the methodology used to detail how the goals of this thesis were achieved. It includes the software used and the details of the setup within in it.

4. Chapter 4: In the chapter for result and discussion the observations are analyzed and interpreted.

5. Chapter 5: This chapter concludes the thesis by summarizing the finding and giving a conclusion. It also mentions the limitations of this thesis.

CHAPTER 2: LITERATURE REVIEW

As we navigate through the challenges posed by our changing global climate, where extreme temperatures and increased cloud cover are becoming the new norm, the demand for resilient energy solutions comes sharply into focus. This sets the backdrop for our exploration towards the realm MPPT. In the face of adverse weather conditions, traditional solar energy systems often face inefficiencies and reduced power output. Mankind developed MPPT as adaptive tools that can dynamically optimize solar panel performance, even under challenging weather scenarios. By understanding what MPPT and their algorithms are and how they function in less-than-ideal conditions, we aim to unearth strategies that promise not only to withstand the blow of climate crises but also to elevate solar energy systems to new heights of efficiency, ensuring optimal power harvest even in the harshest weather conditions.

2.1 Maximum Power Point Tracking (MPPT)

MPPT is a critical technology implemented in solar, wind, and other renewable sources systems. Its primary goal is to optimize the energy output of these systems by periodically checking and maintaining the operating point known as the Maximum Power Point (MPP). The MPP is the peak at which energy source generates the maximum available energy for a given environmental conditions.

MPPT work by continuously monitoring the PV panel's output, specifically the voltage and current it produces. They employ various sensors and circuitry to measure the panel's electrical characteristics in real-time. Sensors include photodiodes, voltage sensors, and current sensors. Based on these measurements, the MPPT calculates the instantaneous power output of the panel. The algorithm compares the calculated power output with the previous values or a predefined reference value representing the MPP. If the calculated power is less than the reference value, it implies that the panel is not operating at its MPP. The algorithm then decides whether to increment or decrement the operating voltage to bring the panel closer to the MPP. The adjustment is typically made by controlling power electronics, like DC to DC converters or inverters, which modify the voltage and current supplied to the load or battery [10].

In PV systems, the relationship of voltage and current is governed by the fundamental principles of electrical circuits and the physical characteristics of solar cells. Understanding this relationship is crucial for optimizing the performance of PV panels, especially when implementing MPPT algorithms. Unlike many linear electrical devices, PV panels exhibit a nonlinear relationship between voltage and current. This nonlinearity arises from the intrinsic properties of semiconductor materials used in solar cells.

As the voltage produced by a PV panel increases, the current generated by the panel decreases. This behavior is described by the panel's IV curve. The IV curve typically shows a steep drop in current as voltage increases. Conversely, if the voltage produced by the PV panel decreases, the current it produces will increase. Lowering the voltage results in a steeper incline in current on the IV curve [11].

The nonlinearity of PV panels can be likened to the behavior of a diode. This is because solar cells can be seen as a semiconductor device with characteristics like a diode. In a diode, operating in reverse biased mode, as voltage increases, current decreases (and vice versa). The same principle applies to a PV cell, which operates as a PN junction in reverse biased mode, falling in the 3rd quadrant of its V-I characteristics. The point of operation of a PV cell on its IV curve determines its power output [12]. Notably, the point of max power output, also called the max power point, is a critical aspect of a solar cell's performance. At the MPP, the product of voltage and current is maximized, signifying the optimal conditions for obtaining power from the solar module. Understanding and effectively tracking the MPP is fundamental in the design and implementation of mppt technique, which play a massive role in optimizing the energy harvesting efficiency of solar panels.

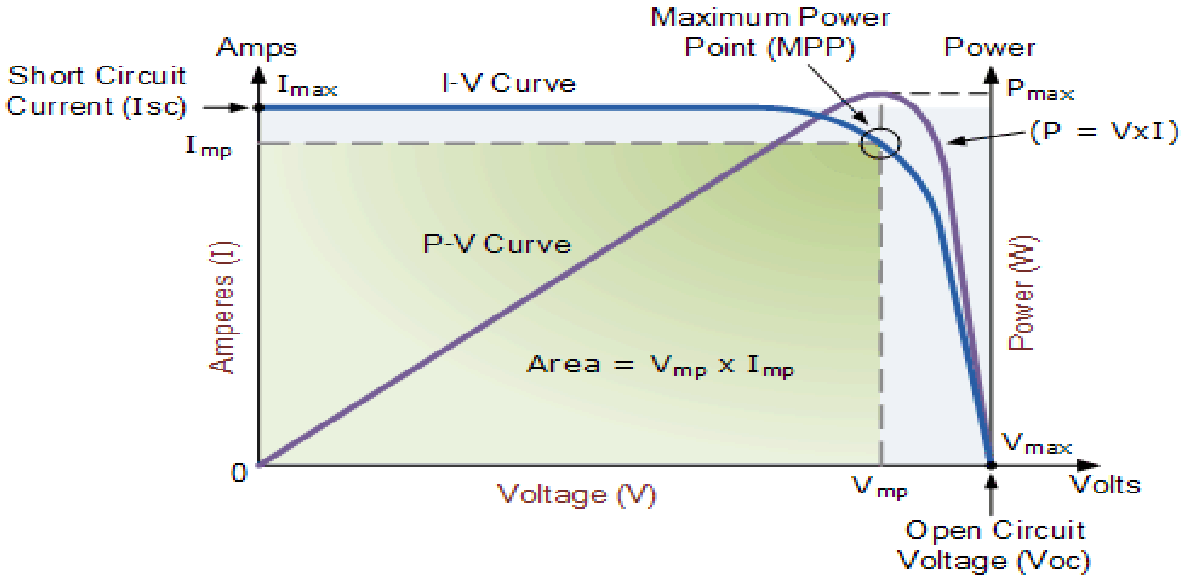

Fig 2.1: I-V curve [46]

It's essential to recognize that point of operation, denoted on the IV curve, is not static and can vary significantly. This variability is attributed to instantaneous changes in solar irradiation and temperature. For optimal performance and to extract the max power from a solar cell, it's imperative to dynamically position the operating point at the max power. Ensuring this alignment guarantees optimal operation of the solar cell, irrespective of the surrounding environmental conditions. Thus, understanding and manipulating the point of operation to track the MPP become central in the quest for obtaining the highest possible energy from the solar cell.

In the pursuit of dynamically adjusting the operating point of a solar cell to the Maximum Power Point (MPP), a crucial component comes into play – the DC to DC converter. This electronic device facilitates the alteration of voltage levels in the solar cell. By modulating the voltage, the DC-DC converter ensures that the solar cell operates optimally under varying environmental conditions. It acts as a automatic tuning feature, allowing for precise adjustments in the operating point to track the fluctuating MPP. In essence, the DC to DC converter has a pivotal role in optimizing the output of solar cells by changing their voltage to match the ever-changing requirements for maximum efficiency and energy extraction.

2.2 Advantages of MPPT

1) Increased Energy Harvesting: MPPT algorithms enable PV systems to consistently work at their MPP, ensuring that the system captures the most energy available from the sun. This results in higher energy yields and increased overall system efficiency.

2) Adaptation to Changing Conditions: PV systems are subject to variations in sunlight intensity and temperature throughout the day and across seasons. MPPT algorithms continuously moves the operating current or voltage to adapt to these changing conditions, maximizing energy production.

3) Improved Energy Conversion Efficiency: By operating at the MPP, MPPT techniques reduce energy losses that occur when the PV array operates at suboptimal points on its voltage-current curve. This leads to higher conversion efficiency and superior utilization of the available sunlight.

4) Enhanced Production in Partial Shading: MPPT algorithms excel in scenarios with partial shading or when only a segment of the PV array is under sunlight. They can identify and track the MPP of the unshaded portion, mitigating the impact of shading on energy generation.

5) Battery Charging Optimization: In off-grid and hybrid PV systems with energy storage, MPPT controllers optimize the charging of batteries. They ensure that the battery bank is charged efficiently, extending battery life and improving system reliability.

6) Reduced Payback Period: By increasing energy production and overall system efficiency, MPPT controllers help reduce the payback period for PV installations. This makes solar energy systems more financially attractive.

7) Environmental Benefits: Maximizing the energy output of PV systems through MPPT reduces the need of fossil fuels and decreases emission of greenhouse gases, contributing to a more sustainable and environmentally friendly energy source.

2.3 Common Traditional MPPT Techniques

In the realm of solar energy systems, several traditional MPPT algorithm have been created to optimize output from PV panels. These methods, although varied in approach, share the common goal of efficiently tracking the MPP in changing environmental scenario. Below are brief descriptions of some commonly used traditional MPPT techniques:

1. Perturb and Observe (P&O):

The Perturb and Observe (P&O) algorithm is one of the most common employed MPPT. It works by disturbing the point of operation of the PV panel and observes the change in output. Using this observation, the method incrementally changes the operating V or I to reach MPP. It may be simple to implement, but the P&O method may suffer from oscillations around the ma power point, particularly under rapidly changing solar irradiation conditions.

2. Incremental Conductance (IncCond):

The Incremental Conductance (IncCond) is another popular MPPT technique utilized in solar systems. IncCond utilizes the derivative of the PV panel's power-voltage curve to know the direction of perturbation. By checking the difference bewteen the instantaneous conductance with the incremental conductance, this method ensures continuous adjustment towards the MPP, offering improved tracking accuracy, especially under dynamic weather conditions.

3. Hill-Climbing:

Hill-Climbing algorithm is a heuristic-based MPPT technique that operates by iteratively adjusting the point of operation of the PV panel in the direction of increasing output. Similar to climbing a hill to reach the peak, this method continuously evaluates the power output at neighboring points and adjusts the operating parameters accordingly. While conceptually straightforward, the Hill-Climbing method may suffer from slow convergence and oscillations, particularly in regions with rapidly changing solar irradiance.

These traditional MPPT techniques provide the foundation for optimizing the performance of solar energy systems. However, advancements in MPPT technology, particularly through the integration of nature-inspired algorithms, offer enhanced efficiency and robustness in tracking the MPP under diverse environmental conditions.

2.4 Superiority of Nature MPPT Techniques Over Traditional Techniques

The advent of nature inspired MPPT algorithms represents a significant leap forward in the field of solar energy systems. These algorithms demonstrate superior performance compared to traditional methods, primarily due to their enhanced capability to reach the MPP under challenging conditions like partial shading. Notably, in [13] and [14] Satyajit Mohanty and R. Sridhar, respectively, presented compelling evidence. Their studies showcased that Grey Wolf Optimization and Ant Colony optimization technique exhibits superior power output in partial shading scenarios, outperforming traditional P and O technique. These findings underscore the promising potential of nature-inspired MPPT methods in upgrading the reliability and production of solar systems, particularly in adverse environmental scenarios.

2.5 Factors Influencing Power Output

Temperature:

The behavior of a solar cell, known as its I-V characteristic, is influenced by two key factors: the intensity of sunlight, represented by “S” in units of W/m^2, and the cell’s temperature in degrees Celsius, denoted as “t”. In simple terms, you can think of it as a relationship of current and voltage the solar cell produces, which is also affected by these two variables, sunlight intensity and temperature. When we consider a load that’s purely resistive, the cell’s behavior may be accurately represented by a specific circuit, as illustrated in the figure. This circuit depiction helps us understand how the solar cell responds to varying conditions [15].

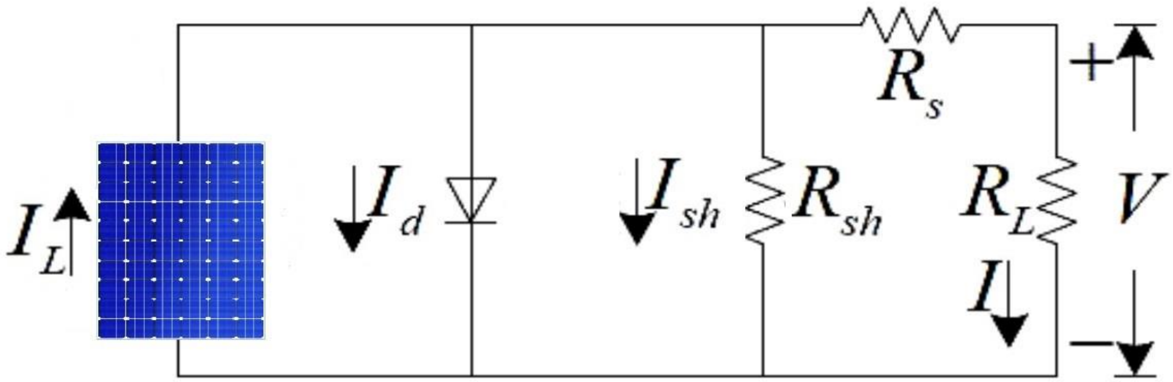

Fig 2.2: Solar Cell's Representation as a Circuit

$$I = IL - Io\left[\frac{\exp q(V+IRs)}{AkT} - 1\right] - (V + \frac{\text{IRs}}{Rsh}) \qquad (2.1)$$

$$Id = Io\left[\frac{\exp q(V+IRs)}{AkT}\right] - 1 \qquad (2.2)$$

$$Voc = \left(\frac{\text{kT}}{q}\right)\ln\left(\frac{IL}{Io}\right) + 1 \qquad (2.3)$$

I – Load's current.

Il -- Photovoltaic current.

Id – Junction's current of the diode.

Io -- Reverse saturation's current.

q -- Boltzmann constant.

V.oc -- Open circuit voltage.

T – Temperature.

A – Diode quality factor.

“Rs” - Resistance

“Rsh” – Resistance in parallel

With rising temperature, two significant effects occur in solar cells. Firstly, as temperature increases, the intrinsic semiconductor's band gap contracts. Consequently, the Voltage (V.oc) of open circuit falls, in accordance with the temperature dependence observed in the “q/kT” diode factor. This means that solar cells exhibit a sub-zero temperature coefficient for V.oc (represented as β). Furthermore, even with the same amount of incident light, higher temperature results in a lower output power due to charge carriers being set free at a lower potential. This temperature-dependent reduction in Voc, as described in the Fill Factor calculation, leads to a decrease in the solar cell's theoretical maximum power, even if the current in short circuit (Isc) remains constant.

Secondly, with rising temperature, the band gap of the intrinsic semiconductor narrows. Consequently, additional energy is captured since a larger portion of the incoming light possesses sufficient energy to elevate carriers of charges from the band known as valence band to the band known as conduction band. This leads to a increased photocurrent; thus, for a given level of solar radiation (insolation), Isc increases. Solar cells, in this context, exhibit a positive temperature coefficient for Isc (denoted as α).

Solar Irradiation:

At the heart of solar energy harnessing lies a fundamental determinant, solar irradiation. The radiant energy from the sun, measured as solar irradiance in W/m^2, stands as the primary architect shaping the output of solar cells. Across the globe, the intensity of this solar irradiation undergoes a symphony of variations; some regions bask in an abundance of radiant energy, while others receive a more modest share. It is within this interplay of sunlight intensity that we discern the essence of solar power generation. Understanding how solar irradiance intricately weaves itself into the fabric of power output is indispensable for unlocking the full potential of PV systems.

Hiroyuki Nakamura in his paper [16] talks about the performance ratio of the module K_A as a performance index for understanding the conditions for operation of a solar setup. The formula for module performance ratio is given by:

$$KA = \left(\frac{\mathrm{EA}}{PAS}\right) / \left(\frac{HA}{GS}\right) \quad (2.4)$$

Where “EA” is the power output from the module

“HA” is the sun’s solar irradiation

“PAS” is the output of the module at STC

“GS” is the solar irradiance at STC

Based on the provided formula for the module performance ratio KA an increase in solar irradiation HA would generally result in an increase in the module output power EA if all other factors remain constant. This is because the ratio (EA/PAS) in the numerator is directly influenced by the actual module yield, and an increase in solar irradiation typically leads to a higher yield, assuming the module operates efficiently. P. Attaviriyanupap [17] in his paper shows the link between PV output and solar irradiance using the data he obtained.

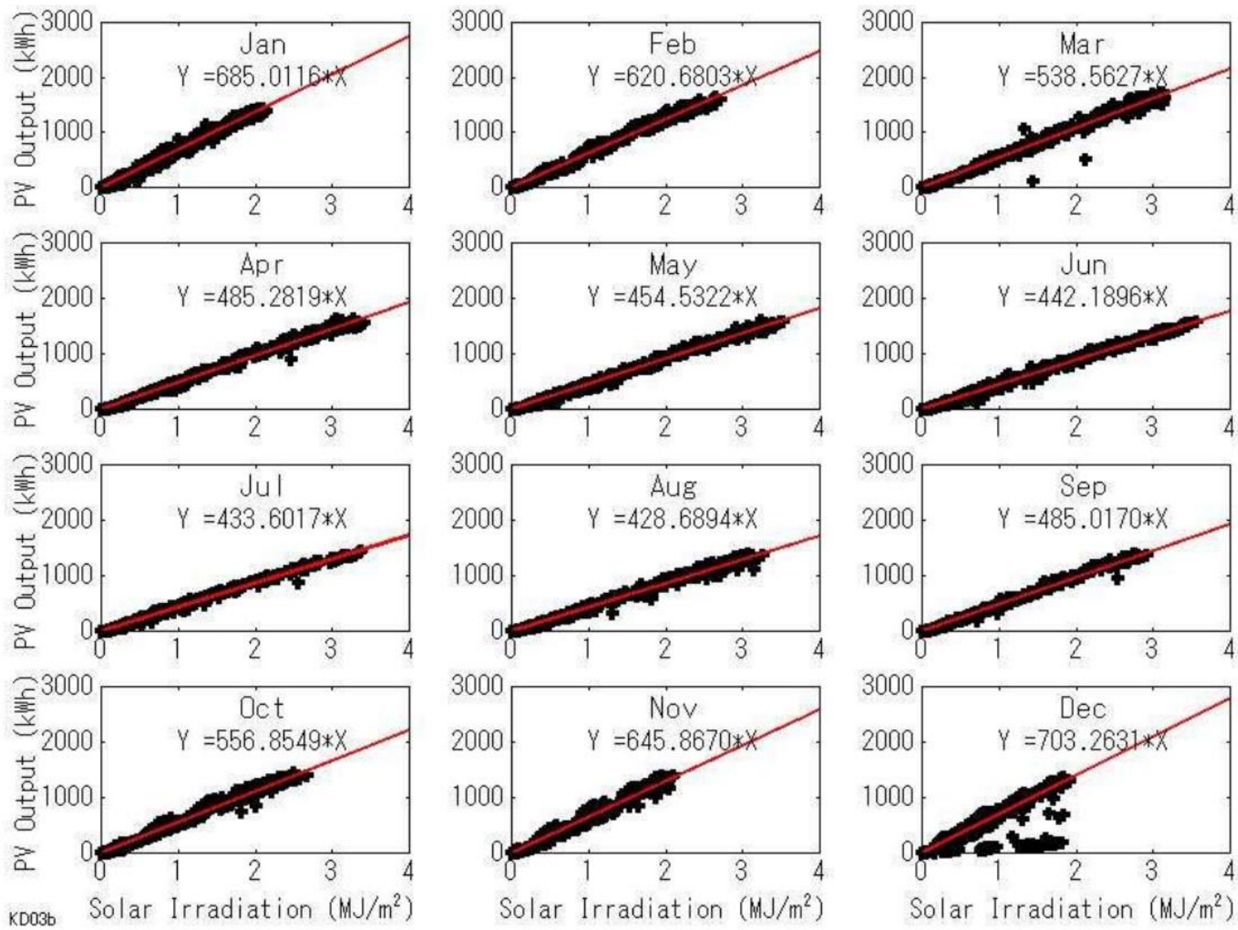

Fig 2.3: Solar Irradiation Relation with Power Output [17]

Here we can see the power output being exactly proportionate to the solar energy the panels receive.

2.6 Limitations of Other Research Papers

In the pursuit of enhancement of the performance of a solar setup, a multitude of MPPT algorithms have been explored in existing database. Noteworthy contributions from various researchers have extensively covered various aspects of MPPT, ranging from conventional methods to cutting-edge nature-inspired algorithms. While each of these works provides valuable insights, a distinct opportunity arises to delve deeper into the unexplored terrain where solar irradiance interacts dynamically with temperature variations. This comparative analysis uniquely navigates the intricate landscape of MPPT by introducing the nuanced interplay between reduced solar irradiance and extreme temperatures, shedding light on critical performance aspects that remain underrepresented in current studies.

Kashif Ishaque [18] delves into a comprehensive examination of MPPT algorithms, encompassing both orthodox and soft computing ones. Notably, he explores widely adopted techniques like P and O and Incremental Conductance. However, the distinctive aspect of his analysis lies in the absence of a specific focus on scenarios involving reduced solar irradiance coupled with varying temperatures. Unlike the unique combination explored in my work, Ishaque's study primarily centers on uniform insolation and partial shading conditions, offering a valuable perspective but stopping short of integrating the intricate interplay of temperature and solar irradiance.

Alivarani Mohapatra's [19] paper contributes significantly to the literature by concentrating on emerging MPPT optimization algorithms, particularly those inspired by nature. Grey wolf, ant colony, firefly, and artificial bee algorithms take center stage in Mohapatra's exploration. However, the distinctive element absent in Mohapatra's comparative analysis is the integration of extreme temperature variations in conjunction with reduced solar irradiance. The dynamics of how solar panels respond to the dual challenges of diminished sunlight and temperature extremes, a central aspect of my investigation, find a unique place in your work that sets it apart from Mohapatra's exploration.

Bo Yang's [20] paper stands out for its all-encompassing survey of MPPT algorithms. From biology-inspired to physics and sociology-inspired algorithms, Yang covers a wide spectrum. Noteworthy is his incorporation of hybrid algorithms, showcasing the multifaceted landscape of MPPT techniques. However, his work introduces a novel dimension by including scenarios with reduced solar irradiance down to 200 W/m², offering a nuanced perspective on the challenges posed by low sunlight conditions. Despite this inclusivity, Yang's study, like others, does not delve into the synergistic effects of solar irradiance and temperature fluctuations, a unique aspect that defines my comparative analysis.

Table 2.1: Solar irradiation and temperature choice of other authors.

Author	Solar Irradiation W/m2	Temperature C
Kashif Ishaque [18]	1000	25
Alivarani Mohapatra [19]	Not Specified	Not Specified
Bo Yang [20]	200-1000	25-40

2.7 MPPT Market Status

The growth of the solar charge controller market is propelled by the rising use of renewable energy sources for power generation. The global market size for Charge Controllers with MPPT was valued at USD 1.55 billion in 2021 and is anticipated to increase from USD 1.70 billion in 2022 to USD 3.27 billion by 2030, with a compound annual growth rate (CAGR) of 9.8% from 2023 to 2030. [21].

The solar charge controller market is segmented based on Type, Current Capacity, and End User. Regarding Type, it includes pulse width modulation (PWM) charge controllers, maximum power point tracking (MPPT) charge controllers, and simple 1 or 2 stage controls. Current Capacity is divided into three categories: less than 20A, 20A to 40A, and more than 40A. The End User segment encompasses the residential users, the commercial & utility users and the industrial users. Geographically, the following markets have been observed: Europe, North America, LAMEA, and Asia-Pacific [22].

MPPT sector, classified by type, reported the prime share of the controller marketplace in 2021, comprising approximately 43.3%. This segment is anticipated to continue its leadership throughout the conjecture period for the solar controller market. This prominence may be attributed to the increasing adoption of solar power generation infrastructure worldwide. Furthermore, MPPT solar charge controllers excel in extracting the max output, and their superior productivity and performance in comparison to PWM controllers are anticipated to be key drivers of market growth in the estimate period [22].

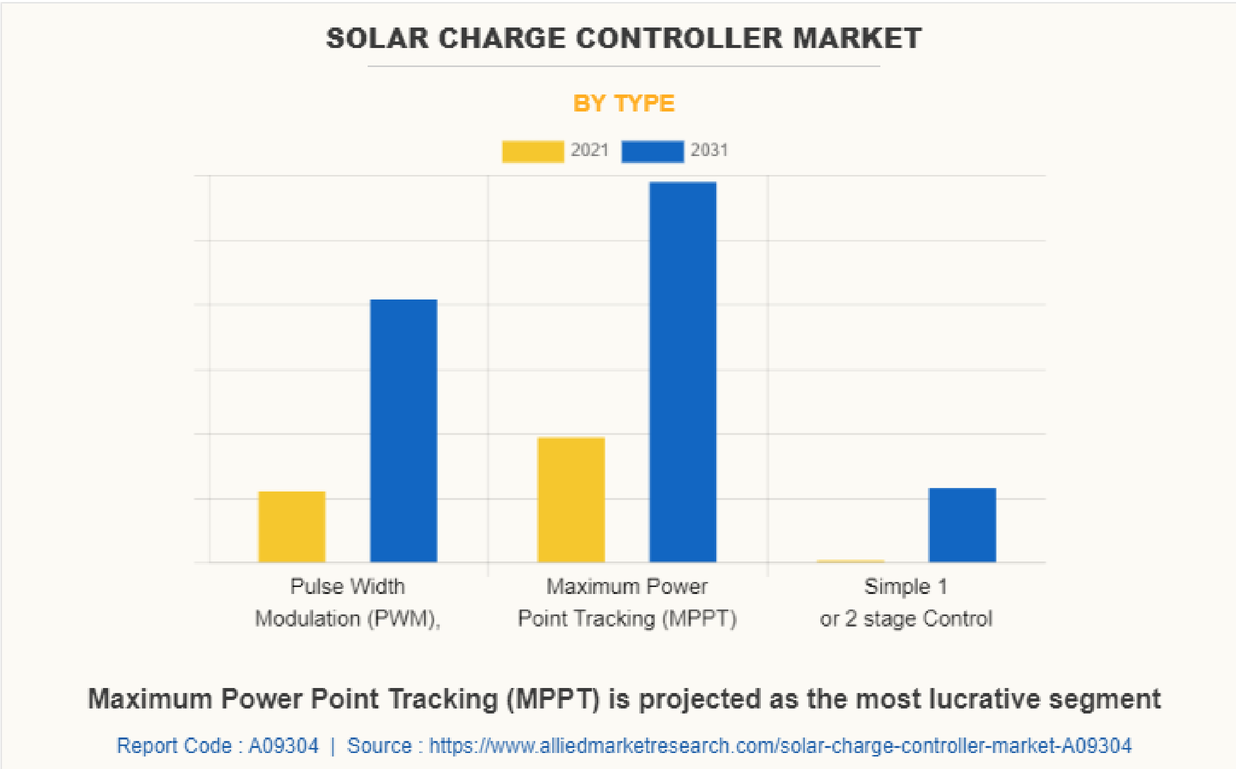

Fig 2.4: Solar Controller By Type [22]

Concerning current size, the 20A - 40A slice currently commands the peak revenue portion and is projected to sustain its headship in the conjecture period. This expansion can be linked to the increasing need for solar controllers with a current size ranging from 20A - 40A in various applications such as off-grid cabinets, residential installations, caravans, telecommunications, and remote solar power generation facilities. Additionally, the substantial investments being made in solar power generation are likely to further drive the growth of the solar controller's market in the forthcoming years [11].

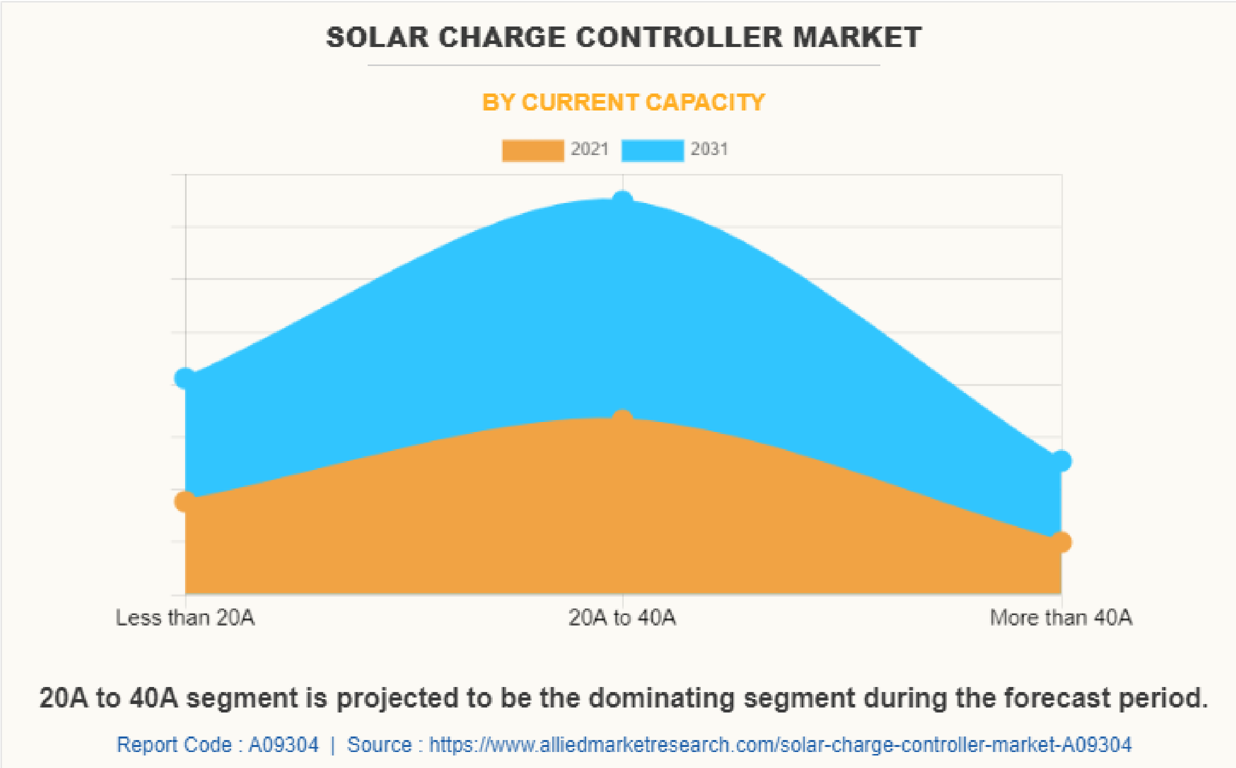

Fig 2.5: Solar Controller By Current Capacity [22]

In terms of end-user segments, the commercial sector currently boasts the major profits share and is projected to endure its predominance in the forecasted period. This surge can be credited to the increasing demand for solar charge controllers in various commercial applications, including information hubs, clinics/hospitals, restaurants/shops, offices, and more. Furthermore, the adoption of solar power solutions within the commercial domain is regarded as a rapid remedy for addressing energy shortages, thus augmenting the call for solar controllers throughout the conjecture period [21, 22].

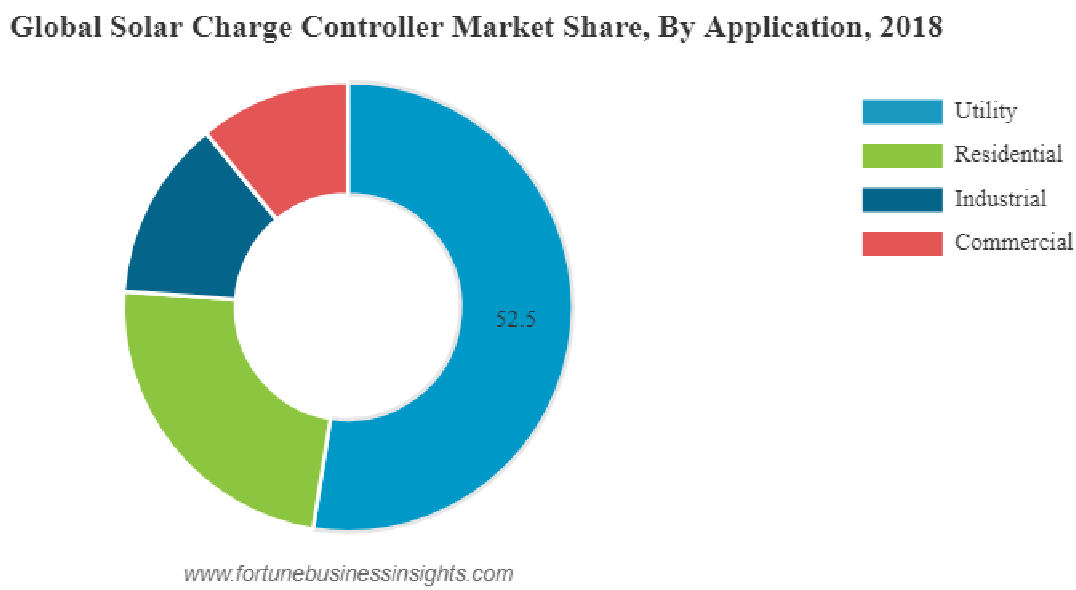

Fig 2.6: Solar Controller By Application [23]

In terms of geographical regions, the marketplace is examined athwart 4 major areas: N. America, LAMEA, Europe, and Asia Pacific. In 2020, Asia Pacific secured the leading segment, and it is expected to continue its supremacy in the solar controller marketplace trends throughout the conjecture period. This can be credited to the region's substantial consumer base and the presence of key industry players [22, 23].

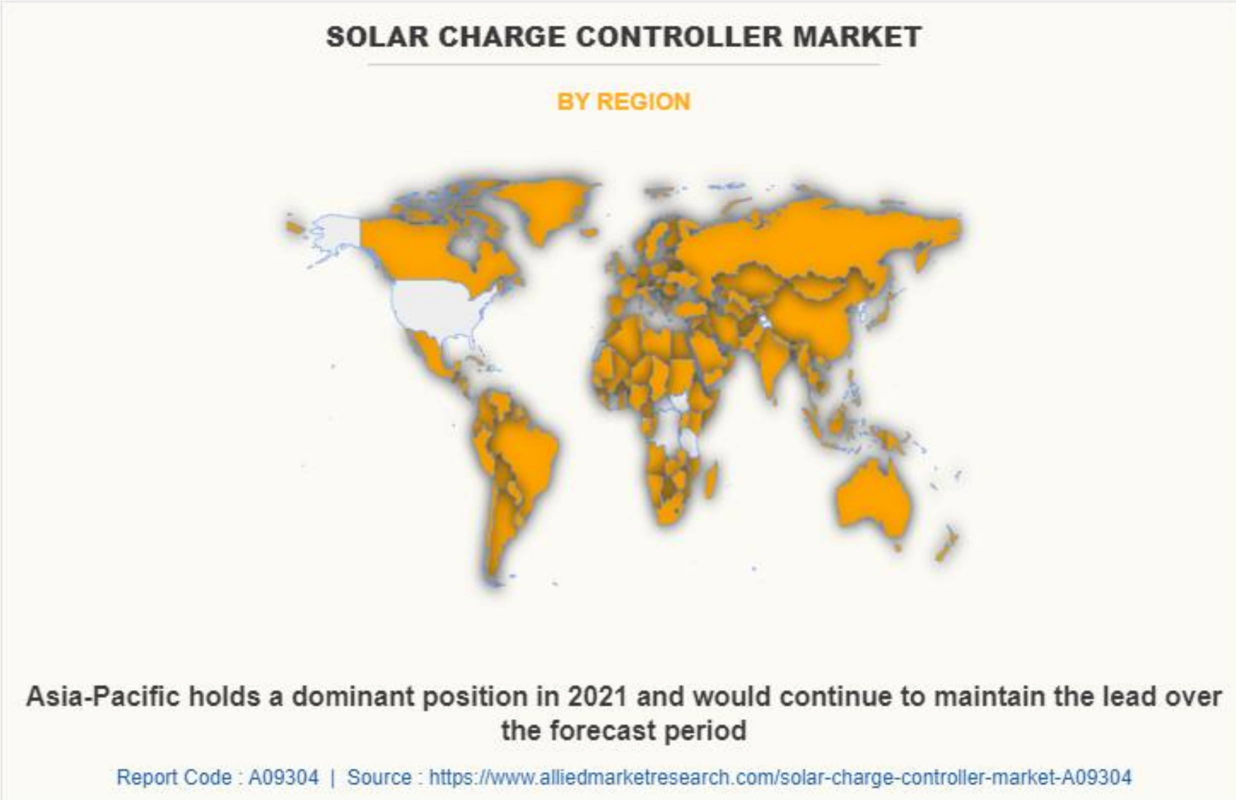

Fig 2.7: Solar Controller By Region [22]

One major potential obstacle to marketplace evolution is the increasing acceptance of alternative clean energy sources. A noteworthy danger to the business comes from the expanding utilization of wind power. Numerous projects are underway to harness wind energy, and fresh technical progressions are creating floating wind power plants economically viable. This development is likely to have an adverse impact on the solar industry, potentially hindering market growth [23]. Another hurdle in the MPPT marketplace is the relatively expensive price of these solar controllers when equated to orthodox controllers. Controllers equipped with MPPT tend to be extra pricy because of the technology being additionally complex and the greater productivity they offer. As a result, they may be less accessible to customers seeking a more budget-friendly solution [21].

CHAPTER 3: NATURE INSPIRED MPPT TECHNIQUES

Nature has long been a source of inspiration for solving complex problems, and the field of MPPT PV systems is no exception. Nature-inspired MPPT algorithms draw inspiration from biological, physical, and social phenomena to optimize the performance of solar energy systems. These algorithms leverage the inherent intelligence of natural processes to dynamically adapt to changing environmental conditions and efficiently track the MPP of PV panels. By mimicking the adaptive behaviors observed in natural systems, such as the foraging patterns of animals or the collective behavior of social insects, nature-inspired MPPT procedures offer robustness, scalability, and improved performance compared to old-style MPPT procedures.

3.1 Grey Wolf Algorithm

3.1.1 Real Behavior of Wolfs

Inspired by the behavior of wolf, the GWO algorithm tries to replicate the hunting strategies of wolfs. When a hunting expedition begins, the wolf pack departs from its den or place of rest, commencing the quest for food. The initiation of a hunt is prompted by hunger. The direction the wolves choose and how far they are willing to journey are influenced by their past experiences, including both successful and unsuccessful hunts. During their search, they rely on their keen senses, making use of wide lateral vision and adjustable ears to survey the environment for possible unsuspecting prey. Once they spot potential target, they begin their approach [24, 25].

If the wolf pack comes across herd of elk or some other creature, they close in at a steady pace. Unlike some other predators, wolves typically do not employ stealth tactics to approach the target, nor will they specifically choose an individual until the herd starts fleeing. This strategy puts them into the category of cursorial predators, setting their hunting etiquette apart from others. When wolves approach, elk will react by either holding their position or fleeing [26].

As the prey attempts to flee, they disperse in various directions, requiring the wolves to divide up to pursue as much as feasible. In this phase, these carnivores meticulously assess the clusters of prey, aiming to identify the most vulnerable target that offers the highest chance of a successful kill. One gain of pursuing the prey until they are exhausted is that it opens up the chances for the prey to make critical mistakes, such as stumbling. Additionally, it serves as a practical means for the wolves to evaluate the weakest animal among the group [24].

At this stage, the wolves are in an intensified pursuit, with a heightened focus on the specific prey individual they've targeted. The objective during this behavioral phase is to close in on the prey closely enough to initiate biting as a try to subdue it. Whether alone or a group of wolves, the act of biting down the prey marks the change into the capture phase.

The primary objective during the capture state is to secure a kill on the prey. When dealing with smaller prey like a calf, a single wolf may directly target the throat as it can effectively handle the animal on its own. In cases where the target is of greater size and there are multiple wolves, their strategy often involves biting at the hindmost legs and rump, aiming to make the prey sluggish before going for the neckline. If the target is genuinely frail, these carnivores are expected to achieve a fruitful kill. However, if they had mistakenly perceived a durable animal as frail, they could encounter difficulties and may either abandon the pursuit or revert to a previous hunting phase.

Contrary to the common perception of wolves as highly coordinated hunters utilizing teamwork and strategic planning to kill the larger target, observations spanning over 2000 hours of wolf behavior pattern in Yellowstone Park suggest a different reality. These observations indicate that wolves do not exhibit signs of elaborate strategies or clear communication during hunts. For instance, when going after the same herd, wolves don't synchronize their change between states: one wolf might identify a feeble prey and move in to attack while the others continue in an attack squad. This disconnection can even lead to a situation where one wolf has successfully slayed a prey and begins consuming it while the rest are in the 'attack squad' state. Interestingly, the wolf that scored the kill does not appear to make any effort to communicate its success to the others [27].

In the untamed wilderness, grey wolves, with their remarkable social structure and hunting prowess, navigate a complex world in search of prey. These apex predators exhibit a finely tuned balance of teamwork and individuality during their hunts, mirroring nature's delicate equilibrium. It is this remarkable interplay between the pack's collective intelligence and the instincts of each wolf that has inspired computer scientists to develop optimization algorithms rooted in the wolves' hunting behavior. In this section, we delve into the world of Grey Wolf Optimization (GWO), an algorithmic marvel that draws its inspiration from the collaborative yet independent strategies of real grey wolves. Much like their wild counterparts, GWO leverages the strength of a 'pack' of solutions to tackle complex optimization challenges while allowing each 'wolf' to adapt its search independently. As we explore the inner workings of the Grey Wolf Algorithm, we reveal how it emulates the intriguing dynamics of wolf pack hunts to efficiently seek optimal solutions in diverse domains.

3.1.2 Social Hierarchy of Wolfs

In the intricate society of grey wolves, a structured hierarchy reigns supreme, with each member playing a distinct role in the pack's survival. At the apex stands the 'alpha' wolf, the leader, and decision-maker. Alpha wolves exhibit dominance, not only in securing the choicest prey but also in guiding the pack's movements. Next in line are the 'beta' wolves, the right-hand wolves of the alpha. They act as lieutenants, assisting the alpha in maintaining order within the pack. Following them are the 'delta' wolves, respected for their skills and contributions. They often lead the pack during hunts, ensuring the pursuit remains coordinated. Lastly, there are the 'omega' wolves, the most submissive members, who play crucial roles in reinforcing pack unity. This hierarchical structure is not only a testament to the remarkable social dynamics of wolves but also serves as a fascinating analogy for the GWO technique. In GWO, a similar hierarchy of results is established, mirroring the “alpha α”, “beta ß”, “delta δ”, and “omega Ω” wolves. This stratified approach enables GWO to explore a diverse solution space efficiently, allowing the 'alpha' solutions to guide the search while 'beta,' 'delta,' and 'omega' solutions adapt and contribute collaboratively, much like the harmonious wolf pack. Through this hierarchical framework, GWO captures the essence of leadership and cooperation observed in grey wolf societies, translating it into a powerful optimization tool [28].

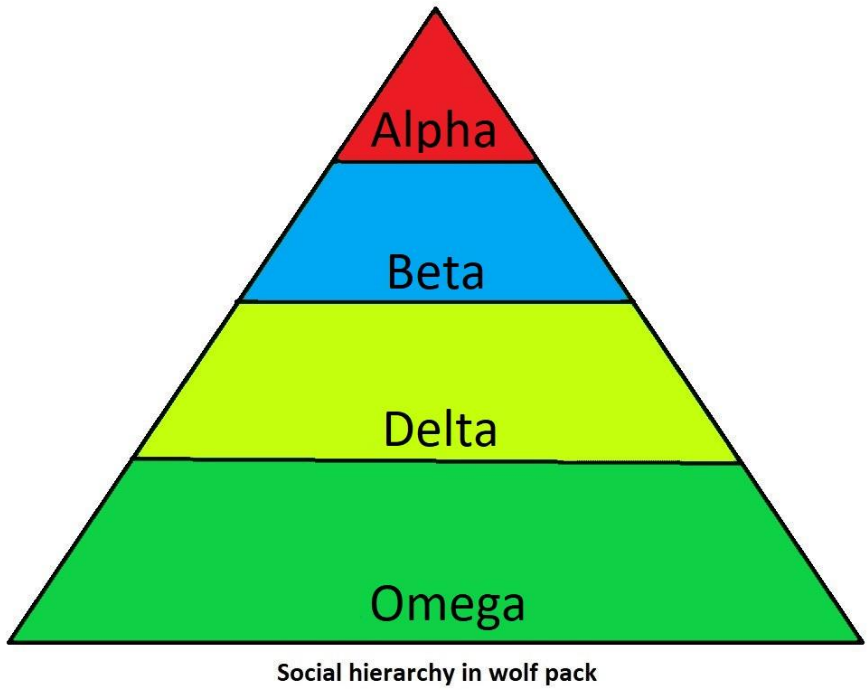

Fig 3.1: Social Hierarchy in Wolf Pack

3.1.3 Flow Chart Grey Wolf Algorithm

The flow chart presented below provides a structured glimpse into the workings of GWO, a fascinating optimization tool motivated by the collaborative hunting strategies of wolf packs. The journey begins with the 'Initialization' step, where a set of potential solutions is generated, much like a pack of wolves setting out in search of prey. These solutions are then evaluated in the 'Evaluate Fitness' phase, akin to wolves assessing the fitness of their prey before launching a coordinated attack. The algorithm then identifies the 'α,' 'ß,' and 'δ' solutions, symbolizing the leaders of the pack, in the 'Find First, Second, and Third Best' phase. With this information in hand, GWO embarks on the 'Update Position' step, mirroring the precise movements of wolves as they close in on their quarry. The algorithm calculates latest solutions' fitness value in the 'Calculate Fitness Value for New Solution' phase, ensuring that it remains on the right track. GWO diligently stores the finest solution in the 'Store the finest/Best' phase, akin to a wolf securing its catch. This process continues until a predefined 'Max Iteration Reached' condition is met, signifying the algorithm's relentless pursuit of optimization. In essence, GWO encapsulates the essence of wolf society, employing teamwork, leadership, and relentless pursuit in its quest for optimal solutions [29, 30].

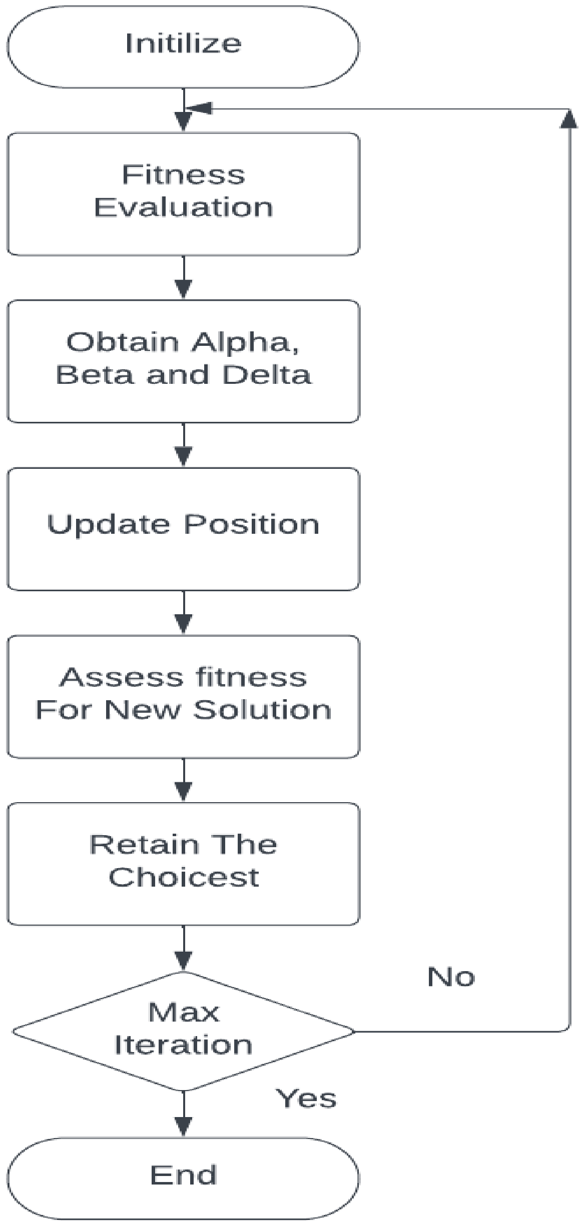

Fig 3.2: Grey Wolf Flow Chart

3.1.4 Pseudo Code Grey Wolf Algorithm

Following is GWO's pseudo code:

Commence

Prepare the populace of grey wolves Xi (i = 1, 2, ..., n)

Prime/Set a, A, and C

Compute the fitness values of each wolf and rank them. (Xα, Xβ, and Xδ)

t = 0

While Loop Start (t < Max number of iterations)

For Loop Start each search agent

Revise the location of the current wolf or search agent!

End For Loop

Renew the value of a, A, and C

Determine the fitness values of all search agents or wolfs and rank them!

Renew the positions or location of Xα, Xβ, and Xδ

t = t+1

End While Loop

End Algorithm

Following is the explanation of the pseudo code:

Initialization:

1) Initialize a population of grey wolves, represented as Xi (i = 1, 2, ..., n), where 'n' is the amount of search agents/wolfs.
2) Initialize control parameters: 'a' represents a constant, while 'A' and 'C' are also constants that will be used during the optimization.

3) Compute the fitness of the initial search agents/wolfs and rank them based on their fitness. Among these agents, identify:

$X\alpha$: The finest result or solution.

$X\beta$: The runner up result or solution.

$X\delta$: The third-best result or solution.

4) Initialize a counter 't' to 0, representing the current iteration.

Iterative Optimization:

Enter a loop that continues until 't' reaches the max number of iterations specified.

For each wolf or search agent:

A) Revise the location of the current wolf or search agent based on specific rules defined by the GWO algorithm.

B) After updating all search agent positions, proceed to update the control parameters 'a', 'A', and 'C'.

C) Recalculate the fitness values of all wolfs or search agents and rank them according to their fitness.

D) Renew the location of $X\alpha$, $X\beta$, and $X\delta$ based on the new fitness evaluations.

E) Increment the iteration counter 't' by 1 to move to the next iteration [29,30].

3.1.5 Mathematical Model of Grey Wolf Algorithm

In GWO we have “alpha α”, “beat β” and ‘delta δ”, which represents the best or finest , runner up and third best results respectively. When the prey has been isolated from the heard and the wolf have surrounded the prey, represented by the equations below:

$$D = C*X_p(t) - X_{(t)} \tag{3.1}$$

$$X_{(t=1)} = X_p(t) - D*A \tag{3.2}$$

In this context, D represents the separation between the hunters and their target, X_P denotes the prey's position vector, and t signifies the ongoing iteration. Meanwhile, A and C are values within the vector associated with the X_{th} grey wolf [20].

$$A = 2ar_1 - a \tag{3.3}$$

$$C = 2r_2 \tag{3.4}$$

Here, ‘r’ is a random vector with its ranging from anywhere from ‘0’ to ‘1’. The ‘a’ vector is to decline from ‘2’ to ‘0’ as the iteration goes on.

Grey wolf optimization involves Alpha in the hunting strategy. In the theoretical space, there's no knowledge of the ideal hunt location. Alpha α, represents the best solution within this hunting method, followed by Beta ß and Delta δ as the next best results. Consequently, the first three readings are documented, and the location of the remaining wolves, including Omega Ω, are adjusted based on the best result [31].

$$D_\alpha = C_1 * X_\alpha - X \tag{3.5}$$

$$D_\beta = C_2 * X_\beta - X \tag{3.6}$$

$$D_\delta = C_3 * X_\delta - X \tag{3.7}$$

$$X_1 = X_\alpha - A_1 * (D_\alpha) \tag{3.8}$$

$$X_2 = X_\beta - A_2 * (D_\beta) \tag{3.9}$$

$$X_3 = X_\delta - A_3 * (D_\delta) \tag{3.10}$$

$$X_{(t+1)} = (X_1 + X_2 + X_3) / 3 \tag{3.11}$$

When the prey comes to a halt, Grey Wolves initiate their attack, marking the conclusion of the hunt. The mathematical model uses vector “A” to depict the route towards the prey. A's amplitude is a random number that lies in the range of [2a, -2a]. The 'a' vector decreases from 2 to 0 during the iterations. When 'A' is within the limits of [-1, 1], the next location for any wolf or search agent might fall within a random location between their current location and the target's location. When the vector 'A' is less than 1, the location of the wolves and target are conducive to an attack, and the wolves engage in the attack. Conversely, when 'A' exceeds 1, the location of the wolves and target favor a retreat, and the wolves begin moving away from the target, preparing for a new hunting endeavor [31].

3.1.6 Modifications Done to Grey Wolf Algorithm

Let see what modification have been made to grey wolf algorithm over time.

D J Krishna Kishore’s work [32]:

In the modified GWO, with Dimension Learning-Based Hunting (DLH), three distinct stages govern its operation: initialization, movement, and choosing and renewing. During the initialization phase, a population of N wolves is randomly distributed within specified limits. The movement stage introduces a key enhancement called Dimension Learning-Based Hunting (DLH). This innovative technique aims to enhance the hunting behavior of individual wolves by leveraging interactions with their peers. In DLH, every wolf learns from the positions and behaviors of its neighboring wolves, leading to updated positions. To regulate the extent of learning and exploration, a radius is computed for each wolf. This radius, determined through the Euclidean distance between a wolf's current position and the positions of neighboring wolves, defines the wolf's search area. The incorporation of DLH and radius calculation aims to mitigate premature convergence and establish a equilibrium between search and exploitation, thereby making the GWO more effective in searching for optimal solutions. The result are decreased time to settle.

Muhammad Ilyas’s work [33]: In the traditional GWO, “Alpha α” and “Beta β” agents or wolves are primarily dedicated to the search process and are not significantly involved in converging to an optimal solution. As a result, this approach leads to a larger population of search agents and increased time consumption in the quest for the best solution. In the modified version of GWO, specifically in the β and omega step, the pursuit of an entirely precise optimal solution is eliminated. Simulation output demonstrate that when contrast to the basic GWO, the proposed algorithm exhibits enhanced convergence speed.

Muhammad Hamza Zafar's work [34]: A novel hybrid algorithm, combining elements of GWO with the Sine Cosine function has been introduced. In this modified approach, the Sine Cosine technique is employed to enhance the speed of the alpha α agent within the framework. The objective is to elevate the overall capabilities of global merging, search, and exploitation. This Hybrid GWO-Sine Cosine Algorithm (HGWOSCA) demonstrates improvements in the convergence rate and the positioning of alpha agents.

Merna M. Eshak's work [35]: The paper highlights a comparison between the GWO and a hybrid AI-MPPT optimizer. This evaluation aimed to strike a balance between time reaction and the accuracy of picking the GMPP or Global Maximum Power Point. The conclusion drawn from the analysis indicates that EGWO is better suited for situations requiring swift responses to changes in irradiance, whereas the hybrid AI-MPPT optimizer is more suitable in scenarios where a high degree of localized clearance is needed.

3.2 Ant Colony Algorithm

3.2.1 Forging Behavior of Ants

Ants are remarkable creatures renowned for their highly efficient foraging behavior, which has long fascinated biologists and inspired the development of optimization algorithms. When ants venture out of their nests in search of food, they don't do so haphazardly. Instead, they employ a sophisticated system that involves both individual actions and collective decision-making to find the shortest path to their goal. This behavior is often referred to as the foraging trail. Ant foraging begins with scouts leaving the nest in search of potential food sources. These scouts roam the surroundings, and when they stumble upon a food item, they assess its quality and quantity. If a scout discovers something promising, it grabs a piece and heads back to the nest, leaving behind a chemical trail known as a "pheromone trail" as it goes. Strength of pheromone trail is directly proportional to the quality of the food source [36].

When a scout returns to the nest with nutriment, it unloads the food and reinforces the pheromone trail on its way back out. The scent of these pheromone trails is a vital form of communication among ants. Other ants in the colony detect the pheromones with their antennae, and the intensity of the scent provides crucial information. Stronger trails indicate higher-quality food sources or shorter paths. As more scouts follow the initial track to the source of food and return with food, they reinforce the pheromone trail. This process creates a positive feedback loop, whereby a stronger trail attracts more ants. Essentially, ants are additional expected to take a well-marked trail with a strong pheromone scent [37, 39].

Over time, the pheromone trail that leads to the best food source becomes the most attractive to foragers. Since ants typically choose the path with the strongest scent, this naturally directs them toward the shortest possible route to the nutrition source. In such a manner, the colony collectively optimizes its foraging path based on the quality of the food and the distance to the source [38]. Ants also display adaptive behavior. If a previously productive food source becomes depleted, scouts eventually stop reinforcing the trail, and it fades away. This encourages scouts to explore alternative routes and discover new food sources.

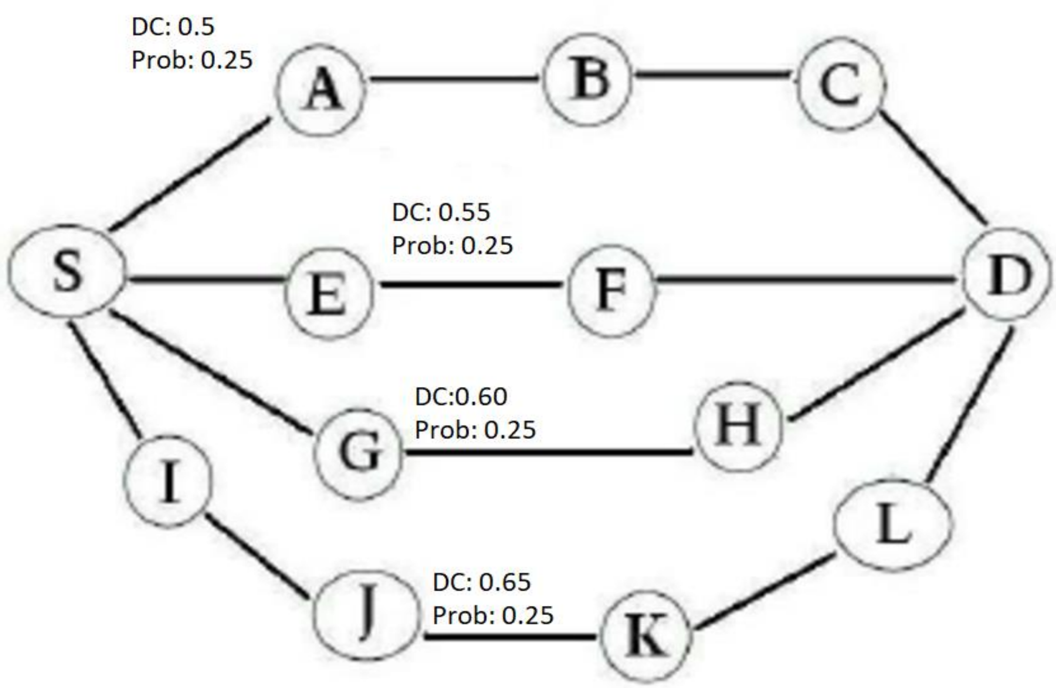

Fig 3.3: Ant Colony Algorithm Starting

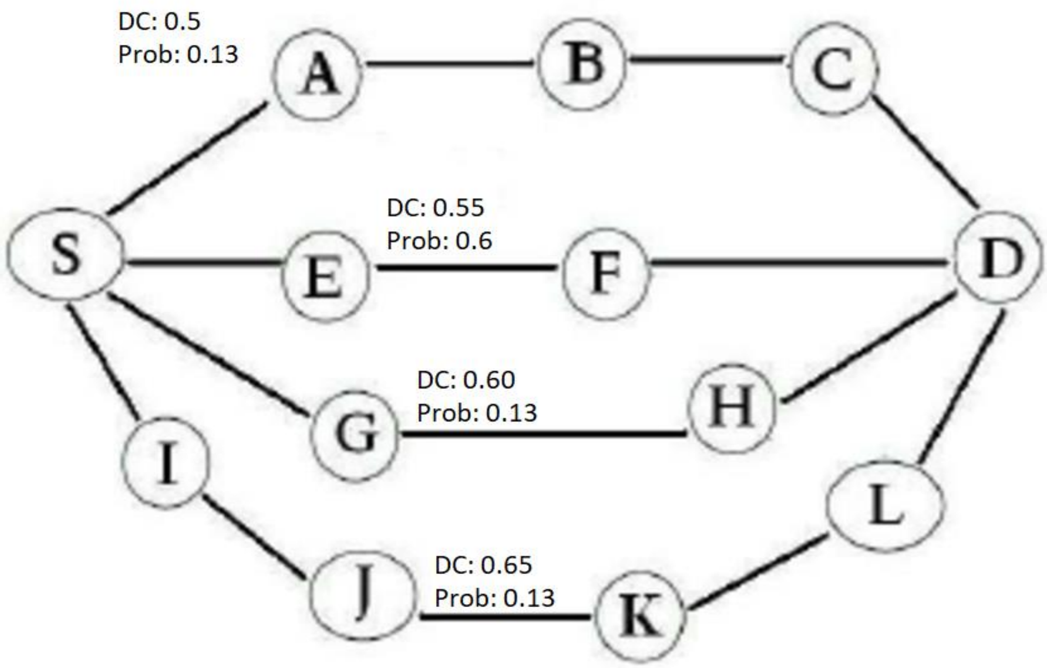

Fig 3.4: Ant Colony Algorithm Middle

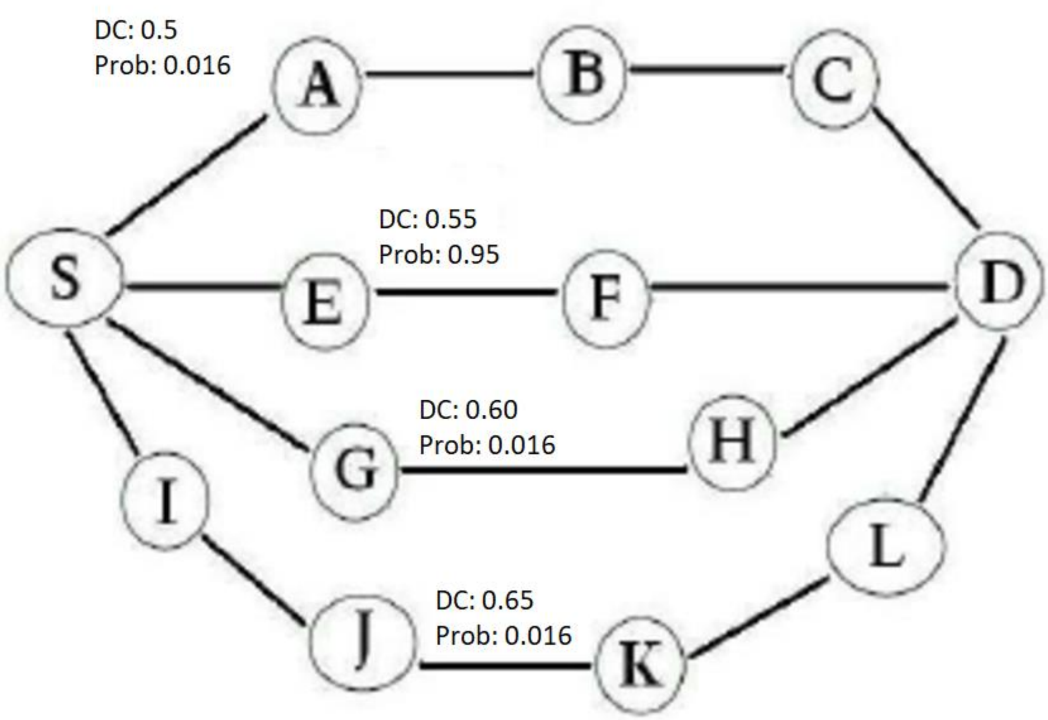

Fig 3.5: Ant Colony Algorithm Near End

3.2.2 Flow Chart Ant Colony Algorithm

The algorithm initiates with the "Start" step, commencing its execution. Following this, the "Launch New Iteration of Ants" phase begins, marking the start of a new iteration cycle. Within each iteration, a group of artificial ants is unleashed to explore the solution space in search of optimal solutions. During the "Find New Solutions" stage, every ant in the population embarks on its journey to seek a solution to the given optimization problem. These ants employ a combination of two guiding mechanisms: pheromone trails collected from previous iterations and heuristic information, which encapsulates problem-specific knowledge.

Once an ant completes its journey and constructs a solution, the "Solution Evaluation" process comes into play. Here, the quality of the solution is meticulously assessed, relying on how effectively it aligns with the optimization criteria pertinent to the problem at hand. The algorithm periodically checks whether "Termination Criteria" have been met. These criteria can encompass factors like a predefined max number of iterations, a target quality for solutions, or specified convergence conditions. If any of these conditions are satisfied, the algorithm proceeds; otherwise, it continues to run iterations.

The "Pheromone Deposition" phase follows, where ants deposit pheromone along the paths they have traversed during solution construction. The quantity of pheromone deposited typically correlates with the worth of the solutions obtained, reinforcing trails that guides to superior outcomes. Lastly, in the "Pheromone Evaporation" step, the algorithm simulates the gradual decay of pheromone on all paths. This emulates the natural evaporation process found in the environment. The rate of pheromone evaporation is a parameter of the algorithm, playing a pivotal role in sustaining diversity in path exploration throughout the optimization process [40].

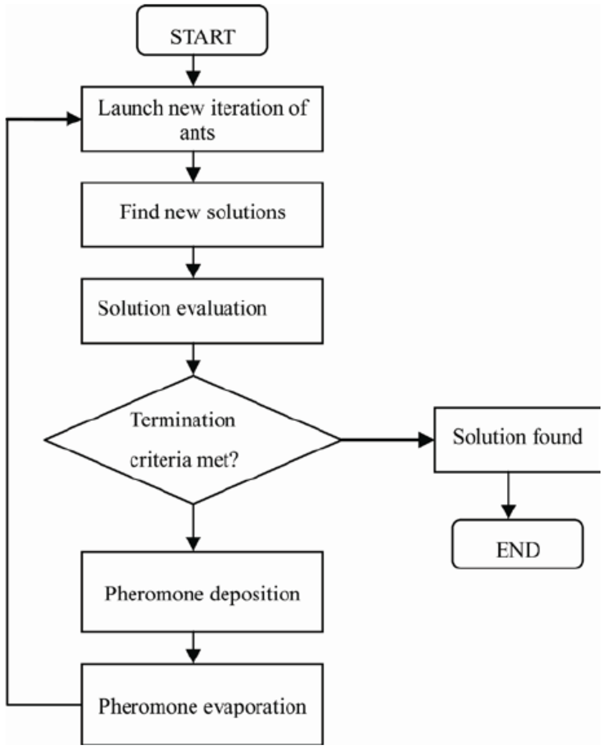

Fig 3.6: Ant Colony Flow Chart

3.2.3 Pseudo Code Ant Colony Algorithm

Below is ACO's pseudo code:

Commence

Prime/Set

While Loop - ending criteria not met, **Do**

place each ant in a initial or starting node

Repeat

For Loop each ant, **Do**

Next node will be chosen by applying the state transition rule

Apply a step-by-step update for pheromones

End For Loop

Until every ant has generated a result

Best result to be updated

Update the pheromones

End While Loop

Conclusion

Below is the code's explanation:

Prime/Set: This initial step serves as the preparation phase for the ACO. It involves the setup and initialization of all the necessary variables and parameters required for the algorithm to function effectively. Essentially, this step lays the groundwork for the problem at hand and gets the artificial ants ready for their exploration journey.

While Loop Stopping Criteria Not Met: This pivotal part of the algorithm introduces the main control loop. As long as the specified stopping criteria are not met, the algorithm remains active. The stopping criteria can vary but typically include conditions like attainment a max number of iterations or achieving a predefined target quality for solutions. This loop governs the execution of the algorithm, ensuring it continues until the desired convergence or result is achieved.

Place Each Ant in a initial Starting Node: At the commencement of each iteration, a crucial task is undertaken: placing each artificial ant in its respective starting node. These starting nodes represent the initial states from which the ants begin their exploration. This step effectively sets the stage for the ants' solution construction process.

Repeat: This instruction initiates a loop within each iteration, marking the beginning of a repetitive process. The primary goal of this loop is to guide each ant through its journey to construct a solution. It ensures that each artificial ant has the opportunity to navigate through the problem space.

For Loop - Each Ant: Nested within the repetition loop, this segment orchestrates the core activities of the algorithm. Within this loop, each ant, representing a potential solution, follows a set of rules known as the state transition rule to select its succeeding node or path. This phase drives the exploration and solution-building process, a fundamental aspect of the ACO algorithm.

Apply Step by Step Pheromone Update: As the ants navigate through their chosen paths, this step is responsible for managing the pheromone levels on the paths in a systematic manner. Pheromones are adjusted incrementally along the routes taken by the ants. This process of gradual pheromone update has a significant part in shaping the collective conduct of the ant population.

Until Every Ant Has Generated Solution: The loop introduced by this statement ensures that the algorithm continues until every artificial ant in the population has successfully constructed a solution. It guarantees that each ant has had the opportunity to explore and contribute to the search for an optimal solution.

Best Result to be Updated: This stage of the algorithm focuses on assessing the superiority of the results made by the individual ants. It selects and updates the finest solution found throughout the AOC's execution. The finest solution represents the most promising outcome in terms of meeting the optimization criteria.

Update the Pheromone: After completing each iteration, the algorithm proceeds to apply a pheromone update. The amount and distribution of pheromone along the paths are adjusted based on the quality of solutions constructed. This step reinforces the paths that lead to better solutions while diminishing the influence of paths associated with poorer outcomes.

End While Loop: Signifying the conclusion of the primary control loop, this statement terminates the iterative process. It does so when the stopping criteria have been met, indicating that the algorithm has either converged or satisfied other predefined conditions.

Conclusion: This is the ultimate endpoint of the ACO algorithm. Once the algorithm has accomplished its task as per the stopping criteria, it concludes, and its execution comes to an end [41].

3.2.4 Mathematical Model of Ant Colony Algorithm

1. Pheromone Update:

The pheromone update process is a fundamental aspect of ACO. It involves both pheromone evaporation and pheromone deposition.

- Pheromone Evaporation:

Evaporate a fraction (ρ) of pheromone on all paths at each iteration:

$\tau\_ij(t+1) = (1 - \rho) * \tau\_ij(t)$, where $\tau\_ij(t)$ is the pheromone level on the edge (i, j) at time step t.

- Pheromone Deposition:

Ants deposit pheromone on the paths they have taken, and the quantity of pheromone depends on the caliber of the result found.

The amount of pheromone ($\Delta\tau\_ij$) deposited by ant k on the edge (i, j) is typically related to the quality (or fitness) of the solution made by ant k:

$\Delta\tau\_ij(k) = Q / L\_k$, where Q is a constant, and L_k is the length (or cost) of the solution found by ant k.

2. State Transition Rule:

The state transition rule guides ants in pick out the next node to visit grounded on pheromone levels and problem-specific heuristic information. The probability of decide on the edge (i, j) by ant k is often expressed using a probabilistic formula, such as:

$p\_ij(k) = [\tau\_ij\hat{}\alpha * \eta\_ij\hat{}\beta] / \Sigma[(\tau\_uv\hat{}\alpha * \eta\_uv\hat{}\beta)$ for all valid edges (u, v)]

Where:

τ_ij: Pheromone level on edge (i, j)

η_{ij}: Heuristic information on the edge (i, j) (problem-specific knowledge)

α and β: Control parameters to balance the influence of pheromone and heuristic information.

3. Objective Function:

In optimization problems, an objective function f(x) is used to appraise the caliber of a result x. The objective function represents the goal of the optimization problem (e.g., minimizing or maximizing a specific criterion). In ACO, the quality of a solution constructed by an ant is evaluated using the objective function.

4. Global Best Solution:

During the algorithm's execution, the global finest solution is tracked.The global best solution (x*) is the best solution found by any ant up to the current iteration:

$x^* = \arg\max\{f(x_k) \text{ for all ants } k\}$

These mathematical expressions represent the core components of the ACO algorithm. The specific formulation may vary based on the problem being solved and the ACO variant used. Researchers often customize these equations to adapt the algorithm to different optimization

Tasks [42].

3.2.5 Modification done to Ant Colony Algorithm

Let's see what modification have been done to ant colony algorithm over time.

In Rakesh Kumar Phanden's work [43] the modifications made aim to fine-tune the ant colony optimization technique for MPPT in PV systems. Instead of starting with a larger population of ants, the researchers begin with only three ants. With a narrow search domain, fewer ants may be sufficient. A crucial modification involves constraining the maximum deviation of ants from the best solution (Best-ant). In this case, the maximum deviation allowed is ±0.2 of the duty ratio. Ants' positions are updated based on a conditional rule. If an ant's deviation from the best solution is greater than 0.2, it is adjusted to be exactly 0.2 greater than the best solution (Ant

= Best-ant + 0.2). Conversely, if an ant's deviation is less than -0.2, it is adjusted to be exactly 0.2 less than the best solution (Ant = Best-ant - 0.2). If neither of these conditions is met, the ant's position remains unchanged. These modifications are intended to prevent the ACO algorithm from overshooting the GMPPT and to improve convergence behavior. By constraining the ant's deviations and using the best solution as a reference, the algorithm is fine-tuned to achieve better MPPT performance in PV systems.

Kinattingal Sundareswaran’s [44] paper discourses the use of ACO and the P and O in the context of MPPT for partially shaded PV systems. The paper highlights the potential of the ACO method in capturing the GMPP in partially shaded PV setups. This suggests that ACO shows promise in optimizing PV system performance under challenging conditions where shading occurs. Despite its promise, the paper acknowledges certain drawbacks associated with the ACO method. These include continued oscillations in PV output during tracking and amplified convergence time. In other words, ACO may exhibit fluctuations in power output and take longer to reach the optimal point. The basic P&O method is mentioned as an alternative. It's noted that P&O has limitations in recognizing the GMPP, potentially settling for a local power peak and, consequently, reducing energy extraction from the PV system. However, the gain of P&O is that it typically results in a smoothly varying output power curve without significant fluctuations. The paper proposes a cross approach that combines the strengths of both ACO and P and O methods. The idea is to use ACO for global search, allowing it to explore a wider solution space and identify the GMPP. Once ACO has found an approximate solution, the system can then transition to the traditional P&O method for local search.

In Badreddine Babes’s paper [45], the hybrid ACO and ANN (Artificial Neural Network) MPPT controller is designed to optimize the operation of PV setup by guiding them to operate as near as it can to their MPP. This controller combines the strengths of both ACO and ANN methodologies. Initially, it starts with an initial duty cycle setting for the DC-to-DC boost converter and an initial population of artificial ants for ACO. ACO conducts a global search, where each artificial ant explores various duty cycle settings. Simultaneously, the ANN takes electrical measurements from the solar setup as feed in and estimates the optimal duty cycle based on its training. The hybrid controller integrates the outcomes of ACO and the ANN's estimation. If ACO's duty cycle deviates significantly from the ANN's estimate, it's adjusted to align with the ANN's value, preventing overshooting. The controller aims to minimize the mistake between the real and optimal power during ACO's global search, ensuring the PV system operates near the MPP. This hybrid approach enhances MPPT performance, particularly under changing environmental conditions or partial shading scenarios.

CHAPTER 4: MATERIALS AND METHOD

4.1 Methodology of Research Design

In our simulation conducted using Simulink, we designed a photovoltaic (PV) system comprising four solar panels connected in series, with each panel modeled after the 'Tata Power Solar Systems TP250MBZ' specifications. Under standard conditions of 1000 (W/m^2) of solar energy or irradiance, each of these panels is designed to produce an output of 30 volts and 8.3 amps.

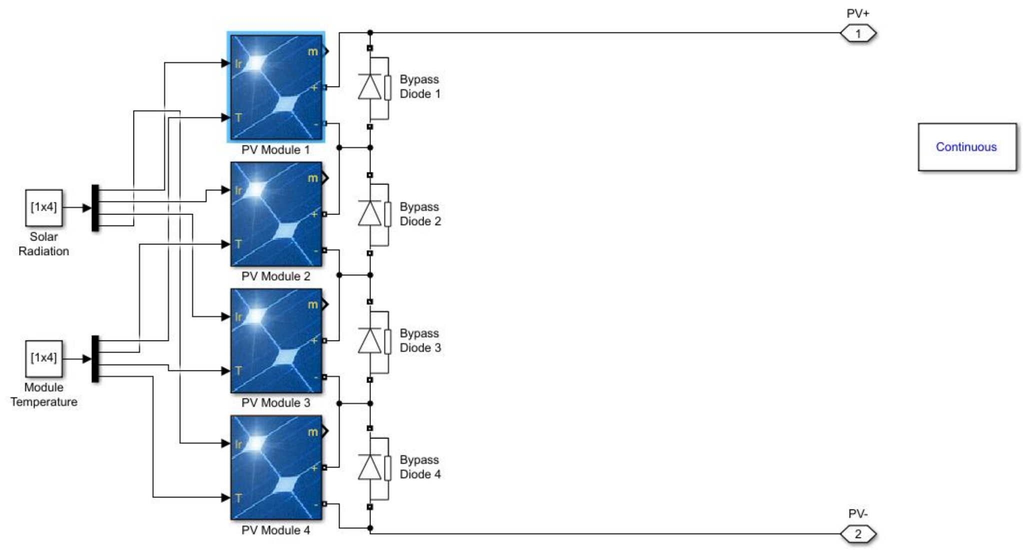

Fig 4.1: Solar Panel Array

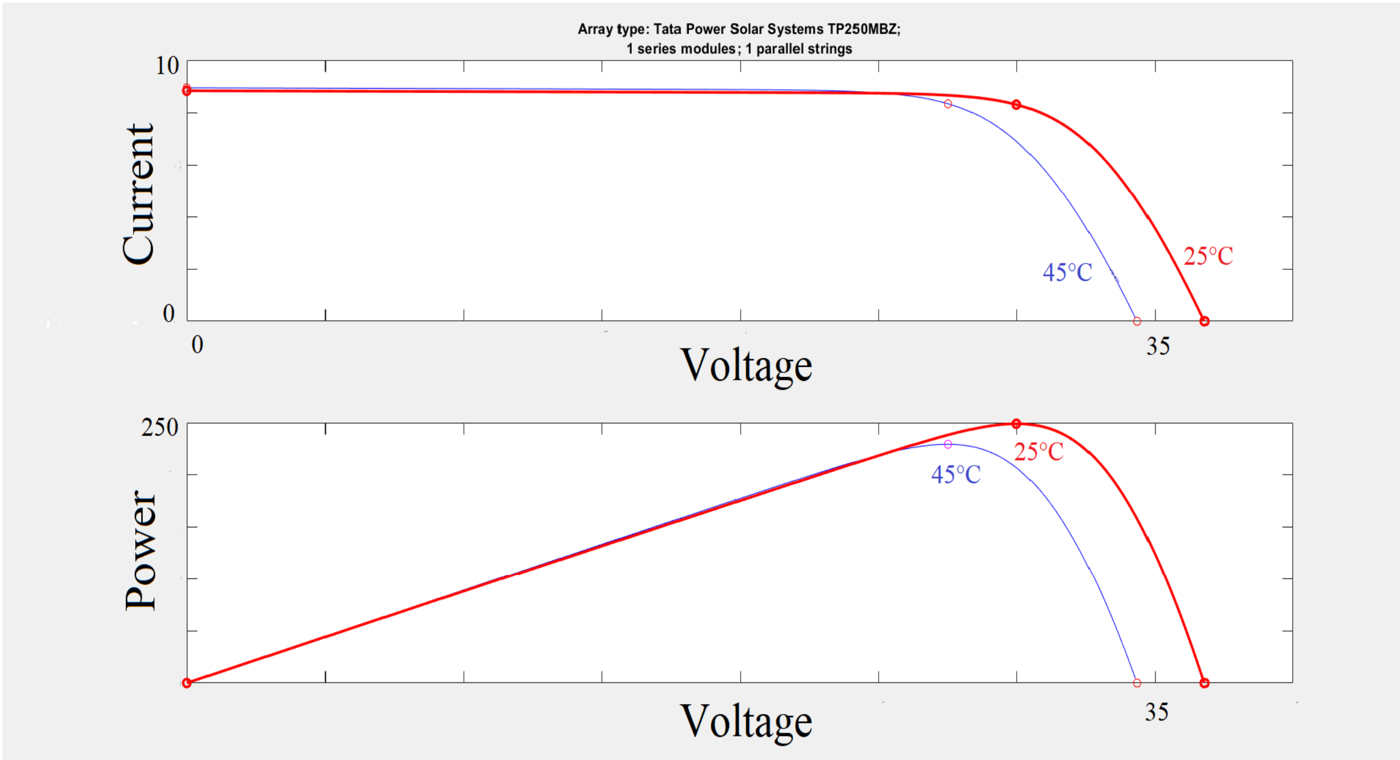

Fig 4.2: Solar Panel IV-Chart

These PV panels are an integral part of our system and serve as the primary energy source. Their combined output is directed to a DC-to-DC converter. To enhance the efficiency and energy harvesting capabilities of our PV system, we've implemented MPPT techniques. Specifically, we've integrated the GW and ACO to continually adjust the operating parameters of the DC-to-DC converter, ensuring that it operates at or near its MPP under changeable environmental circumstances.

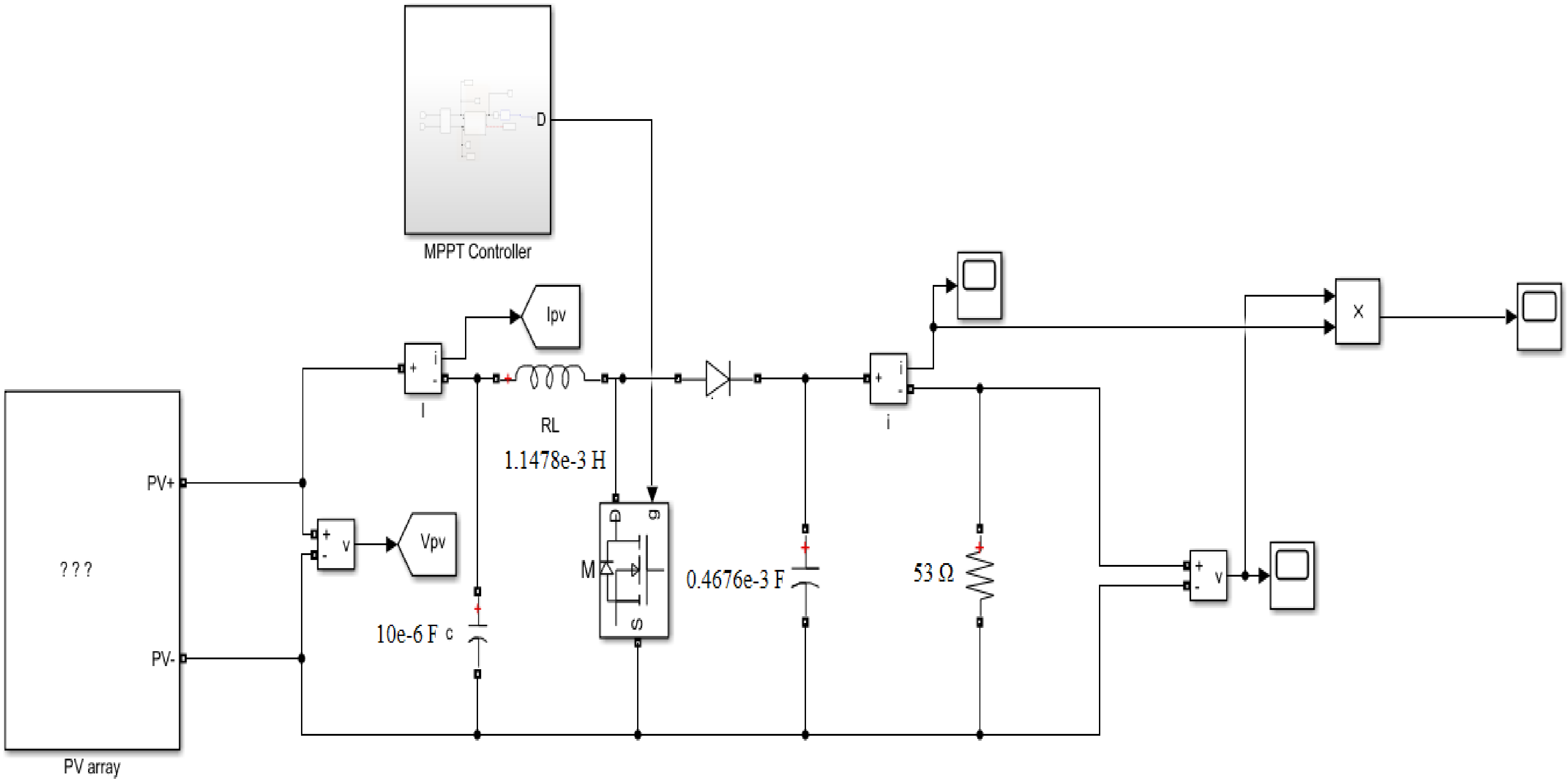

Fig 4.3: Main Circuit

4.2 Research Approach:

Existing literature was given a thorough review for understanding the in MPPT procedures and their uses. This involved an exploration of orthodox algorithms, such as P and O, alongside a comprehensive survey of nature-inspired algorithms, including Ant Colony and Grey Wolf optimization. This literature appraisal smoothed the identification of research slits and guided the selection of algorithms for comparative analysis.

The study strategically selected Ant Colony and Grey Wolf optimization algorithms based on their adaptability and resilience in adverse conditions, as suggested by literature findings. These nature-inspired algorithms were chosen for their potential to address challenges posed by reduced solar irradiance and fluctuating temperatures, which are common in real-world scenarios.

4.3 Data Collection

To enhance the practical relevance of the research, geographical locations with diverse climatic conditions were chosen for analysis. This includes regions with extreme temperatures, such as Lut Desert and Yellowknife, as well as areas with varying solar irradiance levels, like Torshavn. The goal was to assess the algorithms' performance under conditions mirroring actual photovoltaic installations.

4.4 Ethical Consideration

Ensuring the ethical integrity of this research was paramount throughout all stages of planning, execution, and reporting. The privacy and confidentiality of individuals and organizations providing data were strictly maintained. All data, whether obtained from public sources or collaborators, were anonymized, and aggregated to prevent the identification of specific entities. Every effort was made to minimize bias in the selection of geographical locations, data sources, and simulation parameters. Objective criteria guided these decisions to ensure the research remains impartial and unbiased. The findings of this research are reported transparently and accurately, without manipulation or selective reporting. Any limitations or challenges encountered during the research process are openly discussed to provide a comprehensive understanding of the study's scope. All contributions from other researchers, organizations, or sources are duly acknowledged through proper citations. This practice acknowledges the intellectual property and efforts of others, fostering a culture of academic honesty and respect.

Chapter 5: Results and Discussion

Now to first demonstrate the superiority of Nature inspired algorithms using my own simulation, the following are the results obtained when the system was operated during partial shading. The irradiation was kept at 500, 800, 1000, 1000 W/m2 respectively (more detail of the simulation in the simulation section) and the temperature was kept at 25 degrees Celsius. With this, Grey Wolf Optimization and Ant Colony Optimization yielded 627 and 635 watts respectively. While P&O algorithm was lagging behind with 483 watts output.

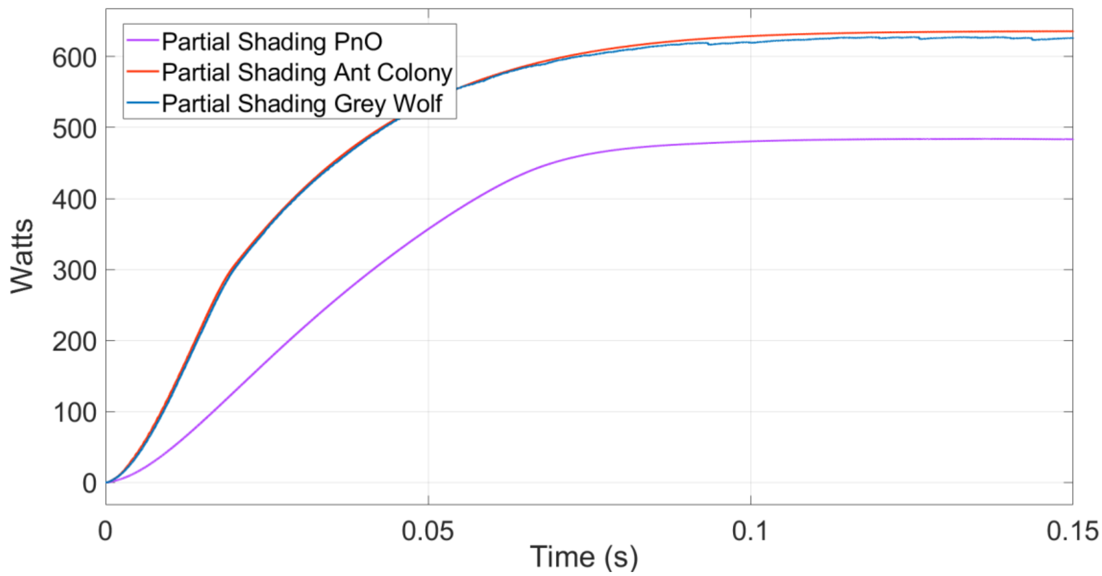

Fig 5.1: Ant Colony, grey wolf and P&O's performance in partial shading

Table 5.1: Reading obtained under partial shading from ant colony, grey wolf and P&O.

Under Partial Shading	
Ant Colony	635 watts
Grey Wolf	627 watts
P and O	483 watts

5.1 Lut Desert, Iran

Located in southeastern Iran, the Lut Desert, also known as Dasht-e Lut, is renowned for being one of the hottest places on Earth. Its extreme arid landscape is marked by vast sand dunes, salt flats, and unique geological formations. In our simulation, we emulated the challenging conditions of Lut Desert, setting the solar radiation at a scorching 1000 watts per square meter (W/m²) and the temperature soaring to a blistering 70 degrees Celsius. Under these harsh environmental parameters, our research explored the performance of two MPPT procedures. The the ACO achieved 798.4 watts in 78.240ms with osilation of 0.6w, while GWO yielded an output of 796.5 watts in 74.700ms with osilation of 1w. Under a normal hot day in summer, 1000 w/m² and 50 degrees Celsius, ACO gives 896.5w and GWO gives 892.3w.

The selection of radiation and temperature levels aligns with the solar irradiance commonly experienced in regions known for their intense sunlight, particularly in areas classified as sunbelts. The term "sunbelt" refers to geographic zones characterized by consistently high levels of solar radiation throughout the year. These regions, often located near the equator or in arid climates, boast minimal cloud cover and atmospheric interference. Consequently, the sun's rays penetrate the atmosphere with greater intensity and are more direct, facilitating the transmission of higher levels of solar radiation to the Earth's surface.

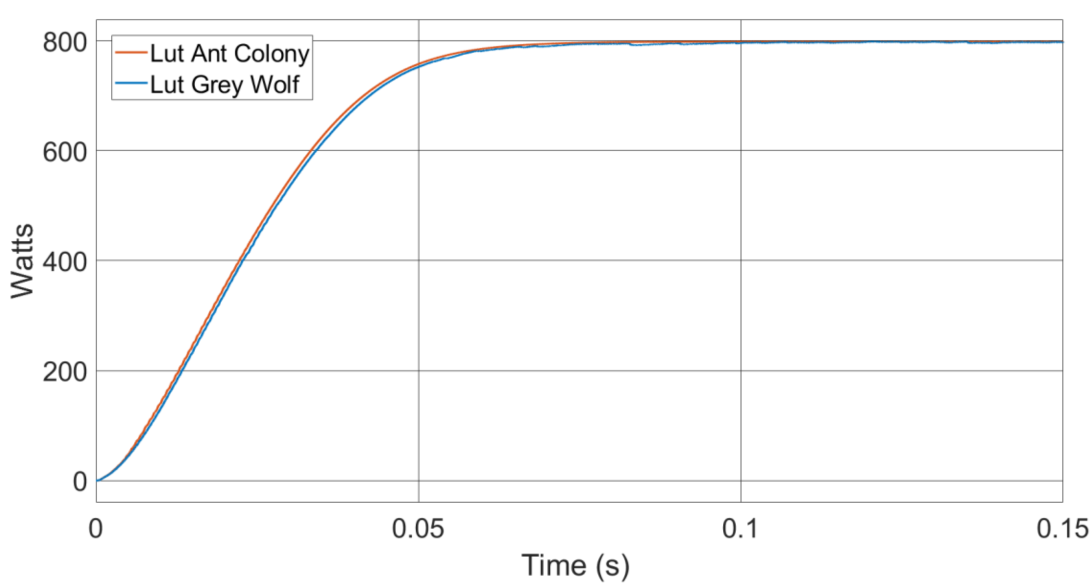

Fig 5.2: Ant Colony and grey wolf’s performance in Lut desert

Table 5.2: Readings obtained in Lut desert from ant colony and grey wolf.

Lut Desert				
MPPT	**Watts Generated**	**Time Taken to Reach Peak**	**Oscillations (watts)**	**Watts in normal summer day**
Ant Colony	798.4w	78.240ms	0.6	896.5
Grey Wolf	796.5w	74.700ms	1	892.3

5.2 Extremadura, Spain

Situated in southwestern Spain, Extremadura is characterized by its diverse landscapes, encompassing vast plains, rugged mountains, and historic towns. It experiences a Mediterranean climate with scorching summers and mild winters. In our simulation, we mirrored the sun-drenched conditions of Extremadura, setting the solar radiation at a blazing 1000 watts per square meter (W/m²) and the temperature at a sizzling 60 degrees Celsius. Within this challenging environment, we assessed the performance of two MPPT procedures. the ACO excelled with 849.4 watts in 88.920ms with osilation of 0.6w, while GWO achieved an output of 846.7 watts in 87.400ms with osilation of 1w. Under a normal hot day in summer, 1000 w/m² and 40 degrees Celsius, ACO gives 936.7w and GWO gives 930.5w.

The choice of radiation and temperature is influenced by its mediterranean climate, characterized by long, hot summers and mild winters, which contribute to high levels of solar irradiance. Additionally, Extremadura boasts relatively clear skies and low levels of atmospheric pollution, further enhancing solar radiation levels.

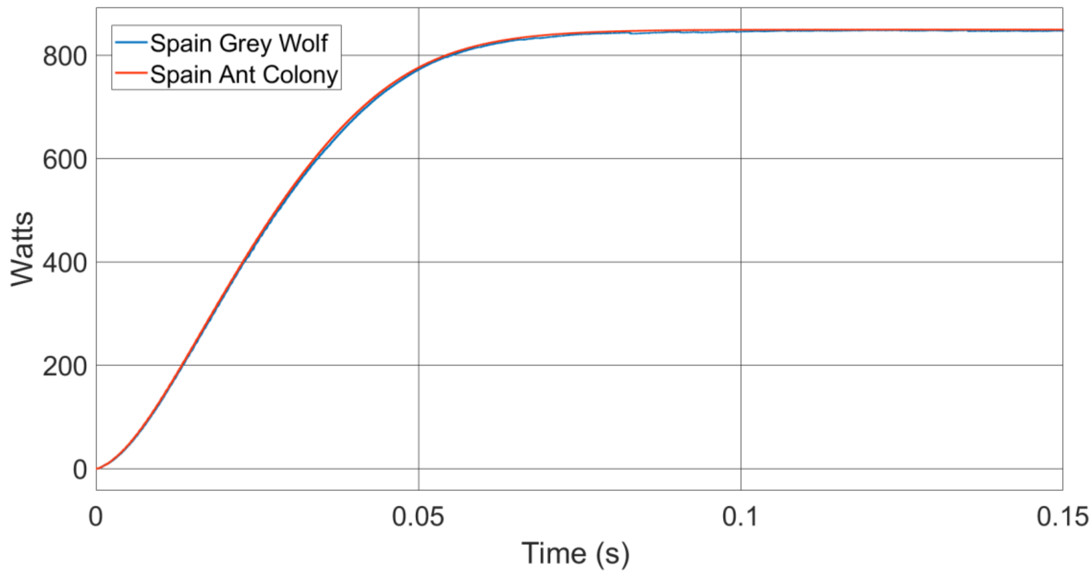

Fig 5.3: Ant Colony and grey wolf's performance in Extremadura

Table 5.3: Readings obtained in Extremadura from ant colony and grey wolf.

Extremadura				
MPPT	**Watts Generated**	**Time Taken to Reach Peak**	**Oscillation**	**Watts in normal summer day**
Ant Colony	849.4w	88.920ms	0.6	936.7
Grey Wolf	846.7w	87.400ms	1	930.5

5.3 Novosibirsk, Russia

Located in southwestern Siberia, Novosibirsk is Russia's third-largest city and an industrial hub. It experiences a harsh continental climate, with bitterly cold winters and warm summers. In our simulation, we emulated Novosibirsk's frigid conditions by setting the temperature at a bone-chilling -46 degrees Celsius and the solar radiation at 300 watts per square meter (W/m²). Within this challenging environment, we evaluated the performance of two optimization algorithms. The Ant Colony Optimization algorithm yielded an output of 84.35 watts in 107.440ms with osilation of 0.15, while the Grey Wolf Optimization algorithm achieved 83.74 watts in 106.100ms with osilation of 0.5w. Under a normal cold day in winter, 450 w/m² and -20 degrees Celsius, ACO gives 195w and GWO gives 193.7w.

The temperature selection is affected by the high latitude and continental climate. The region's location in the heart of Siberia exposes it to frigid Arctic air masses, resulting in bitterly cold winters with temperatures plummeting well below freezing. The presence of the Siberian High, a large area of high pressure centered over Siberia during winter, exacerbates the cold conditions. The low solar irradiance in Novosibirsk can be attributed to its high latitude, which places it far from the equator and reduces the intensity of sunlight reaching the Earth's surface. Additionally, the region experiences short daylight hours during winter due to its proximity to the Arctic Circle, further limiting solar energy input.

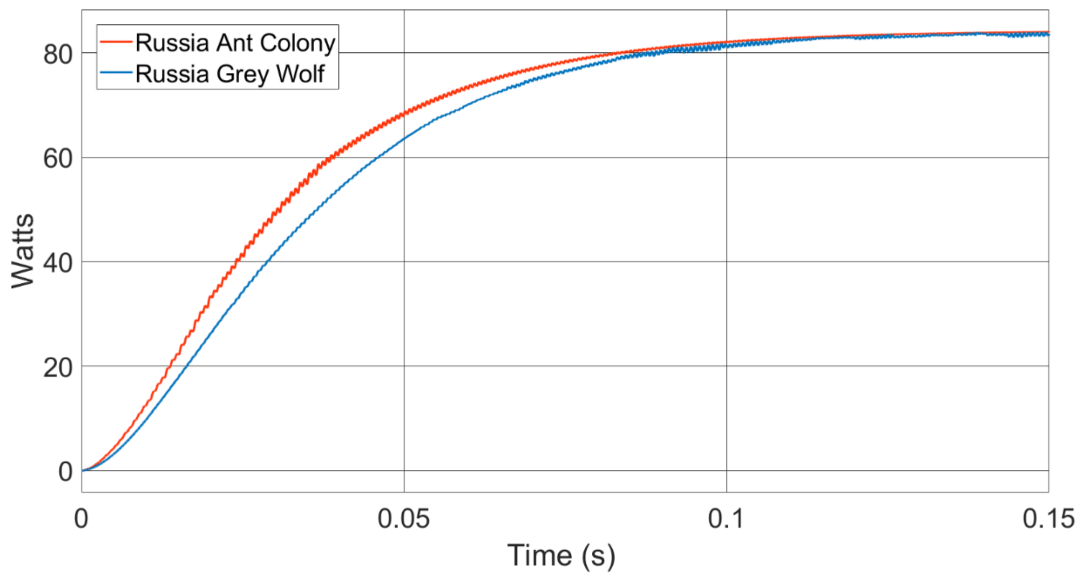

Fig 5.4: Ant colony and grey wolf's performance in Novosibirsk

Table 5.4: Readings obtained in Novosibirsk from ant colony and grey wolf.

Novosibirsk				
MPPT	**Watts Generated**	**Time Taken to Reach Peak**	**Oscillations (watts)**	**Watts in normal winter day**
Ant Colony	84.35	107.440ms	0.15	195
Grey Wolf	83.74	106.100ms	0.5	193.7

5.4 Yellowknife, Canada

Nestled in the Northwest Territories of Canada, Yellowknife is renowned for its stunning wilderness and northern lights. This city faces a subarctic climate, characterized by brutally cold winters and warm summers. In our simulation, we mirrored Yellowknife's icy conditions by setting the temperature at a frosty -30 degrees Celsius and the solar radiation at 250 watts per square meter (W/m^2). Within this challenging environment, we evaluated the performance of two optimization algorithms. The Ant Colony Optimization algorithm generated an output of 59.91 watts in 109.000ms with osilation of 0.17w, while the Grey Wolf Optimization algorithm achieved 59.47 watts in 108.310ms with osilation of 0.6w. Under a normal cold day in winter, 400 w/m^2 and -20 degrees Celsius, ACO gives 154.4w and GWO gives 154w.

The preference of radiation and temperature is guided by being one of Canada's northernmost cities, Yellowknife is situated at approximately 62° latitude, placing it well within the Arctic Circle. This high latitude results in significant variations in daylight hours throughout the year, with extended periods of darkness during winter and continuous daylight during summer. The low solar irradiation in Yellowknife can be attributed to several factors, including its high latitude, which reduces the angle of sunlight reaching the Earth's surface, and the presence of atmospheric conditions such as clouds and haze that further attenuate solar radiation. Additionally, during winter, the city experiences short daylight hours and frequent overcast skies, further limiting solar energy input.

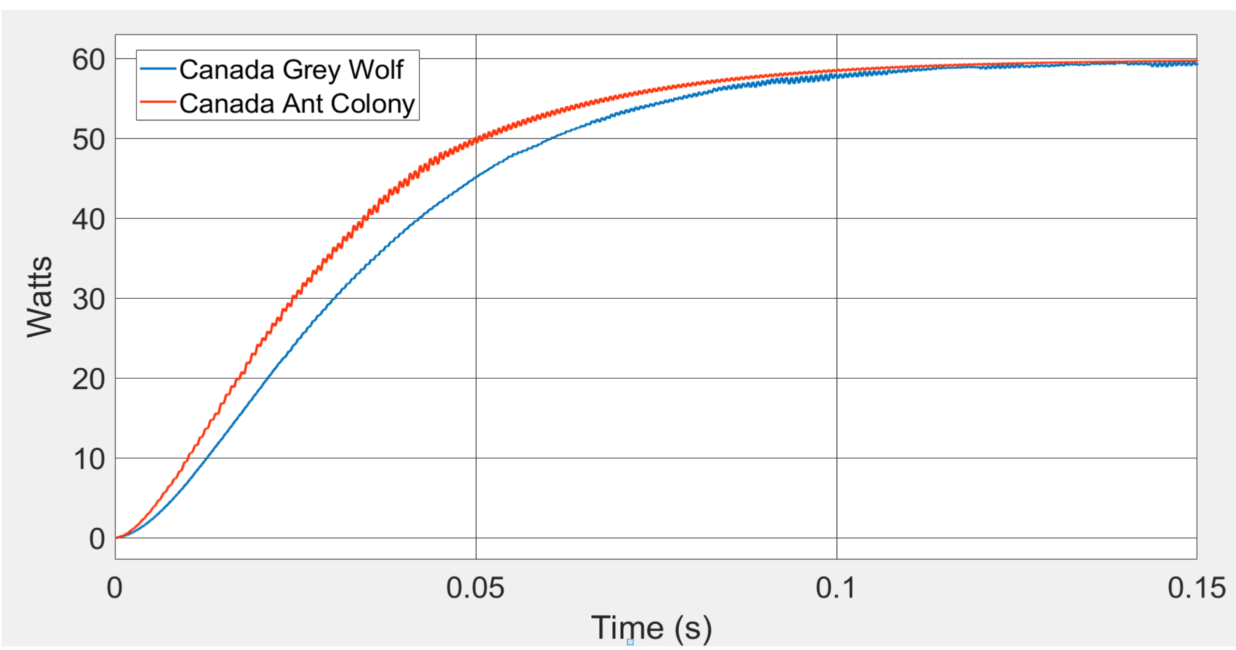

Fig 5.5: Ant colony and grey wolf's performance in Yellowknife

Table 5.5: Readings obtained in Yellowknife from ant coly and grey wolf.

Yellowknife				
MPPT	**Watts Generated**	**Time Taken to Reach Peak**	**Oscillation (watts)**	**Watts in normal winter day**
Ant Colony	59.91	109.000ms	0.17	154.4
Grey Wolf	59.47	108.31ms	0.6	154

5.5 Sao Joaquim, Brazil

Sao Joaquim, situated in south of Brazil, finds itself amid the captivating landscapes of the Santa Catarina state. This region undergoes a subtropic upland weather, characterized by cool winters and mild summers. In our simulation, we mirrored São Joaquim's pleasant climate with a temperature setting of 17 degrees Celsius and a solar radiation level of 480, 275, 330, 200 watts per square meter (W/m²) respectively. Within this temperate environment, we evaluated the performance of two optimization algorithms. The Ant Colony Optimization algorithm yielded an output of 110.9 watts in 109.220ms with osilation of 0.1w, while the Grey Wolf Optimization algorithm achieved 109.5 watts in 91.680ms with osilation of 0.5w. Under a normal cloudy day, 500 w/m² and 20 degrees Celsius, ACO gives 253.2w and GWO gives 252.2w.

The choice of solar irradiation is affected by Soa Joaquim's heavy clouds primarily due to its geographical features and prevailing weather patterns. Situated in the Serra Catarinense region of the state of Santa Catarina, Sao Joaquim is characterized by its elevated terrain, with many areas located at altitudes above 1,000 meters (3,280 feet). The municipality's proximity to the Atlantic Ocean plays a significant role in its weather patterns. Moisture-laden air masses from the ocean often interact with the region's mountainous terrain, leading to orographic lifting, a process in which air is forced to rise over elevated landforms. As the air ascends, it cools and condenses, forming clouds and precipitation. The orographic lifting effect, combined with the region's variable topography and prevailing winds, contributes to the formation of heavy clouds over Sao Joaquim. These clouds can manifest in various forms, including stratocumulus and nimbostratus clouds, which are often associated with overcast skies and periods of rainfall.

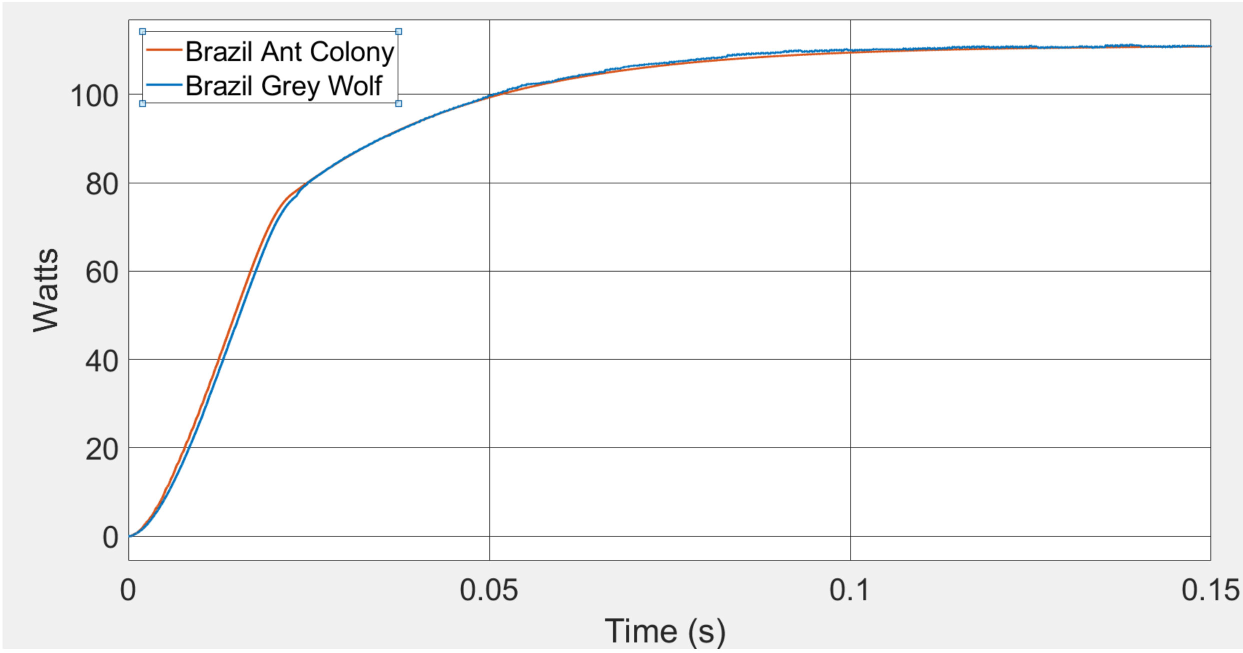

Fig 5.6: Ant colony and grey wolf's performance in Sao Joaquim

Table 5.6: Readings obtained in Sao Joaquim from ant colony and grey wolf.

Sao Joaquim				
MPPT	**Watts Generated**	**Time Taken to Reach Peak**	**Oscillation (watts)**	**Watts in normal cloudy day**
Ant Colony	110.9w	109.220ms	0.1	253.2
Grey Wolf	109.5w	91.680ms	0.5	252.2

5.6 Torshavn, Faroe Islands

Tórshavn, the capital of the Faroe Islands, is nestled on Streymoy's east coast, the biggest island in this North Atlantic archipelago. Renowned for its stunning landscapes, this city is surrounded by mountains, including Mt. Húsareyn and Mt. Kirkjubøreyn. It is worth noting that Tórshavn ranks among the cloudiest places globally, with only 2.4 hours of daily sunshine on average. This unique climate is attributed to its sub polar oceanic climate, resulting in mild winters and cool summers. In our simulation, we emulated Tórshavn's characteristic conditions, setting the temperature at 12 degrees Celsius and solar radiation at 500, 300, 450, 250 watts per square meter (W/m²) respectively. Under these climatic parameters, we assessed the efficiency of two optimization algorithms. The Ant Colony Optimization algorithm produced an output of 201 watts in 116.440ms with osilation of 0.3w, while the Grey Wolf Optimization algorithm achieved 200.7 watts in 115.640ms with osilation of 0.9w, showcasing their adaptability to challenging environments. Under a normal cloudy day, 550 w/m² and 20 degrees Celsius, ACO gives 306w and GWO gives 304.8w.

The choice is shaped by the maritime subpolar climate characterized by frequent cloud cover, precipitation, and relatively mild temperatures. The Faroe Islands are surrounded by the cold waters of the North Atlantic Ocean, which contribute to the formation of dense fog and low-level clouds. The proximity to the ocean moderates temperature extremes but also leads to persistent cloud cover, especially during the cooler months. The rugged terrain of the Faroe Islands, characterized by steep cliffs, fjords, and rolling hills, enhances the orographic lifting effect. As moist air masses encounter the elevated landforms, they are forced to rise, cool, and condense, leading to the formation of clouds and fog. Torshavn and the surrounding areas frequently experience low-level stratocumulus and stratus clouds, which can persist for extended periods, particularly during the cooler seasons. These clouds contribute to the overall cloud cover and reduce the amount of sunlight reaching the surface.

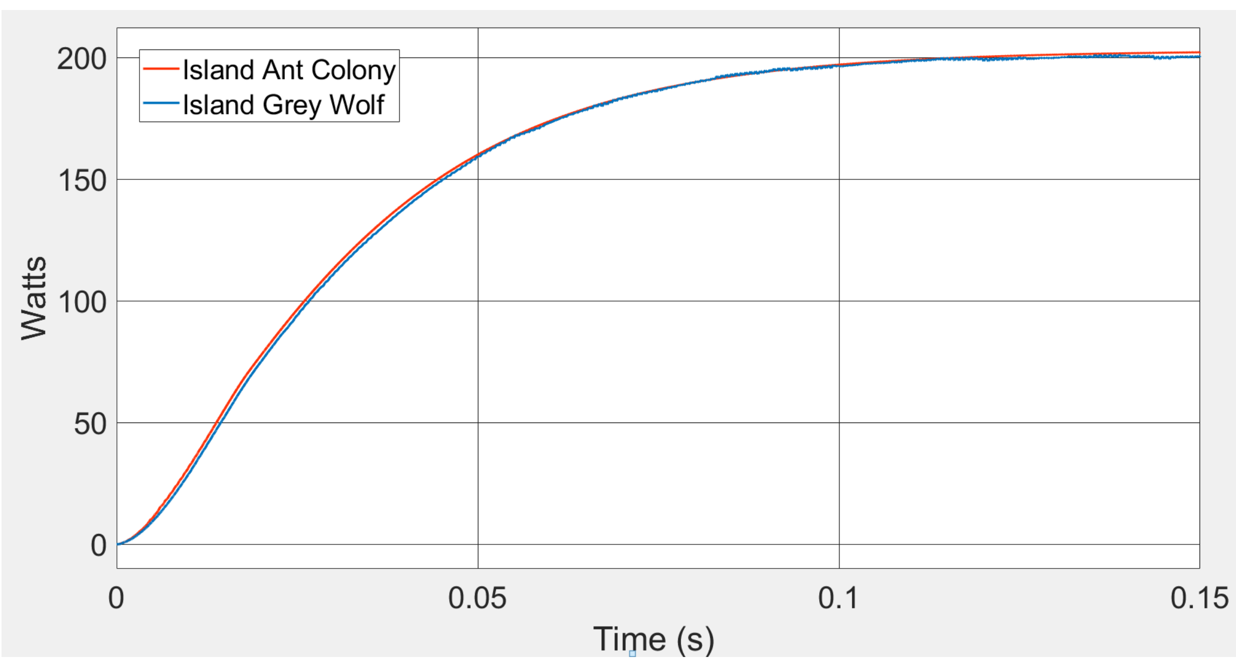

Fig 5.7: Ant colony and grey wolf's performance in Torshavn

Table 5.7: Readings obtained in Torshavn from ant colony and grey wolf.

Torshavn				
MPPT	**Watts Generated**	**Time Taken to Reach Peak**	**Oscillation (watts)**	**Watts in normal cloudy day**
Ant Colony	201w	116.440ms	0.3	306
Grey Wolf	200.7w	115.640ms	0.9	304.8

All locations together:

Table 5.8: Readings from all locations.

All Readings Together					
Location	**MPPT**	**Watts Generated**	**Time Taken To Reach Peak**	**Oscillation (watts)**	**Normal hot/cold/cloudy day**
Lut Desert Iran	Ant Colony	798.4w	78.240ms	0.6	896.5
	Grey Wolf	796.5w	74.700ms	1	892.3
Extremadura Spain	Ant Colony	849.4w	88.920ms	0.6	936.7
	Grey Wolf	846.7w	87.400ms	1	930.5
Novosibirsk Russia	Ant Colony	84.35w	107.440ms	0.15	195
	Grey Wolf	83.74w	106.100ms	0.5	193.7
Yellowknife Canada	Ant Colony	59.91w	109.000ms	0.17	154.4
	Grey Wolf	59.47w	108.310ms	0.6	154
Sao Joaquim Brazil	Ant Colony	100.9w	109.220ms	0.1	253.2
	Grey Wolf	100.2w	91.680ms	0.5	252.2
Torshavn Faroe Islands	Ant Colony	201w	116.440ms	0.3	306
	Grey Wolf	200.7w	115.640ms	0.9	304.8

Conclusion

The results of my comparative analysis between Ant Colony and Grey Wolf optimization algorithms under real-world conditions are intriguing. The minimal differences observed in power outputs suggest that both algorithms perform remarkably well in adverse conditions, such as those encountered in diverse geographical locations. The marginal variations between the two algorithms can be attributed to nuances in the tuning of the DC converter or specific elements within the MPPT convergence mechanisms embedded in the code.

These outcomes underscore the robustness and adaptability of both Ant Colony and Grey Wolf optimization algorithms across a spectrum of challenging environmental scenarios. The convergence of results highlights the effectiveness of nature-inspired algorithms in extracting optimal power from photovoltaic systems under non-ideal conditions. It's worth considering that the intricacies of real-world conditions, including fluctuations in solar irradiance and temperature, can introduce complexities that are sensitively managed by these algorithms.

In conclusion, the close proximity of results indicates the resilience of ACO and GWO in navigating the complexities of diverse environmental parameters. Further investigation into the tuning and specific code elements could provide valuable insights for refining these algorithms, potentially unlocking even greater performance gains in adverse conditions.

While this research endeavors to deliver valued understandings into the presentation of MPPT procedures under diverse environmental conditions, certain limitations should be acknowledged to contextualize the scope and generalizability of the findings.

The study focuses on six distinct geographical locations, namely Lut Desert, Extremadura, Novosibirsk, Yellowknife, Sao Joaquim, and Torshavn. While these locations offer a range of environmental conditions, the research could be enhanced by expanding the geographic scope to include a more comprehensive array of locations, encompassing various climatic and geographical characteristics.

The research primarily employs GWO and ACO to compare their performance in varying conditions. Although GWO and ACO are representative nature-inspired algorithms, the study does not encompass the entire spectrum of available algorithms. Future research could explore additional nature-inspired algorithms to offer a more holistic understanding of their comparative effectiveness.

The study employs the base or standard versions of the Grey Wolf and Ant Colony algorithms. While this choice ensures a foundational understanding of their performance, it leaves out the exploration of modified or advanced versions of these algorithms. Investigating modified iterations could offer nuanced insights into the impact of algorithmic enhancements on performance.

References

[1] "Solar Radiation at the Top of the Atmosphere," in *International Geophysics*, vol. 84, Elsevier, 2002, pp. 37–64. doi: 10.1016/S0074-6142(02)80017-1.

[2] M. Mohseni, J. Abbaszadeh, and A. Nasrollahi Omran, "Radiation resistant of native Deinococcus spp. isolated from the Lout desert of Iran 'the hottest place on Earth,'" *Int. J. Environ. Sci. Technol.*, vol. 11, no. 7, pp. 1939–1946, Oct. 2014, doi: 10.1007/s13762-014-0643-7.

[3] T. A. Scambos *et al.*, "Ultralow Surface Temperatures in East Antarctica From Satellite Thermal Infrared Mapping: The Coldest Places on Earth," *Geophysical Research Letters*, vol. 45, no. 12, pp. 6124–6133, Jun. 2018, doi: 10.1029/2018GL078133.

[4] Ipcc, *Global Warming of 1.5°C: IPCC Special Report on Impacts of Global Warming of 1.5°C above Pre-industrial Levels in Context of Strengthening Response to Climate Change, Sustainable Development, and Efforts to Eradicate Poverty*, 1st ed. Cambridge University Press, 2022. doi: 10.1017/9781009157940.

[5] E. Y. Y. Chan, Z. Huang, C. K. M. Mark, and C. Guo, "Weather Information Acquisition and Health Significance during Extreme Cold Weather in a Subtropical City: A Cross-sectional Survey in Hong Kong," *Int J Disaster Risk Sci*, vol. 8, no. 2, pp. 134–144, Jun. 2017, doi: 10.1007/s13753-017-0127-8.

[6] G. Althor, J. E. M. Watson, and R. A. Fuller, "Global mismatch between greenhouse gas emissions and the burden of climate change," *Sci Rep*, vol. 6, no. 1, p. 20281, Feb. 2016, doi: 10.1038/srep20281.

[7] X. Wang, D. Jiang, and X. Lang, "Future extreme climate changes linked to global warming intensity," *Science Bulletin*, vol. 62, no. 24, pp. 1673–1680, Dec. 2017, doi: 10.1016/j.scib.2017.11.004.

[8] N. S. Diffenbaugh *et al.*, "Quantifying the influence of global warming on unprecedented extreme climate events," *Proc. Natl. Acad. Sci. U.S.A.*, vol. 114, no. 19, pp. 4881–4886, May 2017, doi: 10.1073/pnas.1618082114.

[9} X. Zhang *et al.*, "Extreme Cold Events from East Asia to North America in Winter 2020/21: Comparisons, Causes, and Future Implications," *Adv. Atmos. Sci.*, vol. 39, no. 4, pp. 553–565, Apr. 2022, doi: 10.1007/s00376-021-1229-1.

[10] J. H. R. Enslin, "Maximum power point tracking: a cost saving necessity in solar energy systems," in *[Proceedings] IECON '90: 16th Annual Conference of IEEE Industrial Electronics Society*, Nov. 1990, pp. 1073–1077 vol.2. doi: 10.1109/IECON.1990.149286.

[11] R. Iftikhar, I. Ahmad, M. Arsalan, N. Naz, N. Ali, and H. Armghan, "MPPT for Photovoltaic System Using Nonlinear Controller," *International Journal of Photoenergy*, vol. 2018, pp. 1–11, Apr. 2018, doi: 10.1155/2018/6979723.

[12] G. Ciulla, V. Lo Brano, V. Di Dio, and G. Cipriani, "A comparison of different one-diode models for the representation of I–V characteristic of a PV cell," *Renewable and Sustainable Energy Reviews*, vol. 32, pp. 684–696, Apr. 2014, doi: 10.1016/j.rser.2014.01.027.

[13] S. Mohanty, B. Subudhi, and P. K. Ray, “A New MPPT Design Using Grey Wolf Optimization Technique for Photovoltaic System Under Partial Shading Conditions,” *IEEE Trans. Sustain. Energy*, vol. 7, no. 1, pp. 181–188, Jan. 2016, doi: 10.1109/TSTE.2015.2482120.

[14] R. Sridhar, “Ant Colony Optimization based Maximum Power Point Tracking (MPPT) for Partially Shaded Standalone PV System”.

[15] F. Dincer and M. E. Meral, “Critical Factors that Affecting Efficiency of Solar Cells,” *SGRE*, vol. 01, no. 01, pp. 47–50, 2010, doi: 10.4236/sgre.2010.11007.

[16] H. Nakamura, T. Yamada, T. Sugiura, K. Sakuta, and K. Kurokawa, “Data analysis on solar irradiance and performance characteristics of solar modules with a test facility of various tilted angles and directions,” *Solar Energy Materials and Solar Cells*, vol. 67, no. 1–4, pp. 591–600, Mar. 2001, doi: 10.1016/S0927-0248(00)00331-7.

[17] P. Attaviriyanupap, K. Tokuhara, N. Itaya, M. Marmiroli, Y. Tsukamoto, and Y. Kojima, “Estimation of photovoltaic power generation output based on solar irradiation and frequency classification,” in *2011 IEEE PES Innovative Smart Grid Technologies*, Perth, WA: IEEE, Nov. 2011, pp. 1–7. doi: 10.1109/ISGT-Asia.2011.6167078.

[18] K. Ishaque and Z. Salam, “A review of maximum power point tracking techniques of PV system for uniform insolation and partial shading condition,” *Renewable and Sustainable Energy Reviews*, vol. 19, pp. 475–488, Mar. 2013, doi: 10.1016/j.rser.2012.11.032.

[19] A. Mohapatra, B. Nayak, P. Das, and K. B. Mohanty, “A review on MPPT techniques of PV system under partial shading condition,” *Renewable and Sustainable Energy Reviews*, vol. 80, pp. 854–867, Dec. 2017, doi: 10.1016/j.rser.2017.05.083.

[20] B. Yang *et al.*, “Comprehensive overview of maximum power point tracking algorithms of PV systems under partial shading condition,” *Journal of Cleaner Production*, vol. 268, p. 121983, Sep. 2020, doi: 10.1016/j.jclepro.2020.121983.

[21] “Global Charge Controllers with MPPT Market Size and Forecast to 2030.” Accessed: Feb. 05, 2024. [Online]. Available: https://www.skyquestt.com/report/charge-controllers-with-mppt-market

[22] A. M. R. https://www.alliedmarketresearch.com, “Solar Charge Controller Market Statistical Analysis and Growth - 2031,” Allied Market Research. Accessed: Feb. 11, 2024. [Online]. Available: https://www.alliedmarketresearch.com/solar-charge-controller-market-A09304

[23] “Solar Charge Controller Market Size, Share, Growth Drivers and Opportunities | Outlook Report [2030].” Accessed: Feb. 11, 2024. [Online]. Available: https://www.fortunebusinessinsights.com/solar-charge-controller-market-102158

[24] L. D. Mech and L. Boitani, Eds., *Wolves: Behavior, Ecology, and Conservation*. Chicago, IL: University of Chicago Press, 2007. Accessed: Feb. 11, 2024. [Online]. Available: https://press.uchicago.edu/ucp/books/book/chicago/W/bo3641392.html

[25] L. D. Mech, “Possible Use of Foresight, Understanding, and Planning by Wolves Hunting Muskoxen,” *Arctic*, vol. 60, no. 2, pp. 145–149, 2007.

[26] D. R. MacNulty, L. D. Mech, and D. W. Smith, “A Proposed Ethogram of Large-Carnivore Predatory Behavior, Exemplified by the Wolf,” *Journal of Mammalogy*, vol. 88, no. 3, pp. 595–605, Jun. 2007, doi: 10.1644/06-MAMM-A-119R1.1.

[27] D. R. MacNulty, D. W. Smith, L. D. Mech, J. A. Vucetich, and C. Packer, “Nonlinear effects of group size on the success of wolves hunting elk,” *Behavioral Ecology*, vol. 23, no. 1, pp. 75–82, Jan. 2012, doi: 10.1093/beheco/arr159.

[28] H. Faris, I. Aljarah, M. A. Al-Betar, and S. Mirjalili, “Grey wolf optimizer: a review of recent variants and applications,” *Neural Comput & Applic*, vol. 30, no. 2, pp. 413–435, Jul. 2018, doi: 10.1007/s00521-017-3272-5.

[29] M. Panda and B. Das, “Grey Wolf Optimizer and Its Applications: A Survey,” in *Proceedings of the Third International Conference on Microelectronics, Computing and Communication Systems*, vol. 556, V. Nath and J. K. Mandal, Eds., in Lecture Notes in Electrical Engineering, vol. 556. , Singapore: Springer Singapore, 2019, pp. 179–194. doi: 10.1007/978-981-13-7091-5_17.

[30] H. Rezaei, O. Bozorg-Haddad, and X. Chu, “Grey Wolf Optimization (GWO) Algorithm,” in *Advanced Optimization by Nature-Inspired Algorithms*, vol. 720, O. Bozorg-Haddad, Ed., in Studies in Computational Intelligence, vol. 720. , Singapore: Springer Singapore, 2018, pp. 81–91. doi: 10.1007/978-981-10-5221-7_9.

[31] 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.

[32] D. J. K. Kishore, M. R. Mohamed, K. Sudhakar, and K. Peddakapu, “An improved grey wolf optimization based MPPT algorithm for photovoltaic systems under diverse partial shading conditions,” *J. Phys.: Conf. Ser.*, vol. 2312, no. 1, p. 012063, Aug. 2022, doi: 10.1088/1742-6596/2312/1/012063.

[33] M. Ilyas and H. K. E. Ghazal, “Design of a MPPT System Based on Modified Grey Wolf Optimization Algorithm in Photovoltaic System under Partially Shaded Condition,” vol. 40, no. 1, 2021.

[34] M. H. Zafar, U. A. Khan, and N. M. Khan, “Hybrid Grey Wolf Optimizer Sine Cosine Algorithm based Maximum Power Point Tracking Control of PV Systems under Uniform Irradiance and Partial Shading Condition,” in *2021 4th International Conference on Energy Conservation and Efficiency (ICECE)*, Lahore, Pakistan: IEEE, Mar. 2021, pp. 1–6. doi: 10.1109/ICECE51984.2021.9406309.

[35] M. M. Eshak, M. A. Khafagy, P. Makeen, and S. O. Abdellatif, “Optimizing the performance of a stand-alone PV system under non-uniform irradiance using Gray-Wolf and hybrid neural network AI-MPPT algorithms,” in *2020 2nd Novel Intelligent and Leading Emerging Sciences Conference (NILES)*, Giza, Egypt: IEEE, Oct. 2020, pp. 600–605. doi: 10.1109/NILES50944.2020.9257965.

[36] J. L. Deneubourg, S. Goss, N. Franks, and J. M. Pasteels, “The blind leading the blind: Modeling chemically mediated army ant raid patterns,” *J Insect Behav*, vol. 2, no. 5, pp. 719–725, Sep. 1989, doi: 10.1007/BF01065789.

[37] “The Ants,” Harvard University Press. Accessed: Feb. 11, 2024. [Online]. Available: https://www.hup.harvard.edu/books/9780674040755

[38] S. Goss, S. Aron, J. L. Deneubourg, and J. M. Pasteels, “Self-organized shortcuts in the Argentine ant,” *Naturwissenschaften*, vol. 76, no. 12, pp. 579–581, Dec. 1989, doi: 10.1007/BF00462870.

[39] D. J. T. Sumpter and M. Beekman, “From nonlinearity to optimality: pheromone trail foraging by ants,” *Animal Behaviour*, vol. 66, no. 2, pp. 273–280, Aug. 2003, doi: 10.1006/anbe.2003.2224.

[40] K. Khurshid, S. Irteza, A. A. Khan, and S. I. Shah, “Application of Heuristic (1-Opt local Search) and Metaheuristic (Ant Colony Optimization) Algorithms for Symbol Detection in MIMO Systems,” *CN*, vol. 03, no. 04, pp. 200–209, 2011, doi: 10.4236/cn.2011.34023.

[41] D. N. Kumar and M. J. Reddy, “Ant Colony Optimization for Multi-Purpose Reservoir Operation,” *Water Resour Manage*, vol. 20, no. 6, pp. 879–898, Oct. 2006, doi: 10.1007/s11269-005-9012-0.

[42] S. Mirjalili, “Ant Colony Optimisation,” in *Evolutionary Algorithms and Neural Networks*, vol. 780, in Studies in Computational Intelligence, vol. 780. , Cham: Springer International Publishing, 2019, pp. 33–42. doi: 10.1007/978-3-319-93025-1_3.

[43] R. K. Phanden, L. Sharma, J. Chhabra, and H. İ. Demir, “A novel modified ant colony optimization based maximum power point tracking controller for photovoltaic systems,” *Materials Today: Proceedings*, vol. 38, pp. 89–93, 2021, doi: 10.1016/j.matpr.2020.06.020.

[44] K. Sundareswaran, V. Vigneshkumar, P. Sankar, S. P. Simon, P. Srinivasa Rao Nayak, and S. Palani, “Development of an Improved P&O Algorithm Assisted Through a Colony of Foraging Ants for MPPT in PV System,” *IEEE Trans. Ind. Inf.*, vol. 12, no. 1, pp. 187–200, Feb. 2016, doi: 10.1109/TII.2015.2502428.

[45] B. Babes, A. Boutaghane, and N. Hamouda, “A novel nature-inspired maximum power point tracking (MPPT) controller based on ACO-ANN algorithm for photovoltaic (PV) system fed arc welding machines,” *Neural Comput & Applic*, vol. 34, no. 1, pp. 299–317, Jan. 2022, doi: 10.1007/s00521-021-06393-w.

[46] M. H. Anowar and P. Roy, “A Modified Incremental Conductance Based Photovoltaic MPPT Charge Controller,” in *2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, Cox’sBazar, Bangladesh: IEEE, Feb. 2019, pp. 1–5. doi: 10.1109/ECACE.2019.8679308.

APPENDIX

Tata Power Solar Systems TP250MBZ:

Power at STC (W)250

Power at PTC (W)222.7

Bifacial No

Bifaciality (%) -

Lower Power Tolerance (%) -

Upper Power Tolerance (%) -

Power Density at STC (W / m2) 151.515

Power Density at PTC (W / m2) 134.97

Module Efficiency (%) -

Cell Efficiency (%) -

Vmp: Voltage at Max Power (V) 30.0

Imp: Current at Max Power (A) 8.3

Voc: Open Circuit Voltage (V) 36.8

Isc: Short Circuit Current (A) 8.83

Max System Voltage (V) -

Series Fuse Rating (A) -

Bypass Diode -

Nominal Operating Cell Temp (°C) 48.8

Open Circuit Voltage Temp Coefficient (% / °C) -0.33

Short Circuit Current Temp Coefficient (% / °C) 0.064

Max Power Temp Coefficient (% / °C) -0.438

Cell Type Poly

Connector Type	-
Connector Cable Length (mm)	-
Length (mm)	1660.0
Width (mm)	994.0
Module area (m2)	1.65
Depth (mm)	-
Weight (kg)	-
Frame Color	-