VEER SURENDRA SAI UNIVERSITY OF TECHNOLOGY

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2nd Edition

SPECTRUM

2024

ELECTRICAL AND ELECTRONICS ENGINEERING SOCIETY,
VSSUT, BURLA, SAMBALPUR, ODISHA

Veer Surendra Sai University of Technology, Burla

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SPECTRUM
2024

The Annual Technical Magazine of the Department of Electrical and Electronics Engineering

PREFACE

In penning the preface to this booklet, it is imperative to elucidate upon its origin and objective. The contents herein, curated meticulously by Team Spectrum, stem from a collective endeavour aimed at providing a comprehensive insight into the projects undertaken by students within the Electrical and Electronic Engineering (EEE) department.

With profound appreciation, Team Spectrum extends heartfelt gratitude to all those who have played an instrumental role in the fruition of this endeavour. Their guidance, expertise, and unwavering support have been pivotal in navigating the complexities of compiling these project reports.

Contained within these pages are detailed project reports contributed by students of EEE. Each report offers an intricate exploration of diverse topics, encapsulating the depth and breadth of our department's academic pursuits.

It is our fervent hope that this booklet serves as a valuable resource, providing readers with a profound understanding of the endeavours undertaken within our department. May it illuminate pathways to knowledge, inspire curiosity, and foster a deeper appreciation for the field of Electrical and Electronic Engineering.

Warm regards,

Team Spectrum

Message from Vice Chancellor’s desk

Prof. Banshidhar Majhi

Vice-Chancellor, VSSUT

Being part of a perfect happening is truly an unforgettable experience, and the branch technical symposium is no exception. The unity and integrity of the students who are organizing this spectacular event are simply inspiring, and it's clear that this year is already off to an incredible start, filled with energy and enthusiasm that's positively contagious. It is a celebration of the importance of the branch, and it's amazing to see how it's shining a light on the incredible events and activities that are happening within it.

Speaking of events, I can hardly contain my excitement for SPECTRUM, the fest organized by the student society of the Department of Electrical and Electronics Engineering. This technical symposium is going to be an absolute feast for the senses, a chance for young tech enthusiasts to indulge their passion for innovation and exploration, and to come away feeling refreshed and enlightened.

I am highly optimistic that the organizers of SPECTRUM will knock it out of the park, and I wish them all the very best as they put the finishing touches on this incredible event.

(Prof. B. Majhi)

Message of Head of School of Electrical Sciences

Dr. Sidhartha Panda,

Head School of Electrical Sciences

I am enthusiastic to hear that the Electrical and Electronics Engineering (EEE) branch is organizing a branch technical symposium SPECTRUM as an independent society. This event will provide an excellent opportunity for the students to showcase their skills and talents while celebrating the spirit of collaboration and teamwork.

As the Dean of Electrical Sciences, I am proud of the hard work and dedication that is put into planning this event. I am confident that the efforts will result in an exciting and memorable occasion for everyone involved.

I encourage all EEE students to participate actively in this event, whether it's by showcasing your projects, presenting your research, or participating in fun and engaging activities. This is a chance to demonstrate the creativity, innovation, and passion that makes the branch stand out. I wish all the best for a successful branch symposium. Let the events be truly unforgettable experiences.

(Dr. Sidhartha Panda)

MESSAGE FROM HOD'S DESK

Dr. Santi Behera

Head of Department,
Electrical and
Electronics Engineering

The Department of Electrical and Electronics Engineering is dedicated to delivering a superior education that seamlessly integrates theoretical principles with hands-on practical experience. With a steadfast commitment to excellence, our department is actively involved in pioneering research and innovative endeavours aimed at addressing real-world challenges.

It brings me immense pleasure to introduce SPECTRUM, a groundbreaking initiative poised to serve as a dynamic platform for technology enthusiasts to exchange ideas and showcase their ingenuity. SPECTRUM represents a significant milestone, offering an invaluable opportunity for individuals to share their innovative concepts and contribute to the advancement of the field.

I extend my sincerest gratitude to all involved and look forward to witnessing the remarkable impact of SPECTRUM on our academic community and beyond.

(Dr. Shanti Behera)

MESSAGE FROM FACULTY ADVISOR

I am delighted to commence that our branch is set to organize a technical fest, which I am sure will be a huge success. As the faculty advisor for the event, I would like to extend my warmest congratulations to all those involved in its planning and execution.

Technical fests are a great way to showcase our talents and skills and I am confident that this event will provide an excellent opportunity for our EEE students to display their creative abilities, leadership skills, and teamwork. I encourage all the student members to participate actively in the event and make the most of this wonderful opportunity.

Finally, I would like to wish everyone involved in the event all the very best. Let this technical symposium SPECTRUM spread its colours from its inception and let's carry it forward and make our branch proud!

(Mr. P.K Parida)

Mr. Prashant Kumar Parida

Faculty Advisor , EEE Society

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An Extensive Review on Underwater LiFi Technology in Defence Applications

Soumya Debashis Das, *PhD Scholar*

Abstract – Underwater communication has long been a challenge in the defence sector due to the limitations of traditional radio frequency (RF) systems in maritime environments. However, the emergence of underwater Li-Fi technology offers promising solutions to enhance communication capabilities in defence applications. This paper explores the application of underwater Li-Fi technology in the defence sector, highlighting its potential to revolutionize communication, improve operational effectiveness, and strengthen maritime security. We discuss the advantages of Li-Fi technology in underwater environments, including high-speed data transmission, immunity to electromagnetic interference, and enhanced security. Furthermore, we examine recent developments, case studies, and future prospects of underwater Li-Fi technology in defence applications. By leveraging the unique properties of Li-Fi, defence organizations can address the communication challenges of underwater operations and unlock new possibilities for innovation and strategic advantage in maritime environments.
Keywords – Underwater Li-Fi, Defence Sector, Communication, Maritime Security, High-Speed Data Transmission, Electromagnetic Interference, Operational Effectiveness, Strategic Advantage.

I. Introduction to Underwater Li-Fi Technology

In recent years, the exploration and utilization of underwater resources have become increasingly important, not only for scientific research but also for various industrial and defence applications. However, communicating underwater has long been a significant challenge due to the limitations of traditional radio frequency (RF) communication systems. In response to this challenge, researchers and engineers have been exploring alternative methods, one of which is underwater Li-Fi (Light Fidelity) technology.

Li-Fi technology, which utilizes light to transmit data, has gained significant attention in terrestrial applications due to its high-speed data transmission capabilities and potential to alleviate the increasing congestion of radio frequency spectrum. This technology works by modulating the intensity of light emitted by light-emitting diodes (LEDs) to transmit data, which can then be received and decoded by photosensitive receivers. The use of light waves for data transmission offers several advantages over RF-based communication, including higher data rates, lower latency, and immunity to electromagnetic interference.

Applying Li-Fi technology in underwater environments presents unique challenges and opportunities. Unlike in air or vacuum, light propagation in water is characterized by attenuation and scattering, which can significantly degrade signal quality and limit the range of communication. However, advancements in optical engineering and signal processing techniques have enabled researchers to develop specialized underwater Li-Fi systems capable of overcoming these challenges to some extent [1].

One of the key advantages of underwater Li-Fi technology is its potential for high-speed communication, which is crucial for various defence applications such as underwater surveillance, remote sensing, and autonomous underwater vehicles (AUVs). By leveraging the high data rates offered by Li-Fi, defence agencies can enhance the real-time monitoring and control of underwater assets, improving situational awareness and response capabilities [2].

Furthermore, underwater Li-Fi technology has the potential to enable secure and reliable communication in environments where RF-based systems may be vulnerable to interception or jamming. The inherent directionality of light transmission can also provide enhanced security by limiting signal leakage and reducing the risk of detection by unauthorized parties.

II. Overview of Li-Fi Technology

Li-Fi, is an emerging wireless communication technology that utilizes light to transmit data. Unlike traditional radio frequency (RF) communication systems, which rely on electromagnetic waves, Li-Fi leverages the visible light spectrum to transfer information. This innovative approach offers several advantages over conventional wireless technologies and has garnered significant interest across various industries, including telecommunications, healthcare, automotive, and aerospace.

At the heart of Li-Fi technology are light-emitting diodes (LEDs), which serve as both the light source and data transmitter. By modulating the intensity of the light emitted by LEDs at high speeds, data can be encoded and transmitted to photosensitive receivers, such as photodiodes or image sensors. These receivers then detect the changes in light intensity and convert them back into digital data, enabling seamless communication between devices [3].

One of the primary advantages of Li-Fi technology is its ability to deliver high-speed data transmission. With theoretical data rates surpassing several gigabits per second, Li-Fi has the potential to revolutionize wireless communication by providing faster and more efficient connectivity. This capability is particularly beneficial in environments where RF spectrum congestion is a concern, such as densely populated urban areas or crowded indoor spaces.

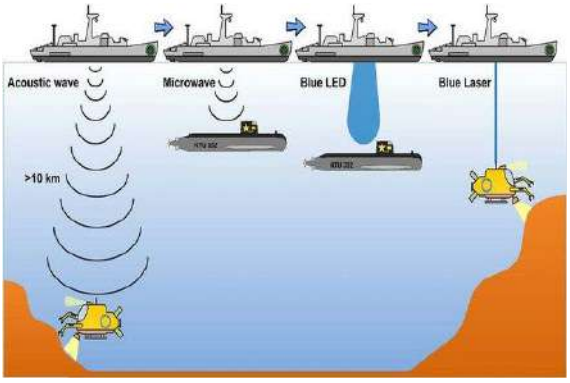

Fig. 1. Underwater Traffic signals being controlled by LIFI technology

Additionally, Li-Fi offers inherent security benefits due to its reliance on visible light for data transmission. Unlike RF signals, which can penetrate walls and be intercepted by unauthorized parties, light waves are confined to the space illuminated by the LED source, reducing the risk of signal interception or eavesdropping. Furthermore, Li-Fi communication can be easily confined to specific areas by controlling the illumination of LEDs, enhancing privacy and security [4].

Another advantage of Li-Fi technology is its compatibility with existing lighting infrastructure. Since LEDs are already widely used for illumination purposes in various applications, integrating Li-Fi functionality into lighting fixtures is relatively straightforward and cost-effective. This dual-use capability not only simplifies deployment but also maximizes the utility of lighting installations by adding communication functionality without the need for additional infrastructure [5].

Despite its numerous advantages, Li-Fi technology also has some limitations and challenges. For instance, light waves cannot penetrate opaque obstacles, meaning that line-of-sight communication is typically required between the transmitter and receiver. Additionally, ambient light interference and signal attenuation in certain environments, such as outdoors or in highly reflective spaces, can affect the reliability and range of Li-Fi communication.

III. Understanding Underwater Communication Challenges

Communication underwater presents unique challenges compared to terrestrial or aerial environments, primarily due to the properties of water and the limitations it imposes on traditional communication methods. These challenges stem from factors such as signal attenuation, limited range, background noise, and the need for specialized equipment. Understanding these obstacles is crucial for developing effective underwater communication systems, particularly in fields such as marine research, offshore industries, and defence.

One of the fundamental challenges of underwater communication is signal attenuation, which refers to the reduction in signal strength as it travels through water. Unlike air, water is a denser medium that absorbs and scatters electromagnetic waves, resulting in significant signal loss over relatively short distances. This attenuation increases with frequency, making higher-frequency signals more susceptible to degradation. As a result, underwater communication systems must operate at lower frequencies or utilize alternative transmission mediums, such as acoustic or optical signals, to overcome this limitation.

Limited range is another critical issue in underwater communication. The range of communication depends on various factors, including the frequency of the signal, water clarity, and environmental conditions. In clear water, optical communication methods, such as lasers or LEDs, offer the potential for higher data rates and longer ranges compared to acoustic methods. However, in turbid or highly attenuative environments, acoustic communication may be more practical due to its ability to penetrate obstacles and travel longer distances.

Background noise, generated by natural sources such as waves, marine life, and geological processes, poses a significant challenge for underwater communication systems. This noise can interfere with signal transmission and reduce the signal-to-noise ratio, degrading communication performance. Signal processing techniques, such as adaptive filtering and noise cancellation algorithms, are often employed to mitigate the effects of background noise and improve signal clarity.

Furthermore, the harsh underwater environment presents mechanical and environmental challenges for communication equipment. Submersible devices must be designed to withstand high pressure, corrosion, and temperature fluctuations while maintaining reliable performance. Additionally, the deployment and maintenance of underwater communication systems can be logistically challenging and costly, particularly in remote or deep-sea environments.

In the context of defence applications, reliable underwater communication is essential for tasks such as submarine navigation, underwater surveillance, and communication with autonomous underwater vehicles (AUVs). Effective communication enables coordinated operations, enhances situational awareness, and facilitates real-time decision-making, contributing to mission success and operational safety.

IV. Importance of Communication in the Defence Sector

Communication plays a pivotal role in the defence sector, serving as a cornerstone for the coordination, command, and execution of military operations. Effective communication is essential for ensuring situational awareness, facilitating decision-making, and enabling seamless coordination among military personnel across various levels of command. The importance of communication in the defence sector can be observed across a wide range of activities, from battlefield operations to strategic planning and logistics support.

At the tactical level, communication is critical for ensuring the success and safety of military operations. In combat situations, real-time communication enables troops to receive orders, exchange information, and coordinate manoeuvres, allowing them to adapt to changing circumstances and respond effectively to threats. Clear and reliable communication enhances situational awareness, enabling commanders to make informed decisions and allocate resources efficiently. Whether conducting ground operations, air strikes, or naval missions, effective communication is essential for maintaining operational tempo and achieving mission objectives.

In addition to tactical operations, communication also plays a vital role in strategic planning and decision-making within the defence sector. Military leaders rely on communication channels to convey orders, disseminate intelligence, and coordinate long-term strategies. Timely and accurate information exchange allows decision-makers to assess threats, evaluate options, and formulate effective responses to emerging challenges. Furthermore, communication facilitates collaboration and coordination among different branches of the military, as well as with allied forces and partner nations, enhancing interoperability and collective security efforts.

Beyond the battlefield, communication is essential for supporting logistics and sustainment operations in the defence sector. Supply chains, transportation networks, and maintenance activities rely on communication systems to coordinate the movement of personnel, equipment, and supplies. Timely communication enables logistics planners to anticipate needs, optimize resource allocation, and mitigate disruptions, ensuring that military forces remain adequately equipped and supported throughout their missions.

Moreover, communication serves as a means of command and control, allowing military leaders to exercise authority, delegate responsibilities, and maintain unity of effort among diverse forces. Through clear and effective communication, commanders can articulate objectives, convey intent, and provide guidance to subordinate units, empowering them to execute missions with precision and initiative. Communication also fosters morale and cohesion within military units, fostering a sense of purpose, camaraderie, and mutual trust among service members.

V. Applications of Li-Fi in Underwater Environments

Li-Fi technology, which harnesses light to transmit data, holds significant promise for various applications in underwater environments. While traditionally associated with terrestrial communication, Li-Fi's unique properties make it well-suited for addressing the challenges of underwater communication, opening up new possibilities for marine research, offshore industries, and defence operations.

One of the primary applications of Li-Fi in underwater environments is underwater data transmission for scientific research and exploration. Researchers studying marine ecosystems, oceanography, and underwater geology rely on data collection instruments deployed in the ocean depths to gather valuable information. Li-Fi technology offers a high-speed and reliable means of transmitting data from these instruments to research vessels or shore-based facilities in real-time. By leveraging Li-Fi, scientists can enhance their ability to monitor and study underwater environments, leading to advancements in our understanding of marine ecosystems, climate dynamics, and geological processes.

In the offshore industry, Li-Fi technology can improve communication and monitoring capabilities for underwater infrastructure such as oil rigs, underwater pipelines, and offshore wind farms. These installations often require constant monitoring for maintenance, safety, and security purposes. By deploying Li-Fi-enabled sensors and cameras, operators can establish high-speed communication links with surface platforms or control centres, allowing for remote monitoring, inspection, and control of underwater assets. This capability not only enhances operational efficiency but also reduces the need for costly and time-consuming manual inspections conducted by divers or remotely operated vehicles (ROVs).

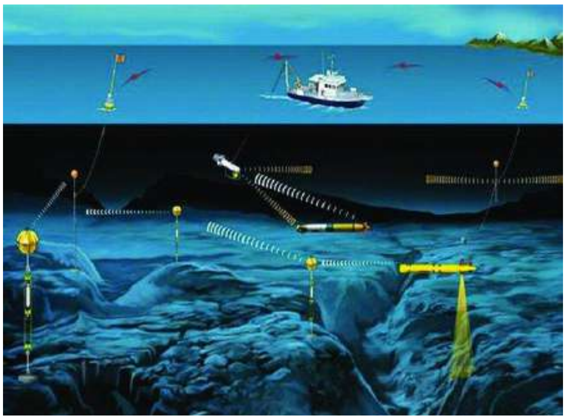

Fig. 2. Application of Li-Fi in deep water

In the defence sector, Li-Fi technology has several potential applications for underwater communication and surveillance. Submarines, autonomous underwater vehicles (AUVs), and underwater sensor networks require reliable communication systems to coordinate missions, gather intelligence, and relay data to command centres. Li-Fi offers a secure and high-speed communication solution that can operate effectively in the challenging underwater environment. By integrating Li-Fi into underwater platforms and sensor networks, defence agencies can enhance their underwater surveillance capabilities, improve situational awareness, and strengthen maritime security.

Moreover, Li-Fi technology can enable innovative applications such as underwater Internet of Things (IoT) and underwater autonomous navigation. By embedding Li-Fi transceivers in underwater sensors, buoys, and navigation beacons, organizations can create interconnected networks of underwater devices capable of exchanging data and coordinating actions. This opens up opportunities for applications such as environmental monitoring, underwater asset tracking, and autonomous underwater vehicle navigation, contributing to advancements in marine science, resource management, and maritime operations.

VI. Advantages and Limitations of Underwater Li-Fi Technology

Underwater Li-Fi technology offers a range of advantages and limitations, making it a promising but nuanced solution for underwater communication needs. Understanding these factors is crucial for evaluating its suitability for specific applications and environments.

Advantages:

- High-Speed Data Transmission: One of the primary advantages of underwater Li-Fi is its ability to deliver high-speed data transmission. By utilizing light waves, Li-Fi can achieve data rates several times faster than traditional acoustic communication methods. This capability is particularly valuable for applications requiring real-time data exchange, such as underwater surveillance, environmental monitoring, and offshore operations.
- Immunity to Electromagnetic Interference: Unlike radio frequency (RF) communication systems, Li-Fi is immune to electromagnetic interference, making it highly reliable in environments where RF signals may be disrupted or jammed. This advantage is particularly relevant in defence applications, where secure and interference-free communication is essential for mission success and operational security.
- Directional Communication: Li-Fi communication is inherently directional, with light waves confined to the space illuminated by the transmitter. This property enables more secure and targeted communication, reducing the risk of signal interception or eavesdropping by unauthorized parties. Additionally, directional communication allows for efficient use of bandwidth and reduces the potential for signal interference in crowded underwater environments.
- Compatibility with Existing Infrastructure: Li-Fi technology can be seamlessly integrated into existing underwater infrastructure, such as underwater vehicles, sensors, and monitoring systems. Since LEDs are already widely used for underwater lighting purposes, adding Li-Fi functionality to these devices requires minimal additional equipment and infrastructure investment. This compatibility facilitates the adoption and deployment of Li-Fi technology in various underwater applications.

Limitations:

- Limited Range and Coverage: One of the main limitations of underwater Li-Fi is its limited range and coverage compared to acoustic communication methods. Light waves are subject to attenuation and scattering in water, resulting in reduced signal strength and range, particularly in turbid or highly attenuative environments. As a result, Li-Fi may be more suitable for short-range communication or localized applications rather than long-distance transmission.
- Line-of-Sight Requirement: Another limitation of Li-Fi technology is its dependence on line-of-sight communication. Since light waves cannot penetrate opaque obstacles, uninterrupted visibility between the transmitter and receiver is necessary for reliable communication. This constraint may restrict the deployment of Li-Fi in environments with obstacles or complex underwater topography, limiting its applicability in certain scenarios.
- Environmental Sensitivity: Li-Fi communication can be affected by environmental factors such as water clarity, ambient light levels, and underwater turbulence. Changes in these conditions can impact signal quality and reliability, potentially affecting the performance of Li-Fi systems. As a result, careful environmental monitoring and system optimization may be required to ensure consistent communication performance in diverse underwater environments.
- Equipment Complexity and Cost: Implementing Li-Fi technology in underwater applications requires specialized equipment and components, including high-power LEDs, photosensitive receivers, and signal processing algorithms. The design, deployment, and maintenance of Li-Fi systems can be complex and costly, particularly for large-scale or mission-critical deployments. Additionally, the need for power-efficient and ruggedized components adds to the overall cost and complexity of underwater Li-Fi technology.

VII. Case Studies: Previous Applications of Li-Fi in Defence

The integration of Li-Fi technology in defence applications has gained traction in recent years, with several notable case studies highlighting its effectiveness in enhancing communication, security, and operational capabilities in various military scenarios. These case studies demonstrate the versatility and potential of Li-Fi technology in addressing the unique communication challenges faced by defence organizations.

- Submarine Communication Enhancement: In one case study, a naval research institute collaborated with technology companies to implement Li-Fi technology for communication within submarines. Traditional RF-based communication systems face challenges in the confined and noisy environment of submarines, often leading to limited bandwidth and vulnerability to interception. By deploying Li-Fi systems within submarines, researchers were able to achieve high-speed and secure communication between crew members and onboard systems. Li-Fi's immunity to electromagnetic interference and its ability to provide high-speed data transmission contributed to improved communication reliability and operational efficiency, enhancing the overall capabilities of the submarine fleet.
- Underwater Surveillance and Reconnaissance: Another case study focused on the use of Li-Fi technology for underwater surveillance and reconnaissance missions. In this scenario, Li-Fi-enabled underwater sensors and autonomous vehicles were deployed in strategic maritime areas to gather real-time intelligence and monitor underwater activities. Li-Fi communication allowed these sensors to transmit data to surface vessels or command centres without the need for physical connections or acoustic signalling, reducing the risk of detection by hostile forces. By leveraging Li-Fi's high-speed communication capabilities, defence agencies were able to enhance situational awareness and response capabilities, thereby strengthening maritime security and border defence.
- Secure Command and Control Systems: A third case study examined the implementation of Li-Fi technology in secure command and control systems for military operations. Traditional RF-based communication systems are susceptible to interception and electronic warfare attacks, posing significant security risks for command and control operations. By utilizing Li-Fi technology, military commanders were able to establish secure communication links between command centres, forward operating bases, and deployed units. Li-Fi's directional communication and immunity to electromagnetic interference provided a secure and reliable means of transmitting sensitive information, enabling commanders to maintain operational secrecy and execute missions with confidence.
- Underwater Mine Countermeasures: Additionally, Li-Fi technology has been explored for use in underwater mine countermeasures (MCM) operations. MCM operations require precise communication and coordination between unmanned underwater vehicles (UUVs), minesweeping vessels, and support teams to detect and neutralize underwater mines safely. Li-Fi-enabled communication systems offer advantages such as high-speed data transmission, low latency, and immunity to electromagnetic interference, enhancing the efficiency and safety of MCM operations. By leveraging Li-Fi technology, defence agencies can improve the responsiveness and effectiveness of their mine countermeasures capabilities, reducing the risk to personnel and naval assets in hazardous environments.

These case studies demonstrate the diverse applications of Li-Fi technology in defence, ranging from submarine communication enhancement to underwater surveillance, secure command and control, and mine countermeasures operations. By leveraging Li-Fi's high-speed, secure, and reliable communication capabilities, defence organizations can enhance their operational effectiveness, situational awareness, and security posture in a variety of military scenarios. As research and development in Li-Fi technology continue to advance, its potential to transform defence communications and operations will likely continue to grow, opening up new possibilities for innovation and capability enhancement in the defence sector.

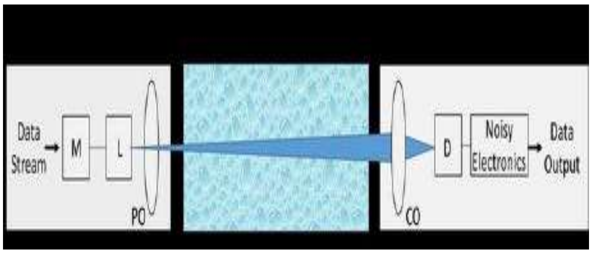

Fig. 3. Schematic of a typical Under Water LiFi link. The transmitter is composed of a modulator (M), laser (L), and projection optics (PO) systems. The receiver is made of collection optics (CO), detector (D) and noisy electronics.

VIII. Current Developments and Research

Underwater Li-Fi technology continues to be an area of active research and development, with ongoing efforts aimed at overcoming existing challenges and unlocking new capabilities for underwater communication. Recent advancements in this field have focused on improving data transmission rates, extending communication range, enhancing system reliability, and exploring innovative applications across various domains.

One of the key areas of research in underwater Li-Fi technology is focused on increasing data transmission rates to meet the growing demand for high-speed communication in underwater environments. Researchers are exploring techniques to optimize modulation schemes, signal processing algorithms, and encoding methods to achieve higher data rates while maintaining robustness and reliability. By leveraging advancements in optical engineering, digital signal processing, and error correction techniques, researchers aim to push the limits of underwater Li-Fi data transmission capabilities, enabling faster and more efficient communication for scientific, industrial, and defence applications.

Another area of research is centred on extending the communication range of underwater Li-Fi systems. While Li-Fi offers advantages such as high data rates and immunity to electromagnetic interference, its range is limited by factors such as signal attenuation and scattering in water. Researchers are investigating methods to mitigate these effects and extend the reach of Li-Fi communication through advancements in optical transceiver design, beamforming techniques, and signal propagation modelling. By optimizing system parameters and leveraging adaptive transmission strategies, researchers aim to increase the coverage area and operational range of underwater Li-Fi systems, enabling communication over longer distances and in more challenging underwater environments.

Furthermore, research efforts are underway to enhance the reliability and robustness of underwater Li-Fi communication systems. Researchers are exploring techniques to mitigate the impact of environmental factors such as water turbidity, ambient light variations, and underwater turbulence on communication performance. Additionally, efforts are focused on developing resilient communication protocols, error correction mechanisms, and adaptive networking algorithms to ensure reliable data transmission in dynamic and unpredictable underwater conditions. By addressing these challenges, researchers aim to improve the overall stability, availability, and performance of underwater Li-Fi systems, making them suitable for mission-critical applications in defence, marine science, and offshore industries.

In addition to technological advancements, research in underwater Li-Fi technology is also exploring innovative applications and use cases. Researchers are investigating the integration of Li-Fi with other emerging technologies such as autonomous underwater vehicles (AUVs), underwater sensor networks, and underwater Internet of Things (IoT) platforms to enable new capabilities such as underwater navigation, environmental monitoring, and underwater asset tracking. By leveraging the unique properties of Li-Fi, researchers aim to develop integrated solutions that address the complex communication challenges of underwater environments and unlock new opportunities for exploration, research, and commercialization.

IX. Integration of Underwater Li-Fi with Existing Defence Systems

The integration of underwater Li-Fi technology with existing defence systems holds great potential for enhancing communication capabilities, situational awareness, and operational effectiveness in maritime environments. By leveraging the unique properties of Li-Fi, defence organizations can augment their existing infrastructure and platforms with high-speed, secure, and reliable underwater communication capabilities, opening up new possibilities for collaboration, coordination, and mission success.

One of the key advantages of integrating Li-Fi with existing defence systems is its compatibility with underwater vehicles, sensors, and platforms already in use by military forces. Since Li-Fi can be seamlessly integrated into existing infrastructure, such as submarines, autonomous underwater vehicles (AUVs), and underwater sensor networks, defence agencies can leverage their existing assets and investments while enhancing their communication capabilities. This compatibility minimizes the need for costly infrastructure upgrades and accelerates the deployment of Li-Fi technology across defence operations.

Furthermore, integrating Li-Fi with existing defence systems enables enhanced communication between underwater and surface platforms, as well as with command centres and deployed units. By establishing high-speed and secure communication links using Li-Fi technology, defence organizations can improve the flow of information, facilitate real-time data exchange, and enhance command and control capabilities across the entire operational spectrum. This seamless integration enhances situational awareness, decision-making, and mission execution, thereby increasing the operational effectiveness of defence forces in maritime environments.

Moreover, integrating Li-Fi with existing defence systems offers advantages such as increased operational flexibility and adaptability. Li-Fi communication systems can be deployed as standalone solutions or integrated into larger networked architectures, depending on the specific operational requirements and objectives. This flexibility allows defence organizations to tailor their communication infrastructure to meet mission-specific needs, adapt to changing operational environments, and scale their capabilities as needed. Whether deployed for covert surveillance, underwater reconnaissance, or coordinated naval operations, Li-Fi technology enhances the agility and versatility of defence forces in responding to evolving threats and challenges.

In addition to enhancing communication capabilities, the integration of Li-Fi with existing defence systems offers opportunities for innovation and collaboration in underwater warfare. By leveraging Li-Fi-enabled sensors, unmanned underwater vehicles (UUVs), and underwater surveillance systems, defence organizations can collect and transmit real-time intelligence, monitor maritime activities, and detect potential threats in contested waters. This enhanced situational awareness enables proactive decision-making, rapid response, and effective coordination of naval forces, contributing to maritime security and stability.

However, challenges remain in fully integrating Li-Fi with existing defence systems, including addressing interoperability issues, ensuring compatibility with legacy equipment, and optimizing system performance in dynamic and harsh underwater environments. Additionally, ongoing research and development efforts are needed to advance Li-Fi technology, improve data transmission rates, extend communication range, and enhance system reliability for defence applications.

X. Security and Reliability Concerns in Underwater Li-Fi Communication

The adoption of underwater Li-Fi communication technology presents several security and reliability concerns that must be addressed to ensure its effective and safe deployment in defence, scientific, and industrial applications. While Li-Fi offers advantages such as high-speed data transmission and immunity to electromagnetic interference, it also introduces unique challenges related to security vulnerabilities, system reliability, and environmental factors.

One of the primary security concerns in underwater Li-Fi communication is the risk of interception and eavesdropping by hostile entities. Unlike terrestrial environments where physical access to communication infrastructure is often restricted, underwater communication systems may be more susceptible to tampering and unauthorized access due to the difficulty of monitoring and securing underwater assets. Additionally, Li-Fi communication signals can be intercepted by adversaries with line-of-sight access to the transmission path, potentially compromising sensitive information and operational security. Defence organizations must implement robust encryption algorithms, authentication mechanisms, and access controls to mitigate the risk of unauthorized access and ensure the confidentiality and integrity of transmitted data.

Moreover, the reliability of underwater Li-Fi communication systems can be impacted by environmental factors such as water turbidity, ambient light variations, and underwater turbulence. These environmental conditions can affect signal propagation, attenuation, and signal-to-noise ratio, leading to degraded communication performance and reduced system reliability. Defence organizations must conduct thorough environmental assessments and system testing to evaluate the impact of environmental factors on Li-Fi communication and develop strategies to mitigate their effects. Additionally, redundancy measures such as multi-path routing, error correction coding, and signal amplification can enhance system resilience and ensure reliable communication in challenging underwater environments.

Another concern in underwater Li-Fi communication is the potential for signal interference and jamming from natural and man-made sources. Ambient light variations, bioluminescence, and other optical phenomena can introduce noise and interference into Li-Fi communication signals, affecting signal quality and reliability. Additionally, adversaries may attempt to disrupt Li-Fi communication by deploying optical countermeasures such as high-intensity light sources or laser dazzlers. Defence organizations must develop countermeasures and mitigation strategies to detect and mitigate signal interference and jamming attempts, including adaptive modulation techniques, frequency hopping, and signal encryption.

Furthermore, the reliability of underwater Li-Fi communication systems can be impacted by equipment failures, power outages, and maintenance issues. Submersible devices and underwater infrastructure must be ruggedized, corrosion-resistant, and designed for long-term deployment in harsh underwater environments. Regular maintenance, testing, and monitoring of Li-Fi communication systems are essential to identify and address potential reliability issues before they affect operational performance. Additionally, backup power sources, redundant communication links, and failover mechanisms can enhance system resilience and ensure continuous communication capability in the event of equipment failures or power disruptions.

XI. Future Prospects and Potential Impacts of Underwater Li-Fi in Defence

The future prospects of underwater Li-Fi technology in defence hold immense promise, offering the potential to revolutionize communication capabilities, enhance operational effectiveness, and strengthen maritime security in a rapidly evolving security landscape. As research and development efforts continue to advance, underwater Li-Fi is poised to play a pivotal role in shaping the future of defence operations and strategic capabilities in maritime environments.

One of the key future prospects of underwater Li-Fi technology in defence is its potential to enable secure and high-speed communication in underwater environments. Li-Fi's immunity to electromagnetic interference and its ability to provide high-speed data transmission offer significant advantages over traditional radio frequency (RF) communication systems, particularly in challenging underwater environments where RF signals may be unreliable or vulnerable to interception. By deploying Li-Fi-enabled communication systems, defence organizations can establish secure and reliable communication links between submarines, surface vessels, autonomous underwater vehicles (AUVs), and shore-based command centres, enhancing command and control capabilities and improving operational efficiency in maritime operations.

Moreover, the integration of underwater Li-Fi technology with autonomous systems and unmanned platforms holds promise for enhancing autonomous navigation, underwater surveillance, and reconnaissance capabilities. Li-Fi-enabled sensors, cameras, and AUVs can transmit real-time data and imagery to surface vessels or command centres, providing situational awareness and intelligence for maritime domain awareness (MDA) and anti-submarine warfare (ASW) operations. By leveraging Li-Fi's high-speed communication capabilities and low latency, defence organizations can improve their ability to detect, track, and respond to potential threats in the maritime domain, enhancing overall maritime security and deterrence.

Furthermore, the potential impact of underwater Li-Fi technology extends beyond communication to include applications such as underwater IoT platforms, environmental monitoring, and underwater asset tracking. Li-Fi-enabled navigation beacons, underwater buoys, and sensor networks can exchange data and coordinate actions, enabling autonomous navigation, habitat monitoring, and resource management in underwater environments. By leveraging Li-Fi's high-speed data transmission capabilities, defence organizations can enhance their situational awareness and operational capabilities in maritime environments, leading to improved mission effectiveness and operational success.

Additionally, the adoption of underwater Li-Fi technology in defence has the potential to foster innovation and collaboration across industry, academia, and government sectors. As defence organizations invest in research and development initiatives to advance underwater Li-Fi technology, partnerships with technology companies, research institutions, and government agencies can accelerate the pace of innovation and drive technological breakthroughs in underwater communication, sensing, and networking. By fostering a collaborative ecosystem of innovation, defense organizations can harness the collective expertise and resources of diverse stakeholders to address complex challenges and unlock new opportunities for enhancing maritime security and defence capabilities.

XII. Economic Feasibility and Cost-Benefit Analysis

The economic feasibility and cost-benefit analysis of integrating underwater Li-Fi technology into defence systems are critical considerations for defence organizations seeking to enhance their maritime communication capabilities while optimizing resource allocation and budgetary constraints. While the initial investment in deploying Li-Fi technology may seem substantial, a comprehensive cost-benefit analysis reveals significant long-term benefits and potential cost savings, making underwater Li-Fi a financially viable option for defence applications.

One of the key factors influencing the economic feasibility of underwater Li-Fi in defence is the total cost of ownership, which includes initial deployment costs, operational expenses, and maintenance costs over the system's lifecycle. Initial deployment costs may include expenses related to equipment procurement, installation, and integration with existing infrastructure. While these upfront costs can be significant, they are often outweighed by the long-term benefits and cost savings associated with Li-Fi technology, such as reduced reliance on expensive and maintenance-intensive RF communication systems, lower energy consumption, and improved operational efficiency.

Moreover, a comprehensive cost-benefit analysis of underwater Li-Fi technology must consider the potential operational benefits and mission enhancements it offers to defence organizations. By enabling secure, high-speed communication in underwater environments, Li-Fi technology enhances command and control capabilities, improves situational awareness, and strengthens operational effectiveness in maritime operations. These operational benefits translate into tangible gains such as reduced response times, enhanced mission success rates, and improved decision-making, which contribute to overall mission effectiveness and operational readiness.

Additionally, the economic feasibility of underwater Li-Fi in defence is influenced by its potential to enable innovative applications and operational efficiencies that drive cost savings and resource optimization. For example, by integrating Li-Fi technology with autonomous underwater vehicles (AUVs) and underwater sensor networks, defence organizations can enhance their maritime surveillance capabilities, reduce the need for manned missions, and minimize operational risks and costs associated with human involvement. Furthermore, the compatibility of Li-Fi technology with existing underwater infrastructure and platforms facilitates seamless integration and interoperability, reducing the need for costly retrofitting or system upgrades.

Furthermore, the economic feasibility of underwater Li-Fi technology in defence is supported by its potential to stimulate technological innovation, foster industry growth, and create economic opportunities in the defence sector. As defence organizations invest in research and development initiatives to advance underwater Li-Fi technology, they stimulate innovation and collaboration across industry, academia, and government sectors. This collaborative ecosystem of innovation not only drives technological breakthroughs but also generates economic value through the creation of new products, services, and job opportunities in the defence and technology sectors.

XIII. Conclusion and Recommendations for Future Research and Implementation

The exploration of underwater Li-Fi technology represents a significant step forward in addressing the longstanding challenges of underwater communication in defence, scientific research, and industrial applications. Through its utilization of light waves for data transmission, Li-Fi offers advantages such as high-speed communication, immunity to electromagnetic interference, and enhanced security, making it a promising solution for enhancing communication capabilities in maritime environments.

As discussed in this paper, the integration of underwater Li-Fi technology with existing defence systems holds immense potential to revolutionize communication, enhance operational effectiveness, and strengthen maritime security. However, it is essential to recognize the complexities and challenges associated with deploying and implementing Li-Fi technology in underwater environments.

One of the key recommendations for future research is to continue advancing the technological capabilities of underwater Li-Fi systems. Research efforts should focus on improving data transmission rates, extending communication range, enhancing system reliability, and addressing security vulnerabilities to ensure the robustness and effectiveness of Li-Fi technology in defence applications. Additionally, further research is needed to explore innovative applications and use cases of Li-Fi technology in areas such as autonomous navigation, underwater surveillance, and environmental monitoring.

Furthermore, future research should also prioritize the development of standardized protocols, interoperable interfaces, and integrated solutions to facilitate the seamless integration of Li-Fi technology with existing defence systems and infrastructure. By establishing interoperability standards and protocols, defence organizations can enhance the compatibility, scalability, and interoperability of Li-Fi-enabled communication systems, enabling seamless communication and collaboration across diverse naval platforms and operational theatres.

Moreover, efforts should be made to conduct comprehensive field testing, validation, and evaluation of Li-Fi technology in real-world underwater environments to assess its performance, reliability, and suitability for defence applications. Field trials and pilot projects can provide valuable insights into the practical challenges and operational considerations associated with deploying Li-Fi technology in diverse maritime conditions, guiding the refinement and optimization of Li-Fi systems for operational deployment.

In terms of implementation, defence organizations should prioritize investment in research, development, and deployment of Li-Fi technology as part of their long-term strategic planning and modernization efforts. Collaboration with industry partners, research institutions, and government agencies can accelerate the pace of innovation and drive technological advancements in underwater Li-Fi technology, leading to enhanced capabilities and operational readiness in maritime environments.

In conclusion, the adoption and integration of underwater Li-Fi technology in defence applications offer significant opportunities to enhance communication capabilities, improve operational effectiveness, and strengthen maritime security. By continuing to invest in research, development, and implementation efforts, defence organizations can harness the full potential of Li-Fi technology to address the communication challenges of underwater operations and unlock new possibilities for innovation and strategic advantage in maritime environments.

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A Comparative Analysis of Optimal MPPT Methods in Boost Converter-Based PV Systems

Kartikeswar Sahoo, Subhashish Meher, Sweta Panda, Dr. Gyan Ranjan Biswal

Abstract - In this research, the Perturb and Observe methodology is evaluated for its efficacy in maximizing power point tracking within photovoltaic (PV) systems, particularly under the influence of variable irradiation and temperature parameters. This method is critically compared against the Incremental Conductance technique, which stands as a conventional approach in the field. Through comprehensive analysis and simulation, the study reveals that the P&O method offers better performance and more consistent control for applications within this domain, positioning it as a superior choice for MPPT in PV systems.

Keywords – PV array, MPPT, MATLAB, DC-DC Boost Converter, Perturb & Observe Algorithm, Incremental Conductance Algorithm

I. INTRODUCTION

Photovoltaic (PV) generating systems are essential components in the realm of renewable energy, but their efficiency heavily depends on optimal power extraction. This necessity arises from the dynamic relationship between the PV array's output and its operating terminal voltage and current. Variations in light intensity cause fluctuations in the array's internal resistance and voltage, underscoring the need for a Maximum Power Point Tracker (MPPT). The key objective of MPPT is to identify the peak power point in the current-voltage characteristic of the PV array, where it delivers the highest output power under uniform irradiance.

Unlike constant DC energy sources, PV arrays exhibit varying output power based on load current, and their characteristics are influenced by temperature and irradiation changes. Implementing MPPT techniques is crucial to track and optimize voltage or current, thereby enhancing output power and system efficiency. By ensuring the array's internal resistance matches the load resistance, maximum power output can be achieved. This is typically accomplished by employing a boost converter among the load and the solar panel array, adjusting the internal resistance through duty cycle variation using MPPT algorithms.

Different maximum power point tracking methods such as, Incremental Conductance, Perturb and Observe, fuzzy method, neural networks, and others exist, each with unique advantages. Of these options, the Incremental conductance and perturb & observe techniques are preferred due to their cost-effectiveness, with P&O being particularly renowned for its straightforward implementation. The P&O algorithm relies on perturbing the PV array's operating voltage and observing changes in power output to determine the direction for further voltage adjustments, ensuring the system operates closer to the MPP for optimal power extraction. This paper delves into the significance of MPPT in enhancing PV system performance and evaluates the effectiveness of both the techniques in achieving maximum power efficiency under dynamic environmental conditions.

II. BLOCK DIAGRAM ILLUSTRATING THE CONVERSION PROCESS OF SOLAR ENERGY IN A PV SYSTEM.

The block diagram depicts the fundamental process of converting solar energy into usable power as shown in Fig.1.

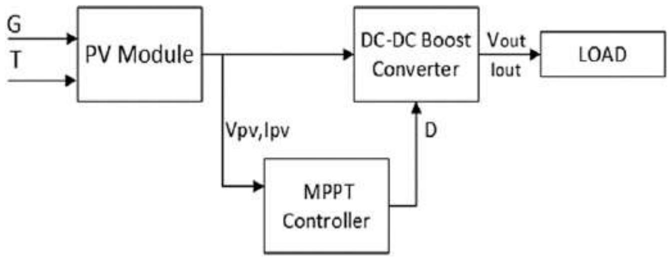


Fig.1. Diagram illustrating solar energy conversion system

The main component of the overall system is the maximum power point controller, which ensures we get the most power possible from the solar panels. It works by adjusting the electrical flow from the panels to find the spot where they produce the most power. This controller is essential in a PV system, which includes solar panels, the MPPT controller, and a converter.

The solar panel's voltage is sent to the controller, which then optimizes the power and transfer to converter. The algorithm within the controller calculates a duty ratio, a kind of instruction for the converter. This duty ratio helps the converter maintain the best voltage and current levels for maximum power output. By using a Boost converter, the system can even increase the input voltage if needed and by the use of both the Algorithm in the MPPT controller it ensures we accurately and efficiently extract the most power possible from the solar panels.

III. MODELLING OF SOLAR CELL

The basic model of solar PV cell is shown in Fig. 2. It comprises of a steady current source, parallel connected with a diode and shunt resistance (R_{sh}) and in with a series resistor (R_{se}).

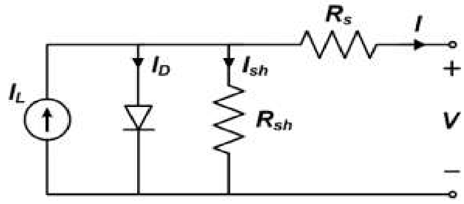


Fig.2. Electrical equivalent circuit of a solar cell

The characteristics equation of current and voltage is

$I = I_L - I_D - I_{sh}$

$$I_o = I_L - I_{sr}\left[e^{\left(q\frac{(V + Rse\,.I)}{rKT}\right)} - 1\right] + \frac{V + Rse\,.I}{Rsh}$$

Where, I_o -Output current, V- output voltage, R_{se} – Series resistance, R_{sh} = Shunt Resistance, I_{sr} – Rev. sat. current of diode, q = 1.679×10^{-19} C, r -Deviation factor, T – Temperature of solar panel, I_L – Current Source, I_D – Diode Current, K - Boltzmann's constant (K= 1.37×10^{-23} J K^{-1})

TABLE 1. PV CELL PARAMETER

Series resistance (R_{se})	0.38339 Ω
SC current (I)	7.65 Amp.
Optimum power	214.963 Watts
Voltage at MPP	28.7 Volts
Current at MPP	7.49 A
Generated current from solar cell	7.7654 A
Reverse saturation current	7.8649 A
Shunt resistance (R_{sh})	314.9319 Ω
OC Voltage (v)	35.9 Volts
No. of Cells in one module	60
Diode ideality factor	0.98117
Photo current	7.7654 A

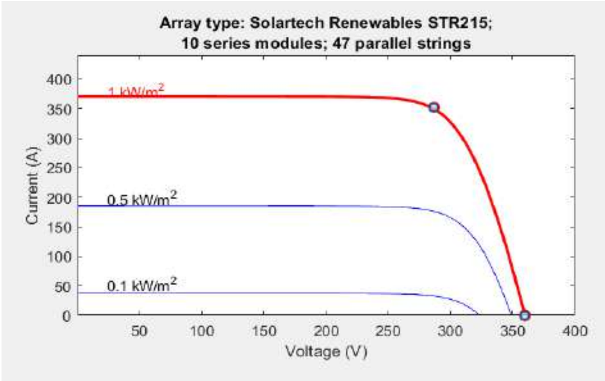


Fig.3. I verses V curve for different value of Irradiance at stable temperature

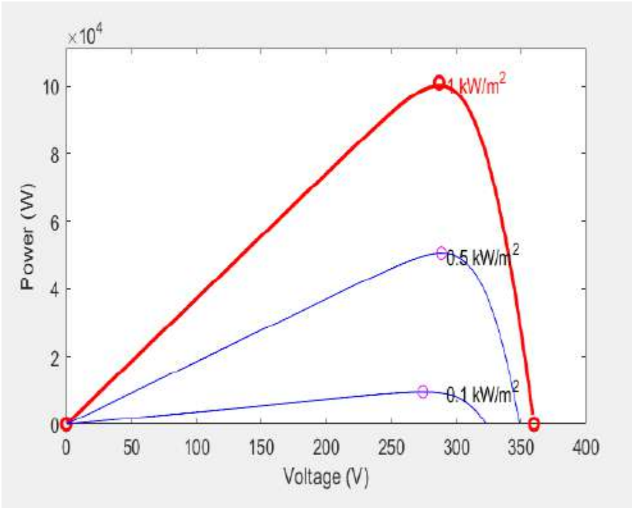


Fig.4. P verses V curve for different value of Irradiance at stable Temperature

TABLE 2. MAXIMUM POWER POINT VALUE OF PV MODULE AT DIFFERENT IRRADIANCE LEVEL

Irradiance Level	**MPP power**	**MPP Voltage**	**MPP Current**
1000 W/metre sq.	101033	287	352.03
500 W/metre sq.	50531.1	288.6	175.1
100 W/metre sq.	9590.68	274.45	34.9

IV. DESIGN OF DC -DC CONVERTER

Electrical circuit of boost converter comprises of constant input voltage, IGBT switch, inductor, filter circuit, diode and load. Output voltage of converter is change by changing the value of duty cycle.

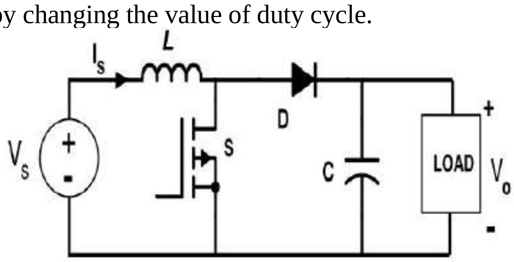
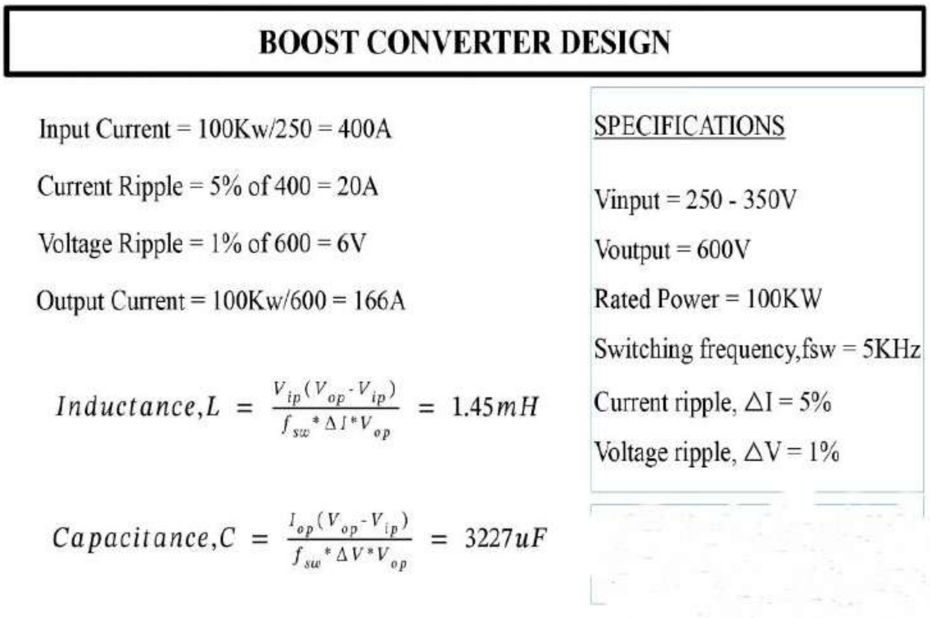


Fig.5. Equivalent circuit of DC-DC Converter

The boost converter increases the input DC voltage, achieving a stable output voltage by adjusting its duty cycle.



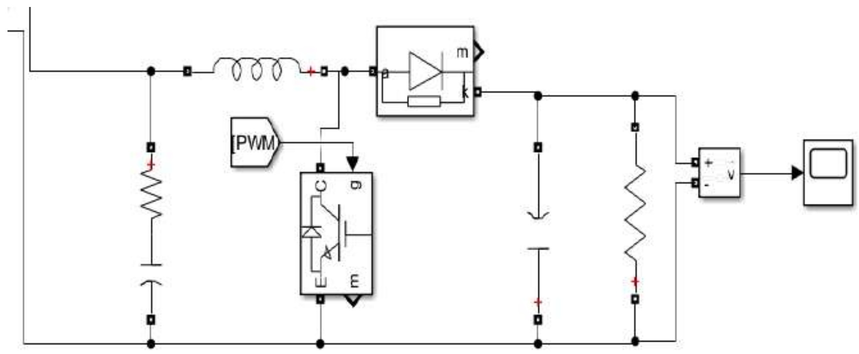


Fig.6. MATLAB Figure of boost converter

IV. IMPLEMENTED MPPT ALGORITHM

There are different MPPT algorithms used to boost the performance of solar panels by finding the best operating point, known as the Maximum Power Point (MPP). The most common MPP algorithm used are:

(A) Perturb and Observe

(B) Incremental Conductance

A. Perturb and Observe Algorithm

The method for MPPT is simple because it uses voltage as input to control the system. It works by adjusting the output power based on changes in voltage. If increasing the voltage increases the power, the algorithm reduces the duty ratio. Conversely, if increasing voltage decreases the power, it increases the duty ratio. Similarly, if reducing the power, it checks how voltage changes and adjusts the duty ratio accordingly. From the below flowchart the algorithm can be determined.

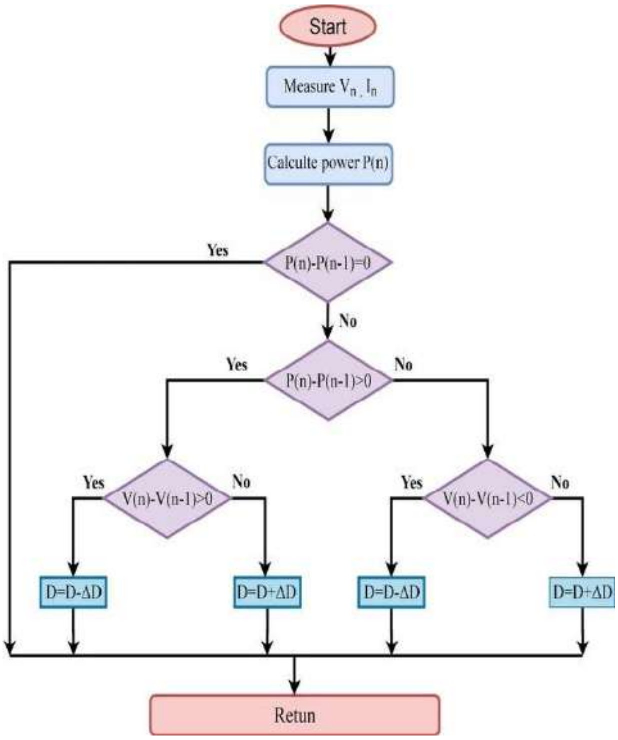
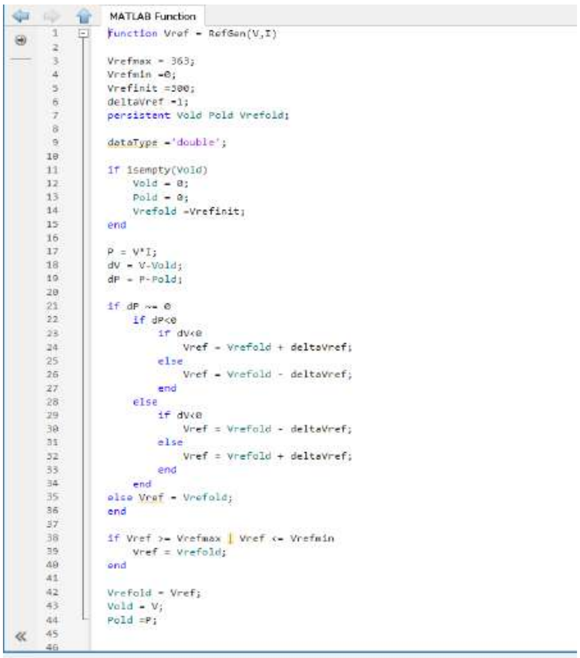


Fig.7. Process Flow Diagram of P&O method



```
MATLAB Function
function Vref = RefGen(V,I)

Vrefmax = 363;
Vrefmin =0;
Vrefinit =300;
deltaVref =1;
persistent Vold Pold Vrefold;

dataType ='double';

if isempty(Vold)
    Vold = 0;
    Pold = 0;
    Vrefold =Vrefinit;
end

P = V*I;
dV = V-Vold;
dP = P-Pold;

if dP ~= 0
    if dP<0
        if dV<0
            Vref = Vrefold + deltaVref;
        else
            Vref = Vrefold - deltaVref;
        end
    else
        if dV<0
            Vref = Vrefold - deltaVref;
        else
            Vref = Vrefold + deltaVref;
        end
    end
else Vref = Vrefold;
end

if Vref >= Vrefmax | Vref <= Vrefmin
    Vref = Vrefold;
end

Vrefold = Vref;
Vold = V;
Pold =P;
```

Fig.8. MATLAB code of Perturb & Observe method

B. Incremental Conductance Algorithm

Under fast-changing weather conditions The INC technique is efficient than the P&O technique . It helps to find the Maximum Power Point of the PV solar panel more accurately. Unlike P&O, INC method doesn't keep oscillating around the MPP. Instead, it figures out when the MPP is reached and stops adjusting the panel's settings. If the MPP hasn't been reached, it knows which direction to adjust the settings by looking at how the current and voltage change. This method tracks changes in sunlight quickly and accurately. However, it's more complicated than the P&O method. From the below flowchart the algorithm can be determined.

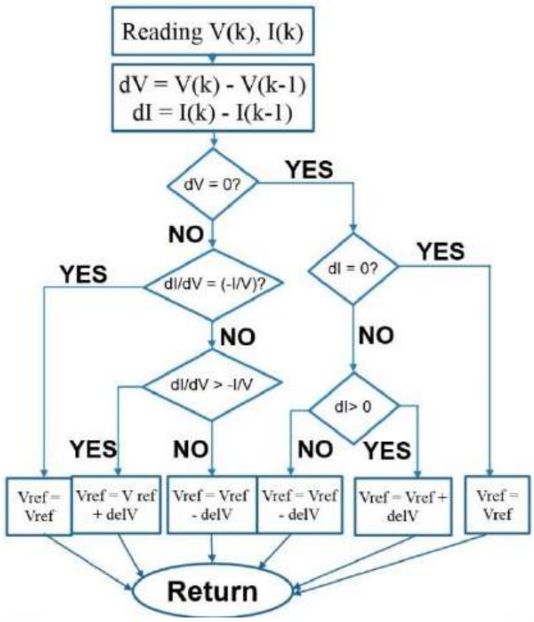
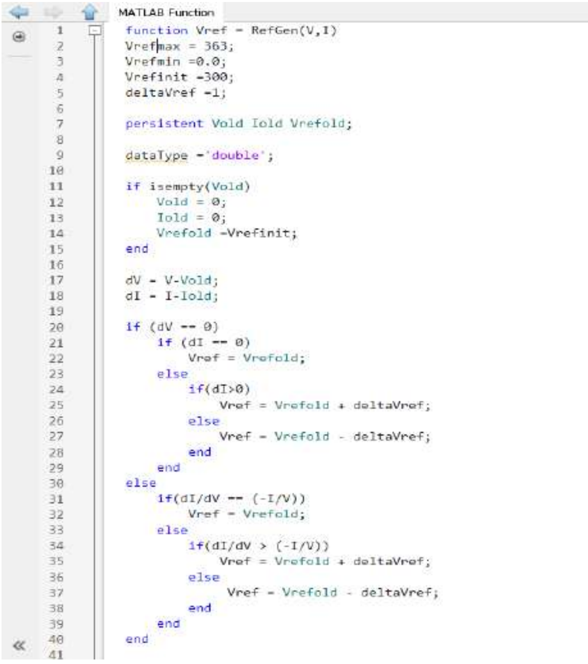


Fig.9. Flowchart of Incremental Conductance algorithm



MATLAB Function

```
function Vref = RefGen(V,I)
Vrefmax = 363;
Vrefmin =0.0;
Vrefinit =300;
deltaVref =1;

persistent Vold Iold Vrefold;

dataType ='double';

if isempty(Vold)
    Vold = 0;
    Iold = 0;
    Vrefold =Vrefinit;
end

dV = V-Vold;
dI = I-Iold;

if (dV == 0)
    if (dI == 0)
        Vref = Vrefold;
    else
        if(dI>0)
            Vref = Vrefold + deltaVref;
        else
            Vref = Vrefold - deltaVref;
        end
    end
else
    if(dI/dV == (-I/V))
        Vref = Vrefold;
    else
        if(dI/dV > (-I/V))
            Vref = Vrefold + deltaVref;
        else
             Vref = Vrefold - deltaVref;
        end
    end
end
```

Fig.10. MATLAB code of Incremental Conductance method

V. RESULT

The below mentioned Figure displays the Simulink model of a photovoltaic system with the MPPT method implemented and observed.

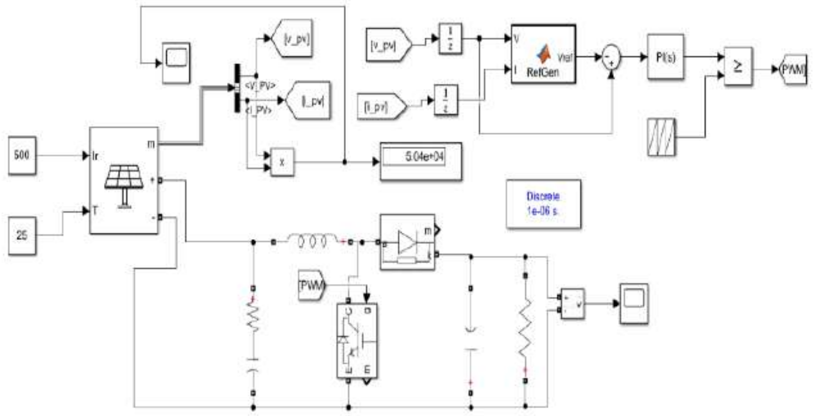


Fig.11. Simulink figure of photovoltaic system MPPT Controller with applied technique.

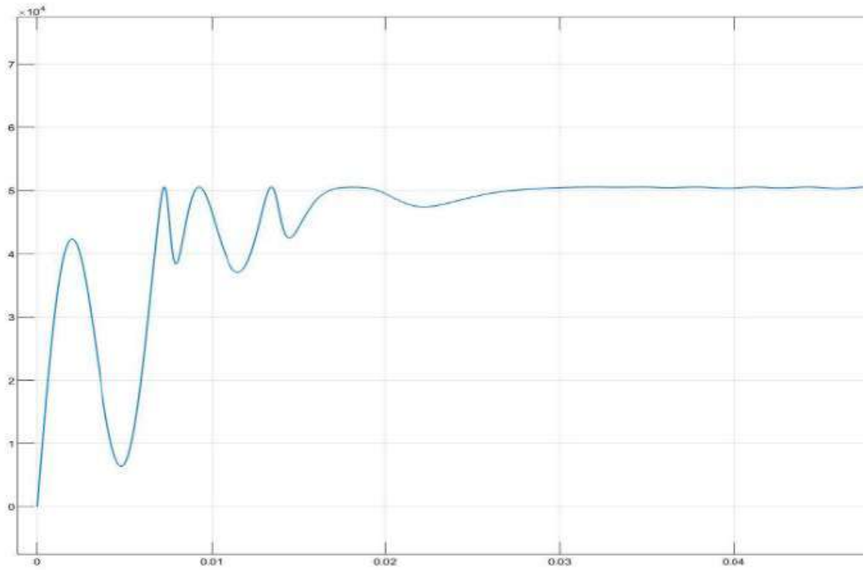


Fig.12. Graph showing Reaching of maximum power at a particular irradiance using Perturb and Observe technique.

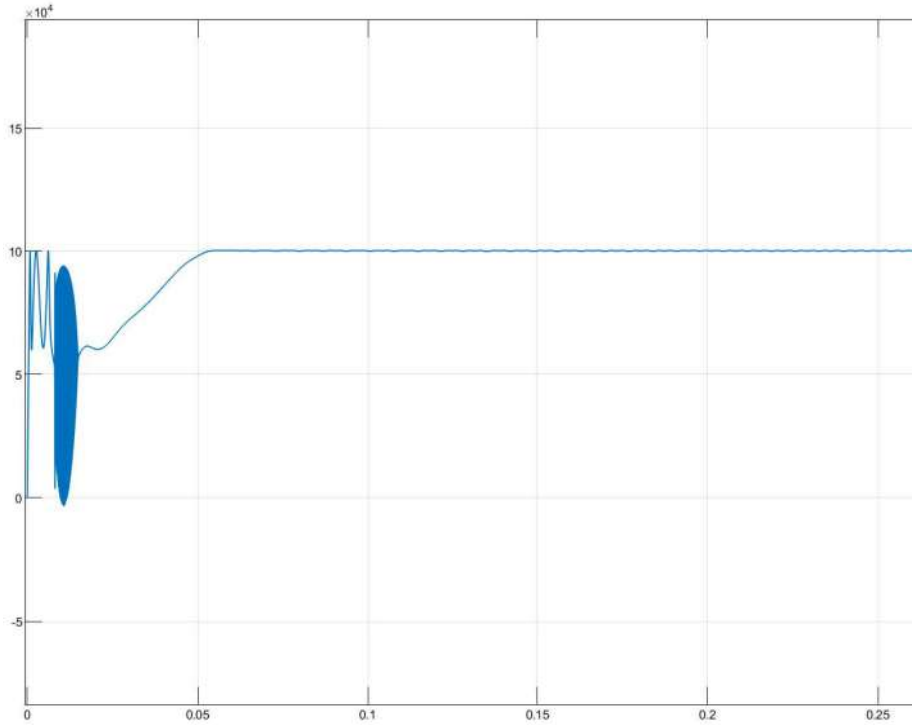


Fig.13. Graph showing Reaching of maximum power at a particular irradiance using Incremental Conductance (INC) algorithm.

VI. CONCLUSION

In conclusion, this study presents the results obtained from applying the P & O and INC algorithm of MPPT methods to a solar photovoltaic (PV) array, showcasing the outcomes of each method's MPP determination. When the weather stays the same or changes slowly, both the P&O and INC MPPT methods work good at finding the best power point for solar panels. But when the weather changes fast, the P&O method moves around a lot while the INC method is better at finding the right spot reliably.

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Harmonic Distortion Study in a Hybrid PV-wind System using the Fuzzy Logic Control Method

Dr. Santi Behera, Chandrika Munda, Raja Rajeswar Panda, Manas Kumar Panda, Somya Ranjan Pradhan, Sneha Singh, Suraj Prasad

Abstract – In this report, a "Harmonic Distortion Study in a Hybrid PV/wind System using the Fuzzy Logic Control Method" is proposed. This work aims at enhancing the performance of a hybrid PV/wind inverter by mitigating harmonic distortion through the application of Fuzzy Logic Control Method. Harmonic distortion, a common issue in renewable energy systems, can affect the efficiency and reliability of inverters. By implementing a Fuzzy Logic Controller, the system adapts vigorously to varying inputs as well as optimizing the THD values. The Fuzzy Logic Control method offers a robust and flexible solution, effectively addressing harmonic distortions caused by the interaction of PV and wind sources. This approach ensures a more stable and reliable power output, contributing to the overall efficiency and longevity of the inverter system. Through a comprehensive analysis of harmonic profiles, this project seeks to elevate the performance standards of hybrid renewable energy systems, fostering a cleaner and more sustainable energy future.

Keywords – Photovoltaic System, Hybrid System, Total Harmonic Distortion, Harmonic Distortion, Fuzzy Logic Control, Maximum Power Point Tracking, Maximum Power, Fuzzy Logic Control, Hybrid Photovoltaic Wind System

I. INTRODUCTION

Renewable energy can be maximized by combining PV and Wind hybrid system. Photovoltaic technology involves panels that convert sunlight into electricity while wind energy systems rely on turbines to convert wind power into electrical power. PV and Wind systems can both generate electricity from renewable sources on their own without external interference [1]. Moreover, the two systems complement one another in a hybrid system, helping to compensate for fluctuations in sunlight or wind availability. A hybrid system combines PV and wind technologies so as to achieve more stable and dependable generation of power [2]. Therefore, this synergy will improve its overall efficiency besides increasing the amount of energy produced. Harmonic distortion is the deviation of an electrical signal from its ideal sinusoidal waveform due to the presence of additional frequencies called harmonics. These harmonics mainly come from non-linear loads and equipment within the system. Total harmonic distortion (THD) quantifies the total harmonic content of a signal relative to the fundamental frequency, usually expressed as a percentage [4]. In hybrid wind-photovoltaic systems, where both wind turbines and photovoltaic modules contribute to the generation of electricity, harmonic distortion can come from various sources, such as power converters and inverters. The operation of these components generates harmonics that may affect the efficiency and reliability of the system [5]. To mitigate these effects, control strategies such as fuzzy logic controllers or modulation techniques are used to manage harmonic distortion to ensure optimal performance and power quality of hybrid systems [6]. By eliminating harmonic distortion, hybrid wind power systems can meet power quality standards, minimize interference with other electrical equipment, and improve overall efficiency and reliability, contributing to a more sustainable energy landscape [3].

Following the introduction this paper describes the HPWS in section I, literature survey in section II, then problem formulation in section III, and its proposed model in section IV, followed by the results in section V. The paper was concluded in the last section.

II. LITERATURE SURVEY

Fuzzy logic controller (FLC) is used for harmonic reduction in a hybrid PV-wind inverter. The FLC is used to adjust the switching frequency of the inverter in order to minimize harmonic distortion. The results of the study show that the FLC is able to achieve a significant reduction in harmonic distortion, without sacrificing power quality or efficiency [7]. It presents the design and implementation of a fuzzy logic controller (FLC) for harmonic distortion reduction in a hybrid PV-wind inverter. The FLC is used to adjust the modulation index of the inverter in order to minimize harmonic distortion. The results of the study show that the FLC is able to achieve a significant reduction in harmonic distortion, even when the inverter is operating at high power levels [8].The FLC-based approach for harmonic distortion reduction in hybrid PV-wind inverters. It is used to adjust the switching frequency and modulation index of the inverter in order to minimize harmonic distortion. The results of the study show that the FLC-based approach is able to achieve a significant reduction in harmonic distortion, without sacrificing power quality or efficiency [12]. FLC for harmonic reduction in hybrid PV-wind inverters operating in microgrids. The results of the study show that the FLC is able to achieve a significant reduction in harmonic distortion, while also maintaining the stability of the microgrid [9]. FLC is able to achieve a significant reduction in harmonic distortion, without sacrificing power quality or efficiency [10]. FLC can also be used for harmonic reduction in a hybrid PV-wind inverter with reduced switching frequency. It can also be used to adjust the modulation index of the inverter in order to minimize harmonic distortion, while also reducing the switching frequency [11].

III. PROBLEM FORMULATION

A. Maximum Power Point Tracking (MPPT) controller

The use of renewable energy sources such as PV systems and wind turbines requires efficient generation of electricity to maximize energy production. This is where the MPPT controller comes into play. In solar photovoltaic systems, the MPPT controller continuously evaluates the output voltage and current and dynamically adjusts the module's operating point to achieve the maximum power point (MPP). This tuning involves changing the duty cycle or operating voltage of the power electronics interface (usually a DC/DC converter or inverter) to match the peak power output of the voltage-current curve. Similarly, in wind turbines, MPPT controllers optimize power output by adjusting blade pitch or generator speed to maintain the turbine's optimal rotational speed based on the most efficient wind speed. The heart of MPPT's functionality lies in its control algorithm, which processes sensor inputs to calculate the optimal operating point. The algorithm is designed to track MPP despite fluctuating environmental conditions, ensuring consistent and efficient solar and wind energy production. In hybrid renewable energy systems, MPPT controllers play a vital role in maximizing power output from sources such as solar photovoltaic systems and wind turbines. To enable seamless interaction with other system components such as fuzzy logic controllers (FLCs) and grid-tied inverters, MPPT controllers often have communication interfaces. This interface allows the MPPT controller to exchange data and commands with the FLC, which is specialized in tasks such as harmonic distortion reduction and other control functions. While the MPPT controller optimizes power output, the FLC can take care of reducing harmonic distortion and other control tasks.

B. DC-DC Boost Controller

DC-DC boost controllers are essential for increasing the voltage of DC power supplies, which is critical for renewable energy systems. It enables efficient energy storage by matching voltage to battery charging requirements and facilitates seamless grid integration by meeting the specific voltage requirements of grid-tied inverters. Additionally, by optimizing renewable energy sources to operate at their maximum power point, boost controllers can significantly improve overall system efficiency, which is critical for stability and reliability under changing environmental conditions.

C. Fuzzy Logic Control Method (FLCM)

The employment of fuzzy logic theory in control systems, known as Fuzzy Logic Control Method (FLCM), has revolutionized the field. Unlike traditional binary logic, FLCM utilizes logical variables that range from 0 to 1, allowing for the accommodation of ambiguity through fuzzy sets without precise boundaries. This breakthrough has found particular success in the realm of DC to AC converters, specifically in converting PV power to AC loads. The adaptability and effectiveness of FLCM are evident in its application across various domains, such as industrial process control, biomedical instrumentation, and securities. As ongoing research continues to push the boundaries, FLCM remains a pivotal area of study, leveraging fuzzy reasoning and logic to address complex control challenges and optimize system performance. The FLC uses fuzzy logic rules to make decisions, and its components include:

1.Fuzzification Module: Converts crisp input signals (e.g., voltage, current) into fuzzy sets using membership functions.

2. Rule Base: A set of IF-THEN rules that encode expert knowledge for harmonic distortion reduction

3. Inference Engine: Evaluates the rules based on fuzzy inputs to determine the appropriate control actions.

4. Defuzzification Module: Converts fuzzy output into crisp control signals.

The reduction of harmonic distortions relies heavily on the indispensable Fuzzy Logic Controller, which effectively handles various inputs, including voltage, current, and frequency, obtained from the hybrid system. By generating control signals, it successfully mitigates the presence of harmonic distortions.

Few of the reasons why we use FLC are:

1. Complex and Nonlinear Systems:

Fuzzy logic controllers skilfully manage harmonic distortions caused by nonlinear loads and complex interactions in power systems, effectively controlling complex and nonlinear dynamics where mathematical equations are insufficient.

2. Adaptability:

Fuzzy logic controllers (FLCs) achieve adaptability by accounting for uncertainties and fluctuations and dynamically adjusting responses to changing conditions such as load fluctuations, renewable energy generation and grid dynamics, thereby improving system stability and performance.

3. Handling Incomplete Information:

The power of fuzzy logic lies in skilfully managing fuzzy or incomplete input information prevalent in energy systems, making it robust to practical applications where precise measurements may be lacking, thereby improving decision-making and system reliability.

4. Multivariable Control:

FLCs excel in multi-variable control, especially in reducing harmonic distortion, as they cleverly integrate multiple variables such as voltage, current and frequency, allowing for effective control decisions taking into account multiple factors simultaneously, thereby improving the power system. stability and efficiency.

IV. SIMULATION

The model was integrated individual wind and solar PV systems, followed by their conversion via inverters. The collective power output from these sources was then transmitted to the grid. Utilizing Simulink, the comprehensive assessment not only calculated the THD but also conducted a detailed examination of the harmonic distortions arising from the combined wind and solar power contributions before integrating them into the grid network.

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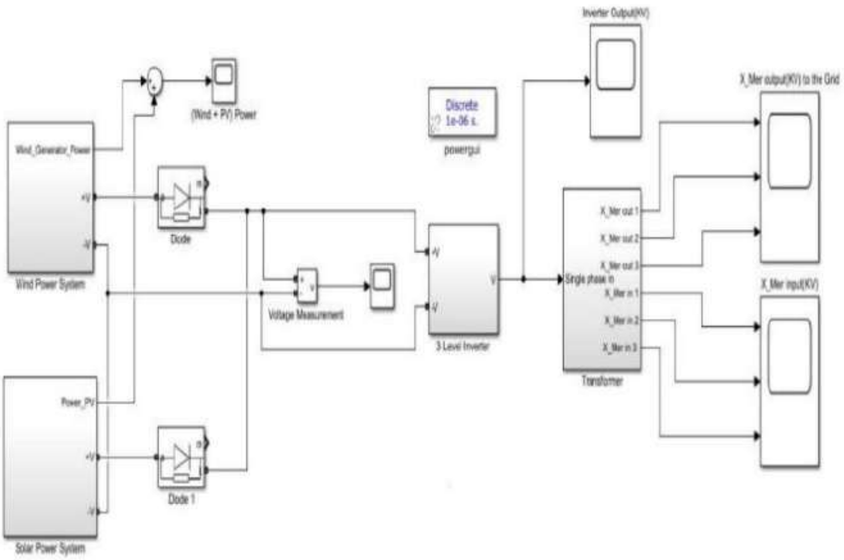

Fig 1.1 PV-Wind Hybrid Power System Overview

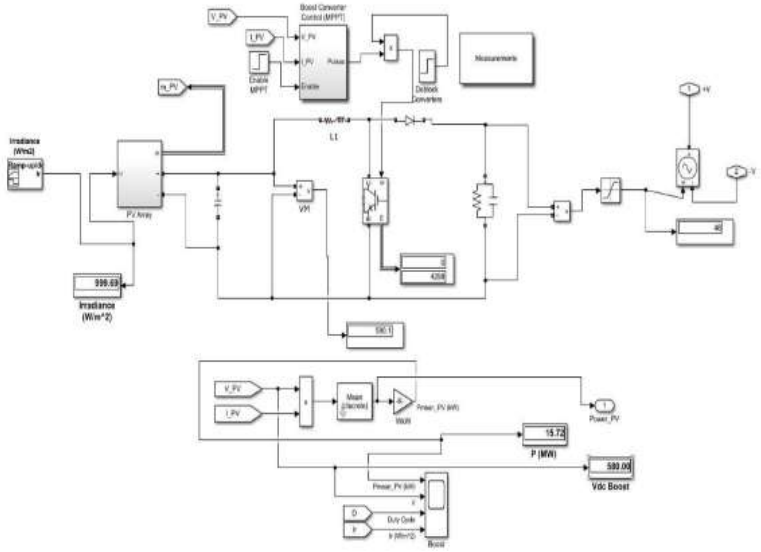

Fig 1.2 PV System Model

Parameter	Value
Number of cells in series -	**100**
Maximum power (MW) -	**3**
Maximum power voltage (KV) -	**500**
Maximum power current (A) -	**6**
Open circuit voltage (V) -	**64.20**
Short circuit current (A) -	**5.96**
Series resistance of PV model (ohms) -	**0.037998**
Parallel resistance of PV model (ohms) -	**993.51**
Diode saturation current of PV model(A)	**1.1753e-08**
Light-generated photo-current of PV model (A) -	**5.9602**
Diode quality factor of PV model -	**1.3**

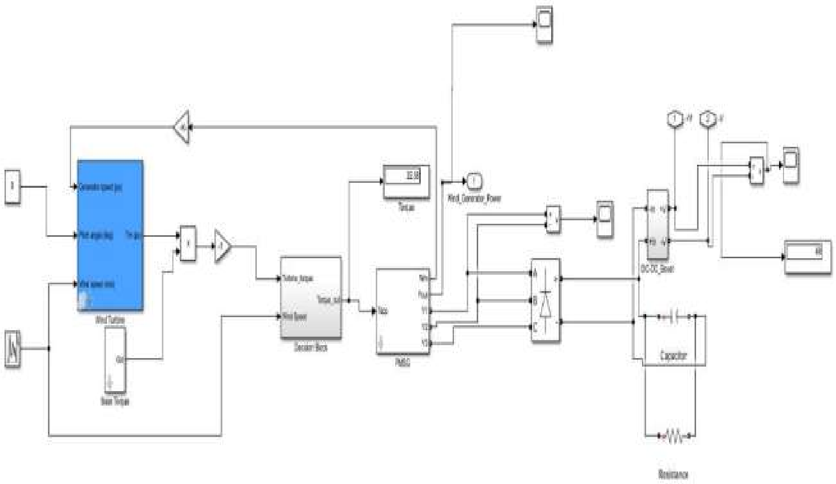

Fig 1.3 Wind System Model

Table 2-Wind System Model Specification

Parameter	Value
Wind Speed (m/s) -	Random value between 8 to 13 m/s
Pitch Angle -	0 degree
PMSG speed (Rpm) -	1000 rpm
Universal Bridge Snubber Resistance(Ω)	1e5
Parallel Resistance branch (Ω) -	1000
Parallel Capacitance branch (F) -	4.8e-4
DC-DC Boost System -	C= 33e-6 F, L= 1e-3 H

V. RESULTS

In the assessment of harmonic distortion within the power generation context, it is crucial to examine the reference values in relation to the actual output values. The comparison between reference and output values are

Table-3 Reference vs Output Value

Parameter	Reference Value	Output Value
PV (Photovoltaic) Power	3 MW	2.4 MW
Duty Cycle Ratio	0.97	0.93
Wind Power	50 kW	48 kW

These variations between reference and actual values underscore the importance of addressing harmonic distortion in renewable energy systems, emphasizing the need for precise monitoring and optimization to ensure that the generated power aligns closely with the anticipated values for both photovoltaic and wind power sources. The project focused on determining the Total Harmonic Distortion (THD) within a hybrid system that combined wind and solar photovoltaic (PV) technologies. Utilizing Simulink, the analysis yielded an approximate THD value of 10.88%. This evaluation occurred within the framework of a designed solar PV plant and wind system, both processed through inverters before feeding the generated power into the grid.

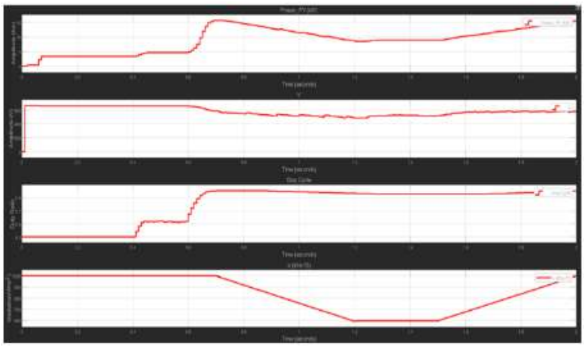

Fig 2.1-PV System Output

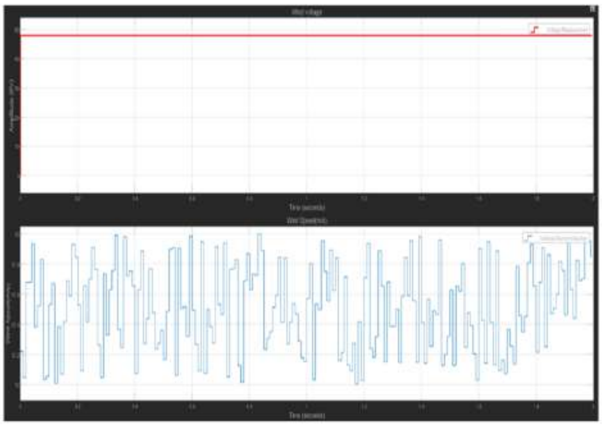

Fig 2.2-Wind System Output

Fundamental (50Hz) =31.3, THD = 10.88%

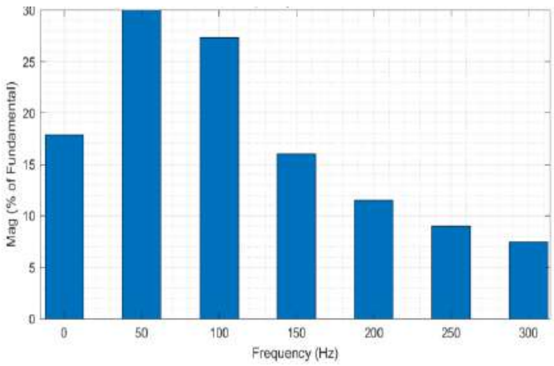

Fig 2.3-Total Harmonic Distortion of Voltage to Grid

VI. CONCLUSION

The application of the Fuzzy Controller Logic Method in harmonic distortion in a hybrid PV-wind system marked a significant stride toward enhancing the overall efficiency and reliability of renewable energy systems. By effectively mitigating harmonic distortions, this method not only ensured optimal energy conversion but also contributed to the longevity of the inverter components. As we continue to advance in renewable energy technologies, the integration of intelligent control methods, such as fuzzy logic, proves instrumental in achieving cleaner and more sustainable power generation. This research paved the way for future innovations in the field, emphasizing the importance of intelligent control strategies in the quest for greener energy solutions. A fuzzy logic controller was utilized to achieve a final THD (total harmonic distortion) percentage of 10.88 % in the PV-wind hybrid system which suggests substantial success achieved in maintaining harmonic distortions within the system. It showed that this technique for changing dynamism could be done using a fuzzy logic controller to reduce total harmonic distortion, thus indicating its high impact on efficient system operation. By incorporating fuzzy-logic control, the host system could adapt itself to variations existing in real time for optimization of modulation and control of an inverter so as to minimize the harmonics content in terms of electricity produced. Such careful management of harmonics ensured quality standards were met throughout by power output generated by hybrid photovoltaic-wind systems improving reliability and efficiency. Moreover, achieving such a low THD percentage underscores how robust and effective advanced control strategies are when used in renewable energy systems.

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Load Frequency Control of a Two-Area System with Two-Degree of Freedom PID Controller

Rutamaan Tripathy, Sayoni Das, Monalisa Maharana

Abstract— In this project, two special computer methods, called HBA and OOA, are used to adjust how a system controls its power in two different areas. These areas have power sources like generators. They use these methods to fine-tune something called a PID controller, which helps manage the power. They compare how well these methods work to regular PID controllers, and they find that OOA works better for keeping the power steady.
Keywords—component, formatting, style, styling, insert (*key words****)***

I. INTRODUCTION

Increasing energy demand, declining conventional sources, and rising environmental pollution drive the shift towards renewable energy resources. Microgrids, resembling small autonomous power systems, offer resilience during main grid failures but face challenges in managing fluctuating electricity demand and generation. Despite the unpredictability of renewable sources, their environmental benefits and adaptability make them suitable for microgrid deployment, particularly in areas lacking robust main power sources. However, synchronizing renewable energy generation with demand poses challenges, especially in multi-microgrid systems. Load Frequency Control (LFC) is crucial for maintaining stable and high-quality power supply, aiming to distribute load among generators, regulate tie-line power, and ensure uniform frequency. In a two-area system, LFC manages the balance between power generation and consumption across interconnected regions to stabilize frequency and ensure reliable power supply. Various algorithms, such as HBA, GWO, and OOA, optimize frequency control in microgrids. This study focuses on comparing the efficacy of the Honey Badger Algorithm (HBA) for tuning PID controllers in the load frequency control of a proposed two-area system, aiming to enhance power system performance.

II. LOAD FREQUENCY CONTROL

Load Frequency Control (LFC)[1] stands as a critical component in managing power systems, gaining particular importance in multi-area grids, notably within a two-area setup. Its primary aim is to carefully oversee the equilibrium between power generation and consumption, ensuring system frequency remains stable and within acceptable bounds. LFC plays a pivotal role in counteracting frequency deviations resulting from load pattern variations, generation fluctuations, and external disturbances. Proportional-Integral (PI) controllers serve as vital tools in this orchestration, dynamically adjusting generator output to restore balance.

In a two-area power system, where the grid is divided into distinct control areas, LFC gains significance in maintaining power interchange equilibrium via tie-lines. This balance is crucial for upholding overall grid stability and reliability. A comprehensive project on Load Frequency Control in such a system would delve into both theoretical underpinnings and practical implementations. It would scrutinize controller design methodologies and conduct simulation studies to replicate system dynamics under diverse scenarios, including sudden load changes and generator failures.

Moreover, the project would explore optimization strategies aimed at refining LFC parameters to enhance system performance. This optimization endeavors involve examining various control strategies and parameters to improve system responsiveness and stability across different operating conditions.

III. SYSTEM MODELLING

To demonstrate practical dynamics of a microgrid, the studied microgrid consists of various types of renewable energy generation units and load including solar energy, wind energy, thermal energy and ESS devices such as EV and BESS. This composition aims to optimize the overall efficiency and resilience of the energy system. Notably, the EV and BESS exhibit faster response times to control signals compared to solar and wind energy components, contributing to the system's dynamic responsiveness.[2]

To maintain the integrity of system dynamics, careful consideration is given to the gains and time constants of each element within the MMG. This ensures that the response of each component aligns with the overall control objectives. The comprehensive nature of the frequency control aspects considered in this study underscores its relevance and applicability in real-world power systems. Transfer functions modelling and illustrations of the studied MMG with various generations and ESS are given in Fig-1.

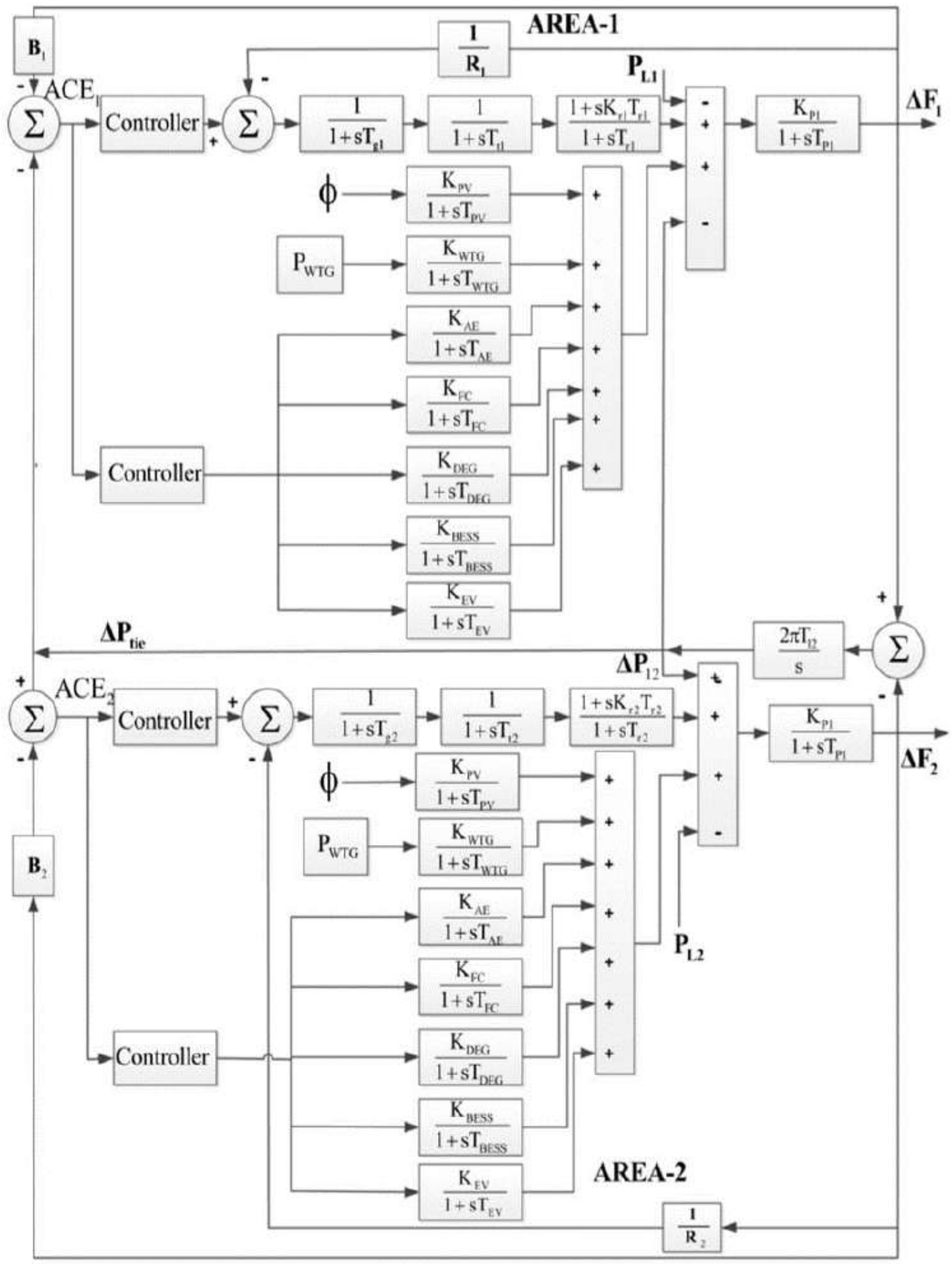

Fig-1: Block diagram of the proposed power system model

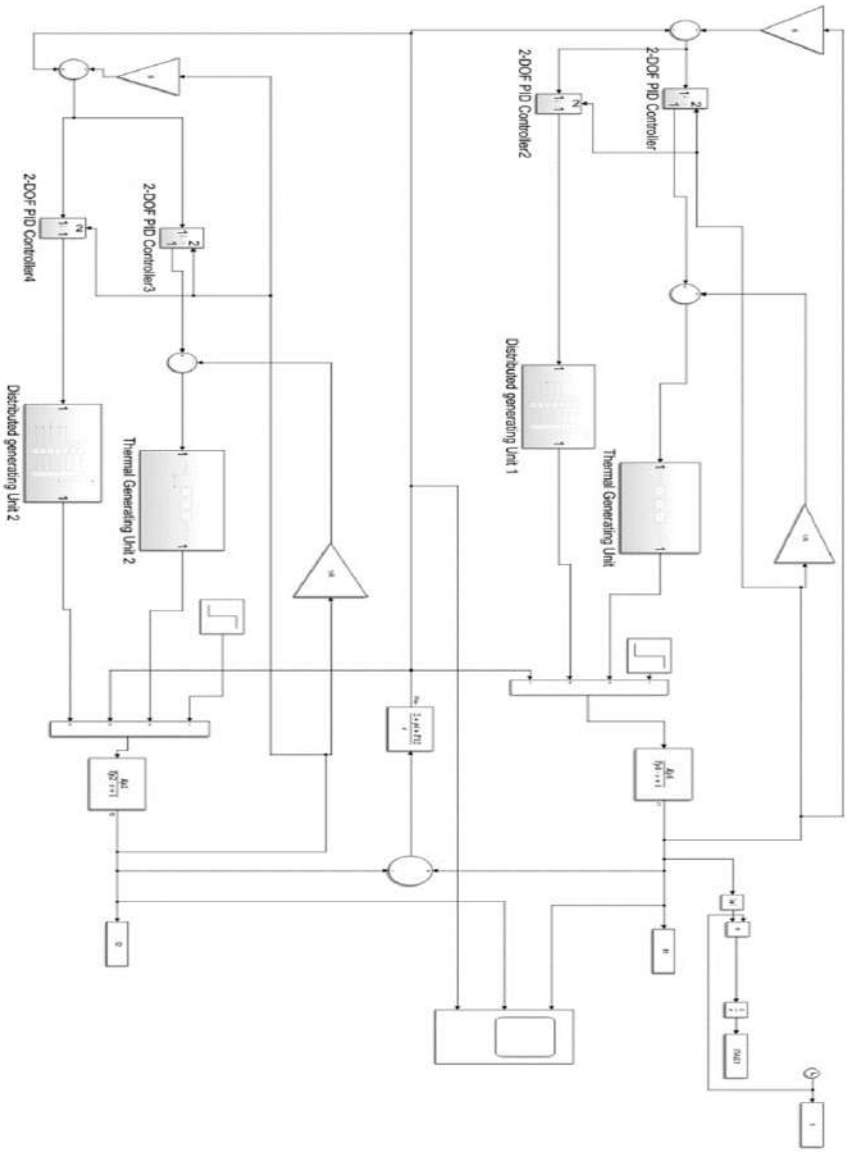

Fig-2: Simulink Model of studied Microgrid

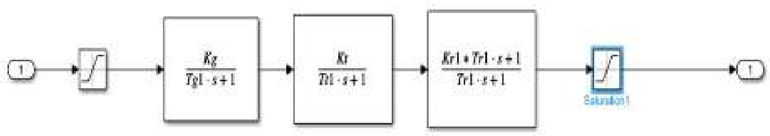

Fig-3: Simulink model of Thermal Generating Unit

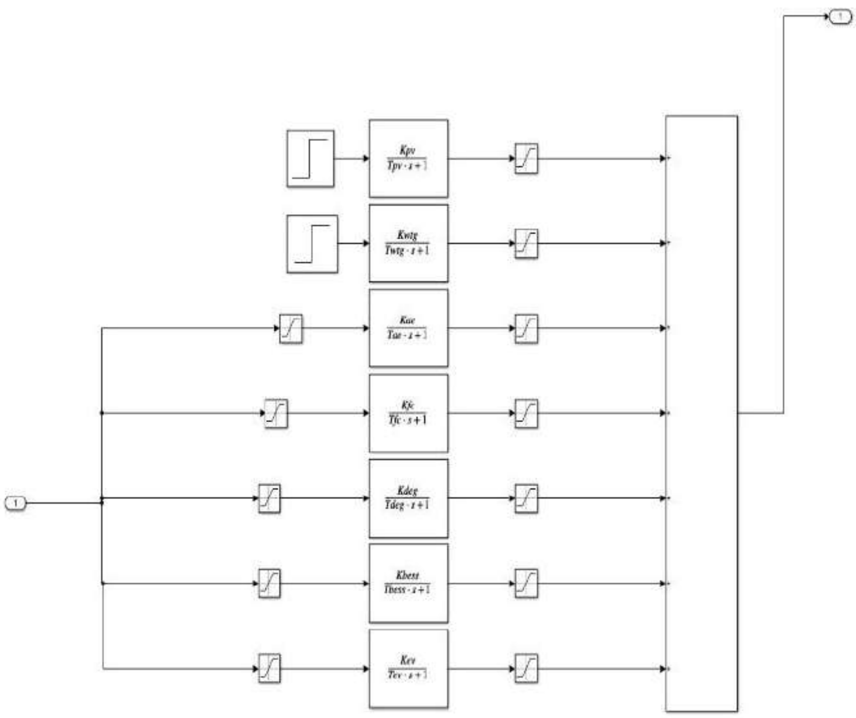

Fig-4: Simulink model of Distributed Generating Unit

IV. CONTROLLER STRUCTURE

After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll down window on the left of the MS Word Formatting toolbar.

a. PID Controller

Proportional-Integral-Derivative (PID)[3] controllers are integral to Load Frequency Control (LFC) systems, ensuring power system stability and performance. LFC, also known as Automatic Generation Control (AGC), maintains the balance between power generation and consumption for system stability. PID controllers excel in LFC for their ability to regulate system changes.

The Proportional (P) component adjusts generator power output proportionally to system frequency deviation, minimizing deviations and restoring balance. The Integral (I) component addresses steady-state errors by continuously integrating cumulative error, correcting long-term frequency deviations caused by load changes or disturbances. The Derivative (D) component anticipates future deviations by considering frequency rate of change, dampening rapid fluctuations caused by sudden load changes or disturbances. PID controllers in LFC aim to maintain system frequency close to its nominal value, respond quickly to disturbances, and eliminate long-term frequency deviations.

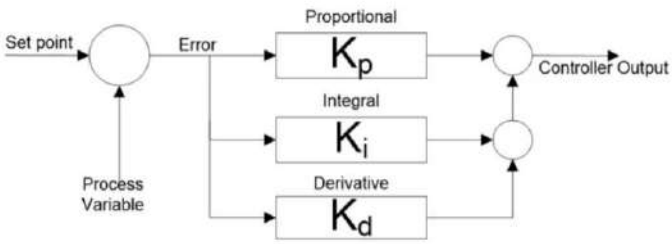

Fig-5: Structure of PID Controller

The equation for PID controller is given as:

$$u = K_p e(t) + K_i \int e(t)\, dt + K_d \frac{de(t)}{dt}$$

A. 2-DOF PID Controller

The 2-DOF PID controller[4] is a two-input, one output controller of the form U(s), as shown in the following figure. The transfer function from each input to the output is itself a PID controller.

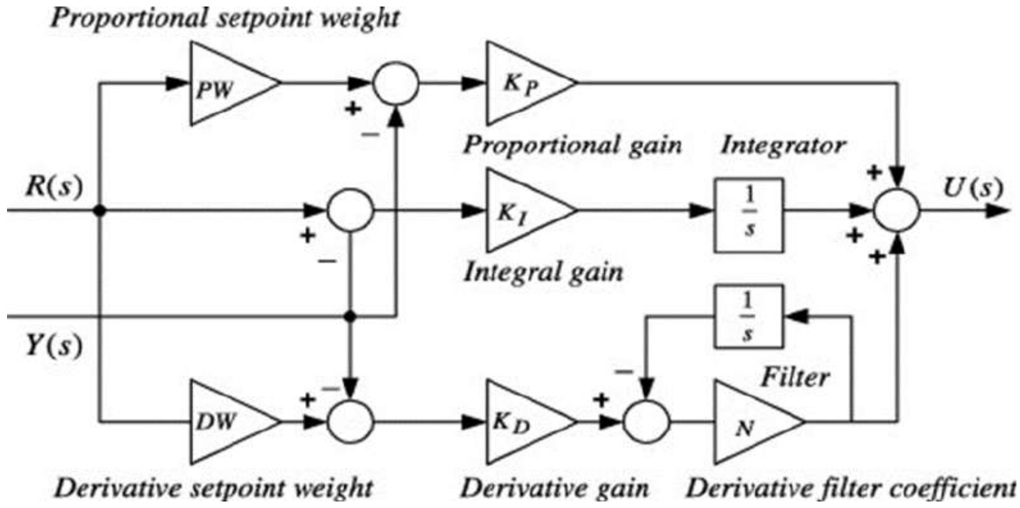

Fig-6: Structure of 2-DOF PID Controller

Two-degree-of-freedom (2-DOF) PID controllers include setpoint weighting on the proportional and derivative terms. A 2-DOF PID controller is capable of fast disturbance rejection without significant increase of over-shoot in setpoint tracking. 2-DOF PID controllers are also useful to mitigate the influence of changes in the reference signal on the control signal. The equation of a 2-DOF PID can be given as:

$$u = K_p[r(PW) - y] + K_i \int (r - y)dt + K_d \frac{d}{dt}[r(DW) - y]$$

VII. OPTIMIZATION ALGORITHM

Optimization problems entail identifying the best solution from various feasible options, with decision variables, constraints, and an objective function. Metaheuristic algorithms are vital in navigating global and local problem spaces, balancing exploration and exploitation.

A. Honey Badger Algorithm

Honey Badger Optimization (HBA) mimics the honey badger's foraging behaviour, leveraging two modes: digging and honey-seeking, akin to the mammal's skills.[5] HBA draws inspiration from the fearless mammal's courageous and intelligent nature, partnering with honeyguide birds to find beehives efficiently. The Computational flowchart of Honey Badger algorithm is given below:

B. Osprey Optimization Algorithm

The Osprey Optimization Algorithm (OOA) mimics the hunting behaviour of ospreys, detecting prey, capturing it, and relocating for optimal consumption.[6] Structured into exploration and exploitation phases, OOA mathematically models' ospreys' natural hunting behaviours, providing a promising nature-inspired method for optimization, balancing exploration and exploitation effectively.

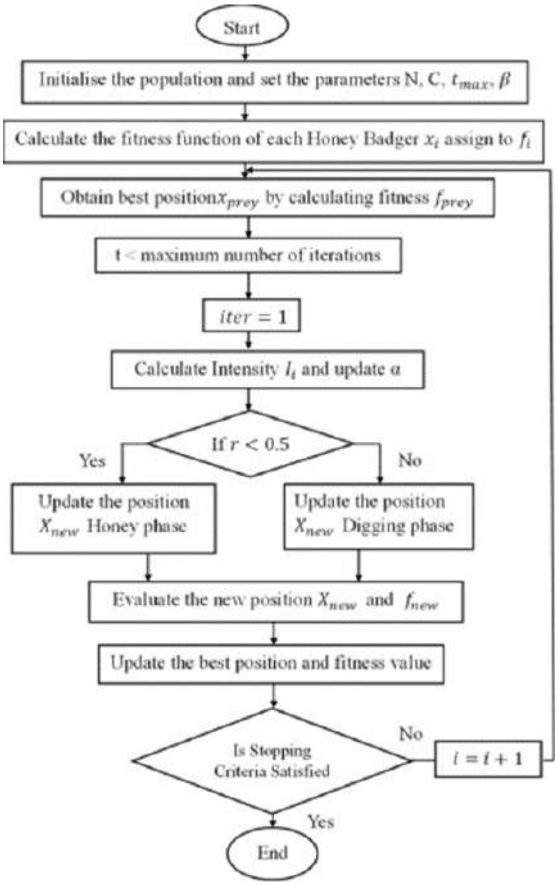

Fig-7: Computational flowchart of HBA

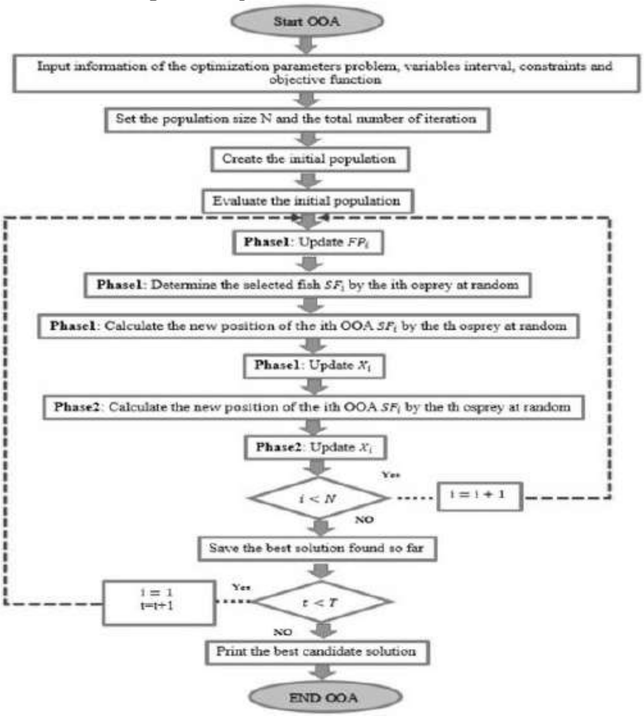

Fig-7: Computational flowchart of OOA

IX. RESULT AND DISCUSSION

The model of the system under study shown in Figure-2 is developed in MATLAB/SIMULINK environment and optimization program is written (in m file). The developed model is simulated in separate program (.m file) considering a 5% step loads perturbation in demand and 10% and 30% disturbances in the PV and Wind generation. In the present study, a population size of NP=20 and the maximum number of iterations=30 is used during simulation. The optimizations were conducted 10 times and the best final solutions among 10 runs is chosen as final control parameters for both PID and 2-DOF PID controllers that can be evidently seen from table 1.2. In the model of Load Frequency Control of Isolated Microgrid System used. ITAE values of conventional PID with HBA & OOA with tuned controller gains were provided in Table 1. It was cleared from Table-1 that OOA based PID controller using ITAE as an objective function gives minimum ITAE value (ITAE=0.4280) compared to HBA based PID controller (ITAE=0.4796) and with the optimal controller gains dynamic responses of frequency change are shown in Figure-8 better. So, OOA based PID controller is proved to be better compared to HOA based PID controller as mentioned in Table-1. So, the OOA to 2-DOF PID Controller was implemented and it was observed that OOA based 2- DOF PID controller using ITAE value as an objective function gives minimum ITAE value (ITAE=0.2158) compared to GOA based PID controller (ITAE=0.4280) it is seen from Table-2 and based on these comparisons the graph was plotted as shown in figure-9. In case of 2-DOF PID controller, improved dynamic response of ΔF is obtained compared to PID. The above analysis shows that the system performance is improved by applying OOA optimized 2-DOF PID controller approach.

Table-1: Comparison between OOA and HBA tuned with PID Controller

	Controller parameter	ITAE
OOA with PID	**Thermal** **Dirtributed** K_p=1.8482 K_p=2.0000 K_i=2.0000 K_i = 2.0000 K_d=1.8722 K_d=0.9809	0.4280
HBA with PID	K_p=2.0000 K_P = 2.0000 K_i=2.0000 K_i = 2.0000 K_d=0.0000 K_d = 0.3189	0.4796
OOA with 2-DOF PID	K_p = 1.9999 K_p = 2.0000 K_i = 2.0000 K_i = 2.0000 K_d = 1.6282 K_d = 2.0000 PW = 4.9999 PW = 4.9999 DW = 4.0608 DW = 4.0960 N = 299.9997 N = 299.9999	0.2158

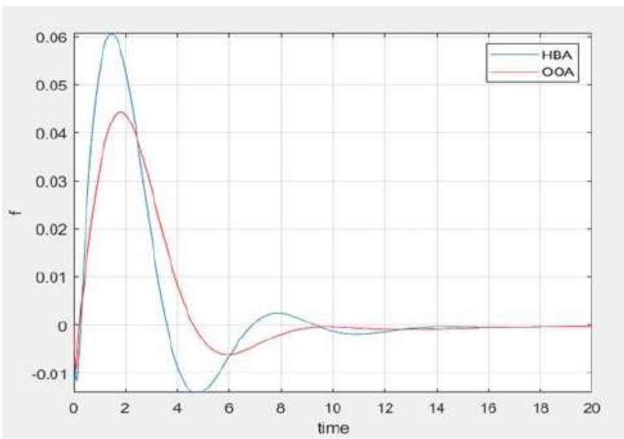

Fig-8: Graph between OOA and HBA PID Controller

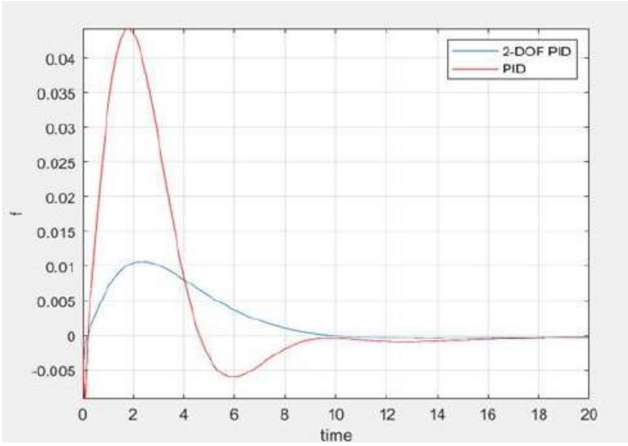

Fig-9: Graph between OOA PID and OOA 2-DOF PID Controller

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ALZHEIMER DISEASE DETECTION WITH DEEP LEARNING MODEL

Lingaraj Dora, Sonam Dhanwar, Nitish Ranjan Kanta, Sushanta Sahu, Pramit Singh, Amartya Aman Sharma, Sarthak Choudhury, Adarsh Mohanty

Abstract— ***Alzheimer's disease is an incurable evolving brain disorder that gradually depreciates memory, cognitive abilities, and the capacity to perform simple tasks. It has emerged as a global health concern with no known cure. Machine learning, particularly deep learning-based Convolutional Neural Network (CNN), has been employed to enhance Alzheimer's disease detection. CNN has demonstrated significant success in analyzing MRI images and biomedical research. Numerous studies have focused on using CNN for Alzheimer's detection based on brain MRI images. This report presents a 16-layer CNN model for binary classification and Alzheimer's detection using brain MRI data. The model's performance is evaluated against existing CNN models on the Augmented Alzheimer MRI Dataset, showcasing a noteworthy accuracy of 92.40%. The report highlights the superiority of the proposed model over pre-trained CNN models (Gaussian NB, Random Forest, MobileNetV2, and VGG16, Decision Tree) through a comprehensive comparison of Key performance indicators including accuracy, precision, recall, F1 score, and the ROC curve. This research contributes to a high-performing CNN model and emphasizes its effectiveness compared to established models in the field.***

Keywords— Alzheimer Disease, Convolutional Neural Network, Classification

I. INTRODUCTION

The human brain, serving as the central command center of the body, assumes a paramount role in the treatment of brain diseases, given their often-irreversible nature. Dementia, marked by a decline in learning and functional thinking, is primarily instigated by Alzheimer's disease, typically manifesting in the mid-60s. Afflicting more than 6.5 million individuals, Alzheimer's exhibits symptoms such as memory loss, language issues, and behavioral changes. The disease progresses through early, moderate, and severe stages, influenced by genetic factors and intricate brain circuits. Biological indicators, encompassing blood, cerebrospinal fluid, and brain imaging, play a pivotal role in understanding Alzheimer's progression. The genetic makeup contributing to early-onset Alzheimer's and the complex brain circuits implicated in its onset further add to the multifaceted nature of the disease. Recognition of Alzheimer's involves a comprehensive examination of changes in the brain, body fluids, lifestyle, and genetic factors. The identification of proteins or chemical aggregates, such as amyloid plaques, fiber tangles known as tau tangles, and the loss of connections between nerve cells, serves as symptomatic evidence of Alzheimer's disease. Ten years post-onset, Alzheimer's symptoms begin to surface, resulting from the accumulation of amyloid plaques and tau protein in the brain. The hippocampus, crucial for memory formation, bears the brunt as the first damaged brain region. This damage progresses, causing affected areas to gradually shrink and spread to other regions. In the final stage, the entire brain undergoes reduction in size, marking the culmination of the disease's devastating impact.

Diagnosing Alzheimer's entails a meticulous study of brain changes, body fluids, lifestyle, and genetics. Hallmarks of Alzheimer's, such as amyloid plaques, tau tangles, and nerve cell tangles, serve as crucial indicators in this diagnostic process. The manifestation of symptoms a decade after onset initiates a gradual shrinking of affected brain areas, commencing with the hippocampus [1]. Sophisticated diagnostic techniques, including Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans, prove instrumental in capturing detailed features of the brain and effectively imaging the deep nervous system. In recent times, advancements in technology have led to the integration of machine learning and deep learning models, particularly Convolutional Neural Networks (CNN), in Alzheimer's diagnosis. These models, trained with extensive datasets, including MRI images, enhance accuracy and efficiency in disease detection. Comparative analyses between proposed CNN models and established ones, such as InceptionV3, Xception, MobilenetV2, and VGG, provide valuable insights into their respective efficacy.

II. RELATED WORKS

This section delves into the state-of-the-art applications of Deep Learning (DL) and Machine Learning (ML) algorithms in diagnosing dementia and Alzheimer's disease, showcasing innovative approaches and methodologies. The study introduces a novel perspective by incorporating pattern similarity scores and proposing new metrics for diagnosing Alzheimer's. Logistic regression is employed to predict conditional probabilities, offering a comprehensive description of the metrics. The authors further explore the effectiveness of anatomical and cognitive impairment, utilizing various data forms to generate output for classifiers. In the realm of Alzheimer's diagnosis, the authors leverage online databases containing MRI scan images and additional cognitive parameters such as RAVLT tests, MOCA, and FDG scores [2]. Notably, logistic regression and Support Vector Machines (SVM) are utilized to create methods for grouping patients with Alzheimer's disease. Ammar et al. [3] contribute to the discourse with a system centered on speech processing for dementia identification. This innovative framework utilizes verbal descriptions and human transcription of speech data to extract distinctive characteristics from individuals with and without dementia. ML classifiers are trained using both speech and textual characteristics, achieving a correct classification rate of 79 percent.

Another noteworthy contribution comes from the work of authors [4], who present a detection technique based on brain MRI images employing the concept of Eigen brain. Their approach involves training a model using SVM and particle swarm optimization, yielding promising results in identifying affected areas of the brain in Alzheimer's disease. Similarly, researchers in [5] utilize MRI data for dementia identification, employing gradient boost and Artificial Neural Network (ANN) models. The hybrid multimodal approach proposed by authors [6], based on cognitive and linguistic aspects, employs ANN for training the model to identify Alzheimer's disease and assess its severity.

The current trend in most applications involves the adoption of deep learning-based technologies, leading to improved results. However, a prevalent challenge in these methods is the class imbalance issue. Recently, Convolutional Neural Networks (CNNs) have replaced Deep Neural Networks (DNNs) for enhanced training time, GPU utilization, and accuracy. The shift to CNNs has been particularly advantageous, addressing the complexity of existing models when handling MRI datasets [7]. In [8] utilization of Gaussian Mixing Model for gray matter segmentation, a technique employed in classical classification problems and density estimation. Features were then extracted using the Partial Least Squares algorithm, facilitating classification through the Support Vector Machine. Meanwhile, Ben Rabeh, Benzarti, and Amiri [9] introduced a classification method based on Level Set segmentation. Their approach involves finding the nearest learning samples to new inputs through four distances, enabling image classification using the Bayes theorem. Mufidah, Wasito, Hanifah, and Faturrahman [10] proposed a method employing Morphometry was employed based on Voxel to extract features, isolating the region of interest (VOI) using a 3D mask. Additionally, a Deep Belief Network, a form of deep learning model, was utilized for image classification. In [10] a separate method was adopted, the Fuzzy C Means technique for segmenting white and gray matter. Subsequent segmentation, they extracted gray level co-occurrence matrix (GLCM) from the segmented tissues, offering insights into their spatial characteristics. Raut and Dalal adopted a two-phase method involving feature extraction (texture, shape) using the GLCM method, followed by image classification using an artificial neural network. Angkoso, Purnama, and Purnomo focused on image segmentation based on Voxel morphometry, isolating, the Kolmogorov-Smirnov distance technique was utilized to extract features from three distinct brain tissues - white matter, gray matter, and cerebrospinal fluid. These features were then employed for image classification using a backpropagation neural network. Deep learning, specifically Convolutional Neural Networks (CNNs), has also found its place in Alzheimer's detection methods. Song et al. employed graph convolutional neural networks (GCNN) for classification, utilizing structural connectivity inputs in graph form. This network, consisting of eleven layers, achieved the classification of individuals with Alzheimer's into four classes. Similarly, in [13] author employed the GCNN classifier, which is based on graph signal processing principles, with feature extraction performed via the Graph Fourier Transform. The main objective of their paper is to investigate the efficacy of deep learning in detecting Alzheimer's disease. The diverse methodologies mentioned showcase the interdisciplinary nature of research in this field, with each method contributing unique insights and techniques.

As research progresses, emphasis on mitigating class imbalance issues and refining existing models contributes to the ongoing improvement in diagnostic capabilities. The intersection of cognitive, linguistic, and anatomical aspects in hybrid multimodal approaches indicates a holistic understanding of Alzheimer's disease. Ultimately, these advancements underscore the potential for technology-driven solutions to play a pivotal role in enhancing our ability to diagnose and manage Alzheimer's disease, offering hope for improved outcomes for individuals affected by this challenging condition. The evolving landscape of DL and ML in dementia and Alzheimer's diagnosis reflects a continuous quest for more effective and accurate methodologies. The integration of novel metrics, diverse data sources, and advanced techniques such as speech processing highlights the interdisciplinary nature of this field. The application of logistic regression, SVM, and CNNs demonstrates the versatility and adaptability of machine learning algorithms in addressing the intricacies of Alzheimer's disease diagnosis.

III. MATERIAL AND METHODS

In this segment, we elaborate on our introduced approach, comprising a 16-layer CNN model. We proceed to evaluate the model's performance by the delineation of our proposed method which involves a structured sequence of seven fundamental steps outlined below:

- Dataset collection.
- CNN model.

A. Dataset collection

The dataset is gathered from Kaggle, an open-source platform that offers data scientists and machine learning engineers opportunities to collaborate and compete, thereby enhancing their skills. Each label in the dataset is carefully hand-collected from various websites and rigorously verified. This collection comprises 500 subjects aged 18 to 96, each having 3 or 4 individual T1-weighted MRI scans acquired during single scan sessions. All subjects are right-handed and encompass both men and women. Among them, 350 subjects aged over 60 have been clinically diagnosed with very mild to moderate Alzheimer's disease (AD). Additionally, the dataset includes a reliable set of data consisting of 150 non-demented subjects imaged during a subsequent visit within 90 days of their initial session. The dimensions for Moderate, Mild, and Very mild demented are set at (200x190), while non-demented is specified as (180x180). The total number of images in the dataset is approximately 7,000. The Images of different class are shown in Fig.1.

Each class in the dataset is represented by four files.

i. Mild-Demented
ii. Very Mild Demented
iii. Non-Demented
iv. Moderate-Demented

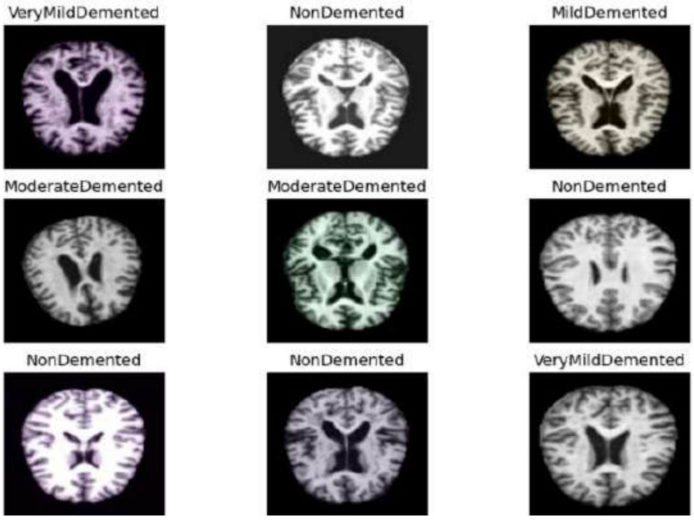

Fig. 1. Images of Each Class

A. CNN

CNNs are a subset of deep neural networks that have transformed the field of machine learning, particularly in tasks such as image classification, object detection, and image segmentation. Their architecture mimics the association of the visual cortex in animals, where neurons are specialized to respond to specific stimuli within localized regions of the visual field. With a layered structure, CNNs can automatically learn and extract hierarchical features from raw pixel values. Each layer in the network performs a specific operation, and the output of one layer serves as the input to the next layer. The first segment of a CNN, known as the convolutional part, plays a crucial role in feature extraction.

In the convolutional part, the input image is convolved with a set of learnable filters or kernels. Each filter detects a specific feature or pattern in the input image, such as edges, textures, or shapes. The convolution operation involves sliding the filter over the input image, computing element-wise multiplications followed by summation to produce a feature map. This process is repeated for each filter, generating multiple feature maps that capture different aspects of the input image. To introduce non-linearity and increase the expressive power of the network, activation functions such as ReLU (Rectified Linear Unit) are applied to the feature maps after convolution. ReLU introduces non-linearities by thresholding the output at zero, effectively filtering out negative values and allowing only positive values to pass through.
After convolution, the feature maps may undergo additional operations such as pooling or down sampling. Pooling layers reduce the spatial dimensions of the feature maps while retaining the most important information. Common pooling operations include max pooling, which selects the maximum value within each pooling region, and average pooling, which computes the average value.
The feature maps produced by the convolutional layers are then flattened into a one-dimensional vector and passed to the classification segment of the CNN. This segment typically consists of fully connected layers, similar to those found in traditional multilayer perceptron's. These layers perform high-level feature representation and map the input features to the output classes through a series of weighted connections and activation functions, such as SoftMax for multi-class classification. Through a process known as backpropagation, the CNN learns to adjust the weights of its connections during training, minimizing a predefined loss function and optimizing its performance on the given task, such as image classification. As shown Fig.2.

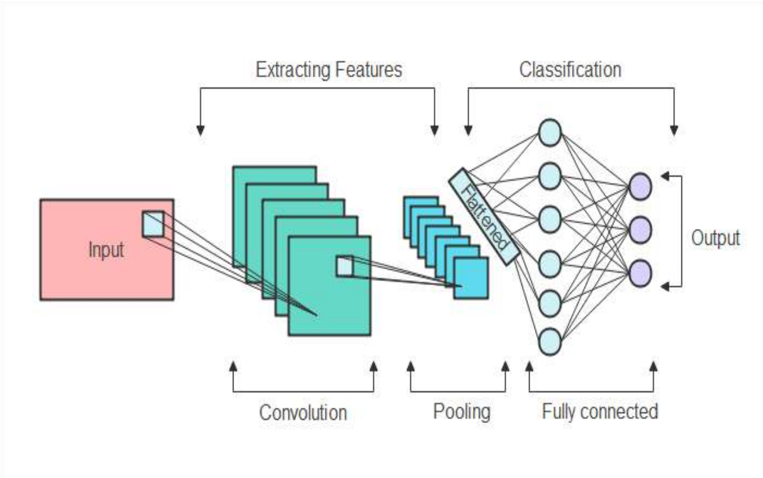

Fig. 2. Block Diagram of CNN

a) Convolutional Layer

The pivotal element and foundational component of Deep Learning Convolutional Neural Networks (DL CNN) is the convolutional layer. This layer plays a crucial role in the feature extraction process, generating sets of 2D matrices known as feature maps. Within each convolutional layer, a fixed number of filters serve as feature detectors, extracting features through the convolution of the input image with these filters. In ResNet50, the chosen filter sizes are (7 × 7), (1 × 1), and (3 × 3). Throughout the training process, each filter develops the capability to identify low-level features in the analyzed images, including colors, edges, blobs, and corners.

b) Batch Normalization Layer

The utilization of the batch normalization layer involves normalizing the output of the convolution layer, adjusting the batch mean to 0 and the variance to 1. This approach expedites the training process by enabling the use of higher learning rates. Additionally, it mitigates the risk of gradients vanishing during backpropagation. Furthermore, incorporating batch normalization layers in Deep Learning models enhances robustness against inadequate weight initialization.

(c) ReLu Layer

The Rectified Linear Unit (ReLU) layer serves as a prevalent activation function employed in artificial neural networks, especially within deep learning architectures. Its role is to introduce non-linearity to the network, thereby enabling the model to effectively learn intricate patterns and representations.

ReLu=max (0, x)

The ReLU layer applies the ReLU activation function element-wise to the input data. The ReLU activation function is defined as f(x) = max (0, x), where x is the input to the function. In simpler terms, if the input is positive, the output is the same as the input; if the input is negative, the output is zero. This results in an output that is zero for all negative values and linear for all positive values.

(d) Max-Pooling Layer

Enabling the reduction of image dimensions while retaining essential features is achievable through a commonly employed technique known as 'Max Pooling.' This method involves diminishing the image size while retaining the highest pixel values. The process entails the movement of a tile, akin to a filter, across the image's surface. For every tile position, the maximum value is selected, creating a new image that retains only the prominent values from the initial image, Fig.3 offers a visual representation of the Max-Pooling procedure.

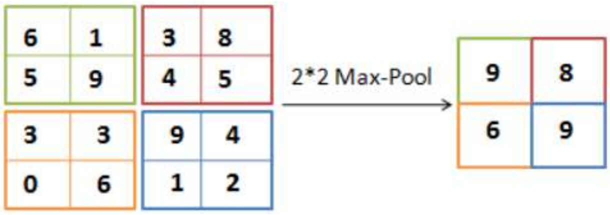

Fig.3. Example of Max-pooling Process

(e) Fully Connected Layers

After a sequence of convolutional and max-pooling layers, the classification phase takes place through fully connected layers. Neurons in this layer establish connections with all neurons from the preceding layer. The outputs of this layer are then processed through the SoftMax function, producing probability distribution vectors. The SoftMax function generates a vector of size N, where N represents the number of classes pertinent to our image classification task. Each element in the vector indicates the probability of the input image belonging to a particular class.

IV. PROPOSED METHOD

Convolutional Neural Networks (CNNs) play a crucial role in Alzheimer's disease detection and classification. In medical imaging, CNNs analyze structural brain images, identifying patterns indicative of Alzheimer's. These networks automatically learn features, recognizing subtle changes in brain structures that might be early signs of the disease. Our proposed model block diagram for Alzheimer disease detection is shown in Fig4.

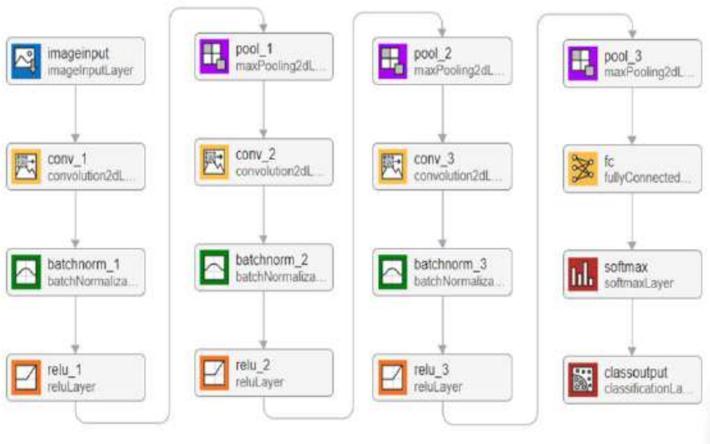

Fig.4. Block Diagram of CNN model for Alzheimer Disease Detection

We utilized a dataset sourced from Kaggle, specifically segmented into four distinct types of Alzheimer's disease. Our initial layer processes images with dimensions (128x128x1). Subsequently, we implemented three convolutional layers, incorporating batch normalization, ReLU activation, and Max-Pooling layers for feature extraction. Specifications of the model are as follows:

a. In the conv1 layer, a filter size of (11x11) with 96 filters and a stride of 4 is utilized. For the max pool layer, a pool size of 3 and a stride of 2 are employed.
b. In conv2, a filter size of (5x5), 256 filters, a stride of 2, and padding of 2 are applied. Max pool 2 uses a pool size of 3 and a stride of 2.
c. Conv3 involves a filter size of (3x3), 384 filters, and a stride and padding of 1. Maxpool3 employs a pool size of 3 and a stride of 2. Finally, in the fully connected layer, the output size is set to 4 to accommodate different classified images.

V. RESULT AND DISCUSSION

a) Demonstrating the performance of our proposed model

In order to analyze the performance of our proposed CNN model, we computed, the accuracy of the model.

Accuracy: The most straightforward performance metric to comprehend is accuracy, representing the ratio of correctly predicted observations to the total number of observations. The formula for accuracy is as follows:

$$ACC = \frac{TP+TN}{P+N}$$

$$= \frac{TP+TN}{TP+TN+FP+FN}$$

Where,

(a) ACC= Accuracy
(b) TP= True Positive
(c) TN= True Negative
(d) P= Condition Positive
(e) N=Condition Negative

To illustrate the superior performance of our suggested 16-layer CNN model, we have depicted the model accuracy and model loss in Fig.5.These figures indicate that our proposed 16-layer CNN model avoids both underfitting and overfitting. This observation elucidates our superior results in terms of accuracy. The data base is partitioned into 70 for training and 30 for validation during training phase. The validation is assessed over 20 epochs with batch size of 64, validation frequency of 30 and utilizing a learning rate of
0.01 o optimize the model performance.

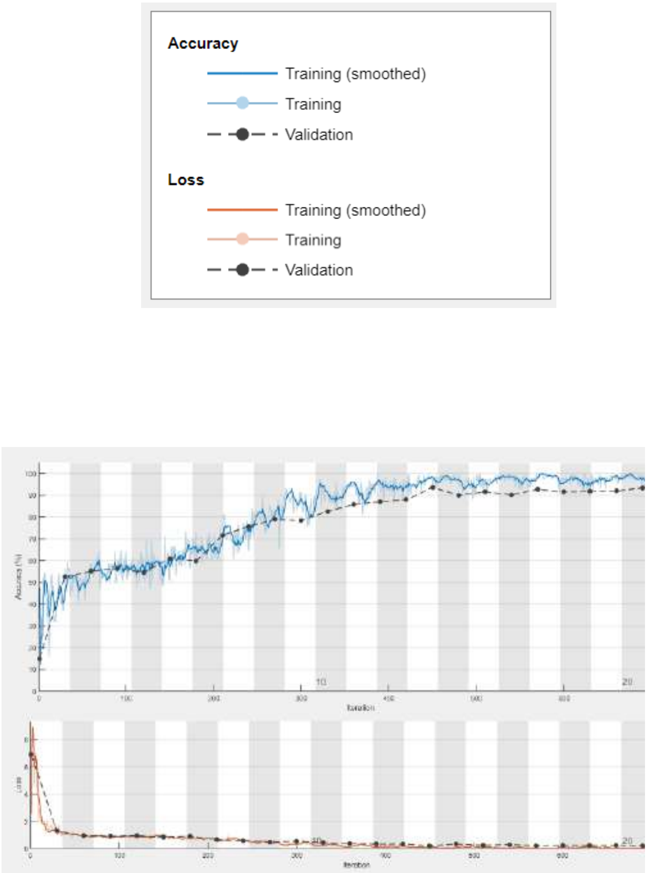

Fig.5 Model Accuracy and Loss Graph

Comparison With other Models

We have compared the performance of our proposed model with five pre-trained models, namely Gaussian NB, Random Forest, MobileNetV2, and VGG16, Decision Tree, with same specification. As Shown in Table-1.

Model	CNN Model	Random Forest	Mobile NetV2	VGG16	Decision Tree
Accuracy (in %)	92.40	*52.45*	*64.78*	*89.24*	*58.43*

Table-1 Performance comparison in terms of accuracy

VI. CONCLUSIONS

In the absence of a definitive treatment for Alzheimer's, the emphasis has shifted towards mitigating risks, implementing early interventions, and precisely assessing symptoms. Existing research, as reviewed in the literature, has explored various machine learning algorithms and micro-simulation techniques in attempts to identify Alzheimer's Disease. Despite these efforts, pinpointing relevant characteristics remains challenging, as highlighted by Kavitha et al.'s Early-stage Alzheimer's Disease Prediction, which demonstrates an ability to detect Alzheimer's in its early stages. To enhance the accuracy of detection methods, future studies will center on extracting and analyzing novel features that are more likely to contribute to Alzheimer's identification, while simultaneously eliminating redundant and unnecessary characteristics from current feature sets.

One avenue for improvement involves leveraging more precise data, incorporating factors such as age, gender, and an individual's previous medical history with the disease. This nuanced approach is anticipated to significantly enhance accuracy, particularly in real-time scenarios. Additionally, refining models to segment affected areas can further contribute to diagnostic efficacy. By training models to discern subtle patterns in data, there is potential for a more comprehensive understanding of Alzheimer's manifestations, enabling earlier and more accurate detection.

In essence, the quest for effective Alzheimer's management pivots towards proactive measures, leveraging advanced techniques to identify the disease in its nascent stages. The ongoing refinement of detection methodologies, coupled with a focus on pertinent data features, holds promise for the development of more precise and reliable diagnostic tools, ultimately advancing our ability to address Alzheimer's disease in its early phases.

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A Preliminary Study On Skin Cancer Detection Using CNN & SVM

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Abstract- Melanoma is a serious form of skin cancer. Early detection is crucial for improving treatment outcomes. This review paper explores various strategies for identifying and diagnosing melanoma. The paper highlights the importance of self-examination, clinical evaluation, and advanced technologies like smartphone apps and AI-based screening devices. Machine learning approaches, such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), are promising for accurate melanoma detection. The paper also discusses the historical development of melanoma detection methods, from relying on visual features to structured protocols like the ABCD rule (Asymmetry, Border irregularity, Color variegation, Diameter). Standardized full-body imaging and computer-assisted image analysis are recent advancements that improve detection sensitivity and specificity. Finally, the paper details a five-step process for classifying skin cancers using image analysis techniques.

I. Introduction

Melanoma, a potentially lethal form of skin cancer, poses a significant public health concern due to its rapid spread and increasing prevalence. Accurate and reliable methods for early detection are imperative to improve treatment outcomes and reduce mortality rates associated with this disease. This research paper aims to explore various strategies for identifying and diagnosing melanoma, emphasizing the importance of early detection and the role of technological advancements in enhancing the precision and efficiency of melanoma diagnosis.

Effective detection of melanoma involves a multifaceted approach, including self-examination of the skin, clinical evaluation by dermatologists, and the utilization of advanced technologies such as smartphone apps and AI-based screening devices. Recent years have witnessed the successful application of machine learning approaches, particularly Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), in accurately identifying melanoma from skin photographs. These technological innovations offer promising avenues for improving the speed and accuracy of melanoma diagnosis, thereby facilitating timely intervention and improving patient outcomes.

In the context of dermatology practice, digital dermoscopy has become a widely employed tool for melanoma detection. However, the subjective nature of clinician diagnosis and the inherent variability between different operators underscore the need for fully automated computer-aided diagnosis systems. These systems can help eliminate inter-operator variability and enhance the consistency and accuracy of melanoma detection, ultimately leading to more effective patient management. Researchers have proposed a novel approach utilizing deep recursive Convolutional Neural Network (CNN) models for the classification and detection of pests on plants. This pioneering research delves into key components of CNN architecture such as Rectified Linear Units (ReLu), Max pooling, and feature pyramid networks. The recursive CNN model they developed demonstrates promising capabilities in accurately identifying and classifying pests present on both the upper and lower sides of plant leaves.

The study focuses on image processing techniques within the context of greenhouse agriculture, utilizing datasets comprising images of pests such as whitefly (Bemisia tabaci) and thrip (Frankliniella occidentalis) in agricultural settings. Methodologically, the research employs image acquisition and insect algorithmic analysis, coupled with neural network-based classification methodologies.

Furthermore, the research extends its application to skin disease classification, leveraging CNNs to process images of pomelo skin lesions to detect plant diseases. The study elaborates on the CNN architecture, including formulations for filter banks or kernels and convolutional layers, as well as dropout layer mechanisms.

In addition to its application in agricultural settings, the research also explores the utility of CNNs in detecting pandemic diseases such as COVID-19 through image processing techniques, utilizing X-RAY and CT images. Techniques such as image segmentation, enhancement, and transfer learning are employed, with augmentation techniques aiding in image classification. Notably, the study achieved an impressive accuracy rate of 93% in classifying images of individuals affected by COVID-19 versus those of normal individuals.

Moreover, the paper investigates the application of CNNs in fake image detection, utilizing convolutional neural networks for image classification. Various machine learning algorithms, including K-Nearest Neighbors (KNN), Naive Bayes, decision trees, and random forests, are compared, with random forests exhibiting the highest accuracy rates. This comprehensive research contributes to the advancement of CNN-based image processing techniques across diverse domains, from agricultural pest detection to pandemic disease identification and fake image detection, showcasing the versatility and efficacy of CNN models in tackling complex classification tasks.

Skin classification models were prepared in a two-stage approach using dermoscopic images. In the firststage, ISIC 2018 Competition, HAM10000, Benign etc. Detailed information was collected from various sources such as malignant and PH2 depots. Each image was carefully classified and diagnosed according to dermoscopic criteria such as asymmetry, color, pigment network, dots, spheres, lines, regression area and blue white cover. This data is split at an 8:2 aspect ratio for training and testing and rigorously preprocessed with image rescaling and labeling to distinguish benign (labeled as “0”) and malignant (labeled as “1”) groups.

Figure 1 shows a block diagram illustrating the use ofconvolutional neural network (CNN) and support vector machine (SVM) classifiers. The standard training procedure involves feeding a pretraining image set into a deep CNN with five hidden layers. These layers use fusion, integration, and antialiasing operations (ReLU) to remove features from the image. Essentially, the design includes a convolutional layer responsible for subtraction, a composite layer for minimization and dimensionality reduction, and a density layer for classification. To avoid overfitting, a global average layer is used to reduce the number of samples.
Neural network architecture is important in understanding the functioning of the model. Artificial neural networks form the backbone of deep learning models by simulating the connection patterns of neurons in the brain. In the case of CNN, the architecture
includes convolutional, pooling, and dense layers that support feature extraction and classification. This hierarchical structure makes CNN efficient in cross-sectional tasks such as image classification and feature extraction. Overall, the proposed model uses advanced techniques in deep learning and image processing to provide a strong basis for accurate skin classification.

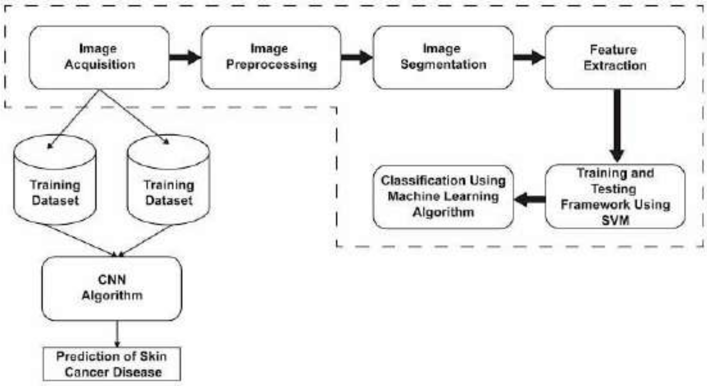

Fig.1 Block diagram using CNN and SVM Classifier

. Neural Network Architecture

An artificial neural network emulates the interconnected structure of neurons in the brain, forming the foundation of deep learning models. Comprising thousands of interconnected nodes, neural networks capture pattern invariance to input data distortions or shifts. In a Deep Convolutional Neural Network (CNN), three fundamental layer types contribute to its architecture: Convolutional Layers, responsible for feature extraction; Pooling Layers, which down sample and reduce dimensionality; and Dense Layers, facilitating classification. This layered structure enables effective representation learning and pattern recognition, making CNNs particularly adept at tasks like image classification and feature extraction in various domains [6].

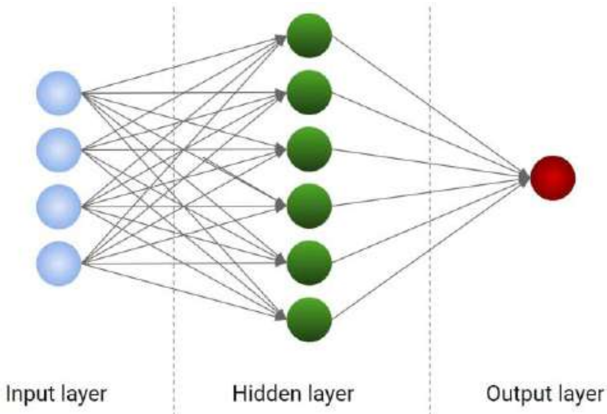

Fig.2 Structure of Neural Network

IV. CNN In Image Classification

In the realm of dermatology, Convolutional Neural Networks (CNNs) have emerged as formidable tools for skin lesion classification, demonstrating remarkable efficacy that often surpasses that of professional dermatologists. The utilization of CNNs in this domain encompasses two primary approaches, each offering unique advantages. Firstly, CNNs serve as proficient image feature extractors, with classification subsequently executed by another classifier. Secondly, CNNs engage in end-to-end learning, which can be further categorized into learning from scratch or leveraging pre-trained models.

Training a CNN from scratch demands a substantial dataset to combat the risk of overfitting, a challenge exacerbated by the limited availability of skin lesion images. Conversely, Transfer Learning (TL) presents a more pragmatic solution by leveraging a pre-trained model. This approach not only adapts well to smaller datasets but also imbues the model with a generalization property, enhancing its ability to classify unseen data accurately.

The adoption of Transfer Learning represents a significant stride in bridging the performance gap between CNNs and professional dermatologists. By harnessing the wealth of knowledge encoded within pre-trained models, TL enables CNNs to achieve superior classification accuracy while mitigating the data scarcity issue inherent in dermatological image datasets. This paradigm shift underscores the transformative potential of deep learning techniques in revolutionizing skin lesion diagnosis and classification, thereby fostering improved medical outcomes and advancing the field of dermatology.

V. Working of CNN Model

CNN is based on a layered structure derived from the multilayer perceptron. It consists of two main components one is convolutive part and another is classification part.

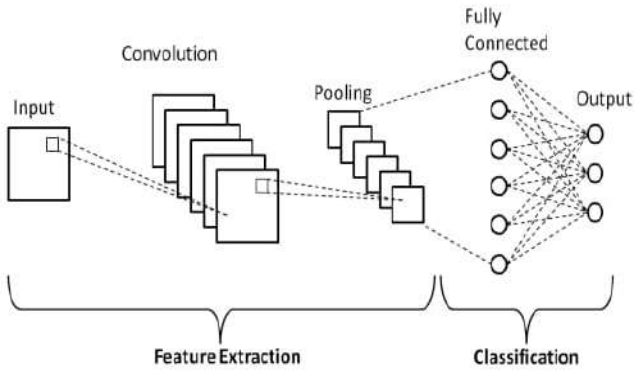

Fig.3 Architecture of CNN Model

A. Convolution Layer

In the convolutional neural network, applications of trained filters to input images are performed methodically through convolutional layers, resulting in the creation of feature maps that are considered an effective outline for the presence of these features within input [2]. This process serves to summarize and outline notable characteristics inherent in the image data. Convolutional layer efficiency cannot be denied, and when deep models are deployed with stacked convolutional layers, it allows the innermost layers closest to the input of the low-level features with elevated fine lines and layers deeper in the model to learn high-order or more abstract features like shapes or the specific objects.

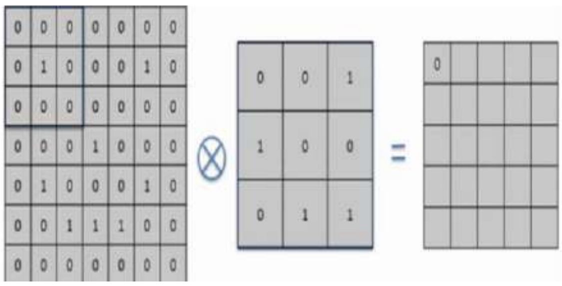

Fig.4 Working of convolution operation

B. Max Polling

In the convolutional neural network (CNN) architecture, the pooling layer plays a crucial role in processing each feature map individually, thereby generating a new set of pooled feature maps. This pooling operation, akin to applying a filter, involves a process that condenses and summarizes information from the feature maps.

Compared to the dimensions of the feature maps, the pooling operation and filter are notably smaller. Typically, the pooling operation utilizes a filter size of 2x2 pixels with a stride of 2 pixels. This strategic downsizing ensures that only the most salient features are retained, effectively reducing the computational burden while preserving essential information.

By systematically pooling information from each feature map, the pooling layer enhances the network's ability to extract meaningful patterns and features from the input data. This meticulous processing contributes to the CNN's capacity for robust and nuanced analysis, ultimately leading to improved performance in tasks such as image classification and recognition.

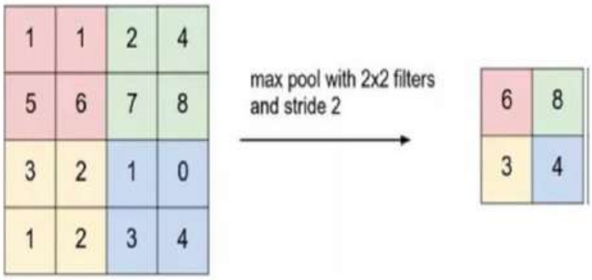

Fig.5 Max Pooling operation

C. Flattening

In the context of transitioning from convolutional layers to the subsequent artificial neural network (ANN) layers, a process known as flattening is employed. This operation involves converting the multi-dimensional feature maps generated by the convolutional layers into a single-column vector format. By flattening the feature maps in this manner, we create a streamlined representation of the image pixels, facilitating seamless integration into the ANN architecture for further processing. This transformation enables the ANN to effectively utilize the extracted features from the convolutional layers, thereby enhancing the network's ability to perform complex tasks such as image classification and recognition.

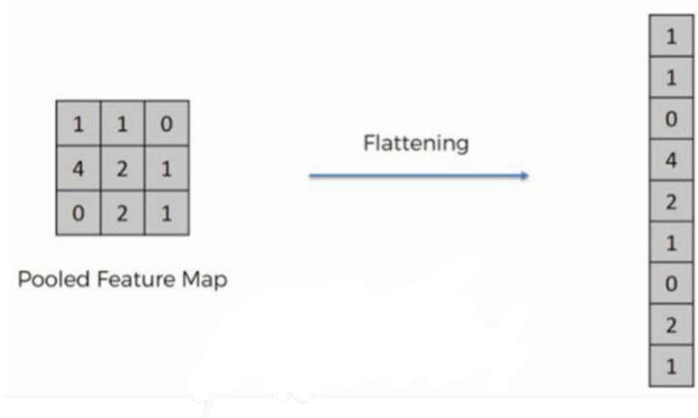

Fig.6 flattening process

D. Full Connection

In the computational architecture of neural networks, the Fully Connected Layer represents the forward-fed layers. Typically situated towards the end of the network, these layers are distinguished by their comprehensive interconnections with preceding layers. The output derived from the final pooling or convolutional layer undergoes a transformation into a flattened format before being transmitted to the Fully Connected Layer. This flattening process ensures the efficient flow of information along connection pathways, optimizing the network's capacity to process and analyze complex data. By integrating the flattened input, the Fully Connected Layer facilitates comprehensive feature utilization, thereby enhancing the network's capability to perform intricate tasks such as classification and prediction.

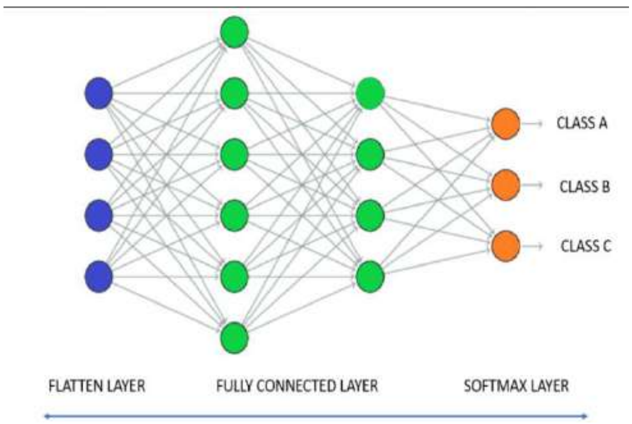

Fig.7 fully connected layer in a neural network

VI. Dataset

The Melanoma Skin Cancer Dataset comprises 10,000 images, serving as a valuable resource for developing deep learning models aimed at accurately classifying melanoma, a potentially fatal form of cancer. Given the critical importance of early detection and treatment in saving lives, this dataset holds significant potential for advancing research in this field.
Specifically, the dataset is partitioned into 9,600 images designated for training the model and 1,000 images reserved for evaluating the model's performance. By leveraging this dataset, researchers can train and test deep learning algorithms to effectively identify melanoma skin cancer, thereby contributing to the development of reliable diagnostic tools and ultimately improving patient outcomes.

VII. SVM Classifier

In the proposed system for cancerous image classification, a Support Vector Machine (SVM) classifier is employed for its simplicity and effectiveness. The SVM algorithm is tasked with taking a set of images and determining whether each input image falls into the cancerous or non-cancerous category. To achieve this, the SVM seeks to establish a hyperplane that maximizes the separation between these two classes, facilitating accurate classification.
Central to the classification process is the utilization of the Gray-Level Co-occurrence Matrix (GLCM) as input to the SVM classifier. The GLCM captures essential textural information from the images, serving as a crucial tool for feature extraction. By leveraging GLCM-derived features, the SVM classifier is trained with pertinent data and grouping information, enabling it to effectively discern between cancerous and non-cancerous images.
Through this approach, the system harnesses the combined power of feature extraction via GLCM and classification by the SVM algorithm to accurately classify input images, thereby contributing to the development of robust diagnostic systems for cancer detection.

VIII. Results and Discussion

Total number of images taken for testing: 1000 [500 (benign) + 500 (malignant)]

- Accuracy=(TP+TN) ÷Total
- Precision=TP÷(TP+FP)
- Recall=Sensitivity=TP÷(TP+FN)
- Specificity=TN÷(FP+TN)
- F1Score=2×Precision×Recall÷(Precision+Recall)

where TP is the true positive count, FP is the false positive count, FN is the false negative count and FP is the false positive count.

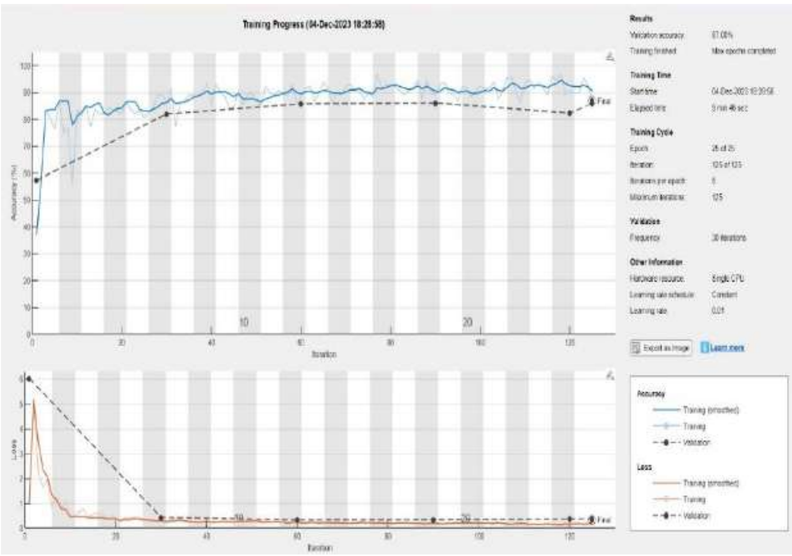

Fig.8 Loss and Accuracy Curve

After 25 EPOCHS it is seen that the loss has gradually decreased and the accuracy of the model has gradually increased.

```
  Name                Size            Bytes  Class     Attributes

  featuresTrain      700x2             5600  single


accuracy =

    0.8600
```

Fig.9 Accuracy report

IX. Conclusions

This study endeavors to employ Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) for the identification of skin cancer, recognizing the persistent challenges hindering the practical application of image-processing techniques in this domain. The acquisition of high-quality images emerges as a paramount obstacle, presenting inherent difficulties, particularly in certain scenarios. Furthermore, the morphological similarities among different types of skin cancers pose a formidable challenge to accurate classification using these methodologies. A prospective avenue for development lies in the creation of an application centered around the proposed model, offering users an interface to upload images of their affected skin regions and obtain predictions along with confidence ratings, thereby enhancing accessibility and usability. While existing research predominantly focuses on discerning whether a given lesion image is cancerous, it falls short in addressing broader inquiries regarding the presence of specific skin cancer symptoms across the body. To address this limitation, future research could explore the integration of autonomous full-body photography, thereby facilitating comprehensive assessment and diagnosis. By automating and expediting the image acquisition process, this approach holds promise in providing holistic insights into the distribution of skin cancer symptoms across the body .Furthermore, recent advancements in deep learning have introduced the concept of auto-organization, a form of unsupervised learning aimed at identifying features and uncovering patterns within image datasets. Operating within the framework of CNNs, auto-organization techniques offer the potential to enhance the representation of features extracted by expert systems, thereby bolstering the accuracy of image processing systems, particularly in medical imaging applications where precise identification of subtle features is critical for accurate disease diagnosis. While auto-organization remains an area of ongoing research and development, its exploration holds significant promise for improving the efficacy and reliability of image processing systems in medical contexts, heralding a potential paradigm shift in the field of diagnostic imaging.

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TRANSMISSION LINE FAULT DETECTION

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Abstract-Electricity has become a basic necessity for all of us. The last few days when Power was once a beautiful treasure hidden in the cities, for it now reaches out far and wide the corner of the world. This spread of electricity created an incredible amount of energy system networks, where transmission wires play an important role in power distribution. However, due to the extensive nature of these pipelines, drawbacks and drawbacks are inherent part of the system. These deficiencies can cause significant damage electrical equipment, including transmission lines, generators and transformers. Ensure consistent and reliable power, is essential to minimize these errors to detect and deal with them as soon as possible and when they occur. The main objective This project should include comprehensive pipeline inspection plan faults, from which nearly 90% of all electrical system faults are found to originate only pipelines. This emphasis is key in managing transmission line faults due to the way these cables work the backbone of the overall power distribution. The proposed system will include latest technologies and techniques for continuous monitoring of the health of infectious lines. It will use a variety of sensors, data analytics and artificial intelligence To detect potential irregularities, discrepancies, or errors in real time. This is a proactive approach, It not only identifies errors as they occur but also provides predictive capability to resolve issues Increasingly, it ultimately contributes to a more robust and reliable power system. Also, the project focuses on creating a user-friendly interface that enables energy system operation.

1. INTRODUCTION

The modern world's continued functioning, growth, and development heavily depend on a consistent and reliable supply of electrical power. From lighting our homes to powering industries and sustaining essential infrastructure, electricity plays a vital role in every aspect of our lives. At the core of this intricate power delivery system are overhead electrical power lines and the transmission sector, working in unison to ensure the seamless flow of electrical energy.

Overhead electrical power lines, also known as transmission lines, are an essential component of the electrical power grid. They consist of a network of high-voltage conductors supported by a complex system of towers and poles that stretch across vast landscapes. These lines are designed to transport electricity from its source, such as power plants or renewable energy facilities, to substations and then further into the distribution network, where it is delivered to homes, businesses, and industries. The use of overhead lines for electrical transmission offers various advantages, including cost-effectiveness, ease of maintenance, and adaptability to diverse geographical terrains. The transmission sector encompasses the planning, construction, operation, and maintenance of the infrastructure necessary for transmitting electrical power. It is a critical link in the energy supply chain, ensuring that the electricity generated at power plants reaches its intended destination reliably and efficiently.

In the pages that follow, we will journey through the key aspects of overhead electrical power lines and the transmission sector, delving into topics such as line design and engineering, grid reliability, safety measures, environmental impacts, and the potential for future advancements. We aim to provide a thorough understanding of the critical role that overhead lines and the transmission sector play in the global energy landscape by the end of this report, along with an outlook on future challenges and opportunities.

A. Line-to-ground faults:

Description: A line-to-ground fault occurs when one of the conductors (power lines) unintentionally comes into contact with the ground or an object that is grounded, causing electricity to flow into the ground.
Power Wastage Statistics: Significant
Impact on Power Sector:
High Energy Losses: Line-to-ground faults result in significant energy losses due to ”leakage currents.” These currents do not contribute to useful work and can dissipate power as heat.
Reduced System Efficiency: As energy is wasted, the overall efficiency of the transmission system decreases.
Increased Maintenance Costs: Frequent faults require maintenance, which is costly and im- pacts the reliability of the power supply.
Potential Environmental Impact: Power wastage due to line-to-ground faults can have environmental consequences as it increases the carbon footprint of power generation.[1]

B. Line-to-Line Faults:

Description: Line-to-line faults occur when two conductors of the transmission line come into direct contact with each other, causing a short-circuit.

Power Wastage Statistics: Substantial. Impact on Power Sector.

Short-Circuits and Power Outages: Line-to-line faults often result in short-circuits that can cause power outages, disrupting the supply to end-users and industries. Equipment Damage: The high currents associated with short-circuits can damage transformers, circuit breakers, and other equipment, leading to costly repairs.

Disruption of Power Supply: The disruption in power supply due to line-to-line faults can have economic implications for businesses and inconvenience for consumers.

Thermal Faults:

Description: Thermal faults occur when the temperature of the overhead line rises excessively due to an overload or high current flow.

Power Wastage Statistics: Notable.

Impact on Power Sector: Reduced Power Transfer Capacity: Thermal faults can reduce the power transfer capacity of the line, limiting the amount of electricity that can be safely transmitted.

Risk of Equipment Damage and Fires:

Overheating of conductors can lead to equipment damage and may even result in fires. This poses a safety hazard for both the infrastructure and nearby communities

.

Necessity for Load Shedding:

During periods of high demand and thermal stress on the lines, utilities may resort to load shedding or curtailment to prevent further overheating and potential damage. Addressing these faults through measures such as regular maintenance, monitoring systems, fault detection technology, and grid modernization is essential to minimize power wastage and ensure the reliability of the electrical power transmission system. Reducing faults not only conserves energy but also enhances the overall performance and resilience of the power sector, ensuring a stable and efficient electricity supply to consumers and industries.

How Much Power Loss in Transmission Lines?

The invention of electricity has been one of the greatest inventions in history. And although people have lived without it at one time, it is impossible to imagine how the world functions today without it.

Power plants generate electricity away from the load. In order to minimize power loss in transmission lines, so many different types of conductors have been installed between power plants and important customers. This is due to the fact that electricity is generated at power plants away from the load. Power loss will be discussed in this article.[2]

What Causes Power Loss in Transmission Lines?

When transmitting electricity, broadband currents are used, which results in the loss of electricity. One significant source of power loss is the Joule effect, which occurs in transformers and power lines. Energy is lost through the heating of conductors. The primary purpose of transmission conductors is to resist current flow. Although the resistance per kilometer is relatively low, it can have a significant impact on transmission lines. Consequently, this causes the conductor to be heated and increases its temperature. As a result, the resistance of the conductor increases as the conductor’s temperature rises, resulting in transmission line loss.

How Much Power Loss in Transmission Lines?

Most people are curious about how much energy is lost when electricity enters their homes. To answer this question, you must break it down into a step-by-step procedure in order to comprehend what it feels like to be electrocuted under the house.

The making of electricity

The principle of power plants remains the same regardless of the raw material used to pro- duce it. For example, power plants can run on natural gas, coal, petroleum, and nuclear energy.

In order to generate electricity, it is necessary to burn energy-producing materials. By con- verting water into steam, the heat is then used to turn the turbine. However, only about two thirds of the energy produced is converted into electricity as a result of the thermodynamic limitations of the process. As a result, other energy is lost.

Transmission and distribution

A method of power distribution that is efficient is necessary because most power plants are located far from residential areas. A high voltage cable was the first form of electrical communication that was used to transport electricity over long distances, reducing energy loss by reducing energy loss. The transformers receive the distributed power.
There is some power loss in the transmission lines during distribution, which causes some power loss in the transformers. The transformers reach voltages that can be as high as 120 volts or more, ensuring your safety.[2]

Different power is lost at different stages

- It is estimated that between 1 and 2% of the power generated by the generator is lost in the step-up transformer.
- Transmission lines lose between 2 and 4 percent of their energy.
- The transition from transmission line to distribution step-down results in a loss of approximately one to two percent of the energy.
- The distribution of energy results in the loss of 4-6% of energy.
- The average energy loss between power plants and consumers is between 8-15%.[2].

Objectives

1. To detect transmission line faults such as Line to Line, Line to Ground and Thermal Faults.
2. To minimize manual investigation of the faults.
3. To protect the load system as soon as fault occurs.

C. SYSTEM MODEL

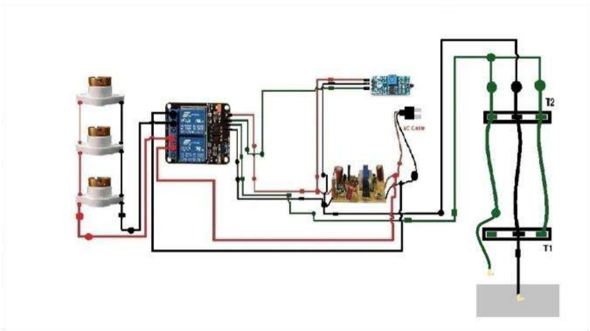

Fig. 1: System Model

Double Channel Relay Module

While a relay can be used to close or open a circuit manually, it can be used to connect or disconnect two circuits as well. Relays are simple electromechanical switches. An electrical signal is used instead of manual operation to control an electromagnet, which in turn controls another circuit in the two-way relay model, which consists of a two-way relay module. A relay module can be used to control two single-signal circuits. Two-channel relays, also known as dual-channel relays, are electrical devices used for a variety of purposes including transmission and over-the-line protection in the case of overhead power lines, generally the two-way relays act as a safety component system to ensure safe and reliable operation of the transmission lines Here is how it works on wireless safety.

1. Fault Detection: The primary function of a double-channel relay in overhead line safety is to detect faults or abnormalities in the power transmission system. These faults can include short circuits, line overloads, insulation failures, or other electrical issues.

2. Redundancy: A double-channel relay consists of two separate and redundant channels, often labelled as Channel A and Channel B. This redundancy is crucial for reliability and safety. Both channels continuously monitor the electrical parameters of the transmission line independently.

3. Comparison: The key safety feature of a double-channel relay is its ability to compare the data from the two channels. If both channels report the same parameters within specified tolerances, it indicates that the transmission line is operating normally.

4. Divergence Detection: If the data from the two channels diverge beyond the preset tolerances, it is a clear sign that a fault or abnormal condition has occurred. This could be a short circuit, an overload, or some other issue on the transmission line.

5. Trip Action: When a divergence is detected, the double-channel relay can be programmed to initiate a trip action. This action could include opening circuit breakers, disconnecting the power supply, or triggering an alarm to alert operators or maintenance personnel. The specific response depends on the design and programming of the relay.

6. Safety Enhancement: The redundancy of the double-channel relay significantly enhances safety. Even if one channel were to malfunction or provide inaccurate data, the comparison with the other channel ensures that false alarms or missed faults are minimized, helping to prevent potentially catastrophic failures on the transmission line.

7. Remote Monitoring: In modern power systems, double-channel relays can often be integrated into remote monitoring and control systems. This allows for real-time monitoring of the transmission lines from a central control station, improving the efficiency and responsiveness of maintenance and safety measures. The Double Channels Relay Module is a convenient board dual channel relay module are also used

- Switching mains powered loads
- Controlling a circuit by one signal
- Controlling larger loads and devices
- Serving as remote and intelligent control of the connected circuit's power supply and disconnection
- Independent control of two form C contacts

Specifications :

• 250V AC and 30V DC.
• Operating Voltage (VDC): 2.55˜.5
• Trigger Voltage (VDC): 5
• Trigger Current (mA): 20
• Switching Voltage (VAC): 250@10A • Switching Voltage (VDC): 30@10A
• Operating Temperature (°C): -40 to 85 • Storage condition (°C): -65 to 125
• Transmission Distance: 400m (max.) • Baud Rate: 9600

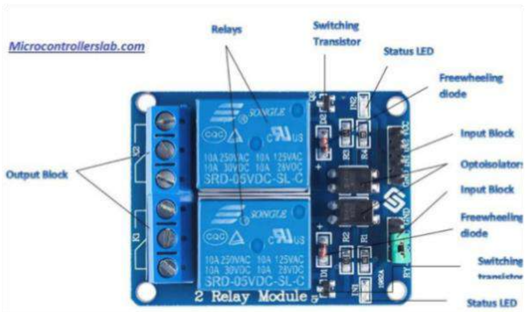

Fig. 2: Dual Channel Relay

a. *Thermistor Module*

Fig. 3: Thermistor Module

A thermistor is a temperature indicator made of sintered semiconductor material that drastically changes resistance in response to even small changes in temperature The resistance of a heat sink typically decreases with increasing temperature because thermistors generally have temperature negative thoughts. Thermistor The main thermal temperature sensor modules are the NTC thermistor, LM393 comparator, switching resistor (Trimmer), power LED, and output LED.[4]

Working of the thermistor:

As the temperature around the thermistor increases, the conductivity of the element in- creases, causing the resistance of the thermistor to decrease. Thus, a considerable amount of energy is used in the LM393 comparison. This value is then compared to the threshold voltage by the LM393. When this voltage crosses the threshold value, the output of the temperature sensor is low 0. In other words, as the temperature near the thermistor increases, the resistance of the thermistor increases and the conductivity of the element decreases so that a voltage is applied across the LM393 comparator. This voltage again compares to the threshold voltage supplied by LM393. However, the voltage is less than the limit at this time. Thus, the output of the temperature sensor is high (1).[4]

Specifications:

- Digital Output (DO): 0 or 1
- VCC+: +5V Power Supply
- Ground (GND): Ground(-ve) power supply
- Analog Output (AO): Analog output (0 or 1023)

b. *AC to DC Converter*

Fig. 4: ADC Module

An AC to DC converter, also known as a rectifier, is an electronic device or circuit that converts alternating current (AC) to direct current (DC) This conversion is important because many electronic devices and circuits operate on DC power, while utilities provide it , electrical appliances Most of the electricity produced was AC.[5]

AC to DC converters play an important role in a variety of applications, including powering consumer electrical appliances, industrial equipment and alternative energy systems. There are a number of methods for this conversion, each with n 'own advantages and disadvantages. Here are common types of AC to DC converters:

1. Half-Wave Rectifier: A half-wave rectifier can take only half of the input AC cycle, effectively converting AC to pulsating DC While simple it is inefficient and not suitable for most applications because of power loss the value is greater

2. Full-Wave Rectifier: Full-wave rectifier is an efficient way to convert both phases of AC cycle to DC. To do this, it usually uses a diode, which keeps the DC pulse low.

3. Bridge Rectifier: A bridge rectifier is a type of full-wave rectifier that uses the bridge structure of a diode to convert AC to DC. It provides a smooth DC output and is widely used in power supply circuits.

4. Voltage Multiplier: Voltage multipliers are circuits that use capacitors and diodes to increase the DC output voltage above what a simple rectifier can They are usually used in high-voltage applications or special purposes.

5. Switched-Mode Power Supply (SMPS): SMPS is a modern and efficient way to convert AC to DC. It uses high-frequency switching techniques and incorporates components such as transformers and inductors to monitor and regulate the output voltage. SMPS is commonly used in powering computers, smartphones, and many other electronic devices.

6. Linear Power Supply: Linear power supply is an alternative to AC-DC conversion. A transformer is used to step down the voltage, followed by linear regulators to stabilize the output voltage. Although linear power supplies are not as efficient as SMPS, they provide a very stable and low-noise DC output, making them suitable for some applications.[5]

The choice of AC to DC converter depends on the specific requirements of the application. Factors such as efficiency output voltage stability, size, and cost play an important role in selecting the right converter. Often, you will find a combination of these methods used to meet the needs of different electrical circuits in the same device or system. In summary, AC to DC converters are essential components in the world of electronics and electrical engineering, capable of powering a wide range of devices and systems through direct current, even if the primary power source is alternating current . The choice of the converter type depends on the specific application and the desired performance characteristics.

. Specifications:

- Input voltage : 12V DC
- Output voltage : 220V AC
- Power rating : 40Watt
- Frequency : 50HZ/60HZ
- Inbuilt over voltage, over current, and short circuit protection

DC to DC Converter

Fig. 5: DC – DC Converter Module

A DC to DC converter, also known as a voltage regulator or a DC-DC power converter, is an electronic device that converts one direct current (DC) voltage into another DC voltage. These converters are essential components in various electronic systems, as they allow for the efficient and reliable regulation of power supply voltages. DC to DC converters can be found in a wide range of applications, from mobile devices and automotive electronics to industrial machinery and renewable energy systems.[5]

DC to DC converters serve several important purposes, including:

1. Voltage Regulation: The main function of DC to DC converters is to control and stabilize the voltage level. The input voltage can be increased or decreased to achieve the desired output voltage, ensuring adequate voltage for the electronics.

2. Voltage Conversion: DC to DC converters can convert high-voltage DC to low-voltage DC or vice versa. This is particularly useful in situations where different components or subsystems require different energies for proper operation.

3. Efficiency Improvement: DC to DC converters can improve the overall energy efficiency of a system by ensuring that power is delivered at the optimal voltage for the load. This can reduce power losses and extend the life of batteries in portable devices.

There are several different types of DC to DC converters, each with its own characteristics and use cases:

1. Buck Converter (Step-Down): A buck converter reduces the input voltage to give a lower output voltage. It is commonly used to power devices that require less power than an input source such as most electronic devices.

2. Boost Converter (Step-Up): The boost converter increases the input voltage to give a higher output voltage. This is useful in applications such as LED lighting and battery- powered devices that require power in excess of the battery's nominal capacity.

3. Buck-Boost Converter: This converter can either step down or step up input voltage to give a stable output voltage. It is versatile and can be used in applications where the input voltage can vary or when a fixed output voltage is required.

4. Flyback Converter: Flyback converters are commonly used to separate input and output voltages in power supplies. It stores energy in a transformer over time.

5. Cuk Converter: The Cuk converter is designed for applications that require both step-up and step-down voltage conversions. It's suitable for applications with input voltage fluctuations.

6. SEPIC Converter: The Single-Ended Primary-Inductor Converter (SEPIC) is a versa- tile converter that can step up or step down the input voltage, making it useful for battery charging and LED driver circuits.

7. Full-Bridge Converter: Full-bridge converters are often used in high-power applications, such as electric vehicles and renewable energy systems, to efficiently convert DC power.[5]

The choice of DC to DC converter depends on the specific requirements of the application, including input voltage range, output voltage, current, and efficiency considerations. These devices play a critical role in modern electronics and power systems by ensuring stable and efficient power delivery, making them an integral part of our technologically advanced world.

Jumper wires

Fig. 6: Jumper Wires

Jumper wires are essential components in electronics and prototyping. They are short, flexible wires with connectors on each end, typically used to create electrical connections be- tween various electronic components, such as micro-controllers, sensors, and circuit boards. Jumper wires allow for quick and temporary connections, making it easy to experiment, test, and modify circuits during the development and troubleshooting of electronic projects. They come in various lengths, colors, and connector types, making them versatile tools for connecting and bridging components in a wide range of applications.

Bulbs

3 bulbs are used in the prototype in order to help detect the fault in the transmission line. Power required : 9 watts

D. SYSTEM ARCHITECTURE

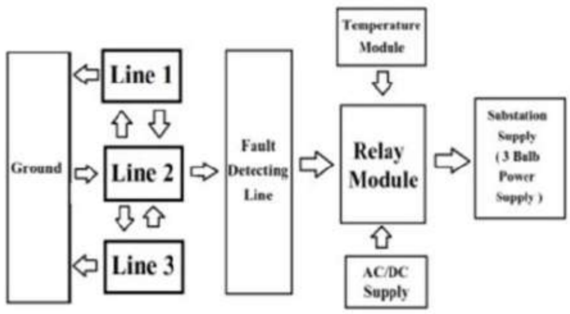

Fig. 7: System Architecture

E. WORKING OF THE SYSTEM

In order to prevent any accidents from occurring on the transmission lines, we are using a novel approach for detecting transmission line faults, such as line-to-line and line-to-earth faults, and for automatically disconnecting the transmission line. We use a microcontroller that is connected to a DC 5 volt power supply to ensure operational safety, and the micro controller’s digital pins are connected to various line and ground inputs. We use a 16 MHz crystal connected to a microcontroller (suspected) in order to generate oscillations and to carry out the programme for line-to-line detection. Additionally, the microcontroller activates and disables the relay whenever a short circuit is established between the digital pin and the Vcc line, disconnecting the load. We also utilize DC 5 volts and digital pins. In the controller, a program continuously monitors the short circuit between the digital pin and the Vcc line; the Vcc line and the digital pin are placed on the pole for monitoring purposes. As with line-to-line transmission, we utilize a similar method when operating line-to-ground. If the transmission line pole is disconnected or broken, the live wire falls to the ground as a result. Digital pin wire is suspended from the pole in this instance and is therefore at risk of falling to the ground in case of a disconnect or broken cable. Upon receiving the ground potential from the wire, the Arduino controller runs the programme and immediately disables the relay to disconnect the transmission line. Use flame sensors located near the cable joints to keep watch for any type of fire or flame that may occur on the transmission line. A signal is sent to the microcontroller unit upon detection of a fire or flame in the transmission line, which disables the relay, disconnecting the transmission line and preventing further unintentional damage.

V.ADVANTAGES ANDD APPLICATIONS

A. Advantages

1. In transmission lines, losses due to line-to-line faults can be stopped.
2. Losses caused by transmission line ground to line faults can be stopped.
3. We are able to prevent transmission line losses caused by fire and temperature faults.
4. Improves the efficiency of gearbox.
5. This project saves money for our government by preventing gearbox line faults.

B. Applications

1. Printed circuit board traces.
2. Telephone lines
3. Applications of microwave technology, such as radar and global positioning systems (GPS).
4. Employed for electromagnetic wave guidance.
5. High frequency circuit boards

VI.TRANSMISSION LINE PROTECTION TRENDS

The market size for Transmission & Distribution Fault Detection is expected to experience a notable increase during the period spanning 2022 to 2027. This growth is attributed to a growing emphasis on minimizing power losses on a global scale. As the power demand continues to evolve, both governmental bodies and private entities are placing significant importance on the reduction of power wastage. This heightened focus is consequently con tributing to the positive trends observed in the transmission and fault detection industry. Fault identification is currently performed by comparing PSCADs (Positive Sequence Current Angle Differences) of the faulty line with those of all the other nodes, where the maximum PSCAD indicates the faulty line. The market landscape of the global transmission and distribution fault detection sector is anticipated to exhibit a degree of fragmentation, featuring the participation of various key players, including but not limited to G&W Electric, Fuji Electric, Applied Material, Schnei der Electric, Sentient Energy, and OptaSense. These industry participants are poised to place a strong emphasis on the implementation of strategic alliances, engagement in mergers and acquisitions, the introduction of new products to the market, and active involvement in research and development endeavours. Such concerted efforts are geared towards attaining a competitive edge within the industry. As an illustrative example, in the month of July 2020, Schneider Electric made a noteworthy announcement regarding the establishment of four control centers dedicated to overseeing Egypt's national energy grid. Furthermore, the company is actively considering the deployment of 12,000 smart ring main units, strategically designed to augment energy availability by facilitating fault detection and the reconfiguration of the network to ensure optimal stability. In addition to these initiatives, Schneider Electric is contemplating a comprehensive upgrade of 1,000 distribution points and substations, intending to seamlessly integrate them into the evolving landscape of the smart grid. The growth of the sector is projected between 2022 and 2028.[7]

VII. CONCLUSION AND FUTURE SCOPE/WORK

In conclusion, the successful completion of this minor design on transmission line fault discovery, integrating a double-channel relay, thermistor module, AC-DC motor, and DC-DC motor, marks a substantial corner in enhancing the trustability and safety of power transmission systems. The combined operation of these technologies has redounded in a comprehensive fault discovery model able to address thermal, line-to-line, and line-to-ground faults. The objectification of the double-channel relay adds a subcaste of complication to the fault discovery process, offering bettered delicacy and responsiveness. The thermistor module contributes to the system's capability to describe thermal faults instantly, icing the forestallment of overheating and implicit damage to the transmission line factors. The AC- DC and DC- DC transformers play a vital part in converting and regulating the power force, easing flawless integration of the fault discovery system into transmission networks. Through rigorous testing and confirmation, we've demonstrated the efficacity of our model in relating and segregating colourful fault types, thereby securing the integrity of the transmission line. The versatility of our approach not only contributes to the trustability of power distribution and establishes a foundation for unborn inventions in power system protection. As we look ahead, exploring openings for scalability and further refinement of the fault discovery model is essential. also, considerations for real-world perpetration, including comity with different transmission architectures and rigidity to evolving technological norms, should be addressed in unborn exploration. In conclusion, this design signifies a significant step towards creating a robust and adaptive transmission line fault discovery system. By integrating multiple factors, we've developed a model that isn't only able to guard against colourful faults but also showcases the eventuality of advancements in power system adaptability. This work sets the stage for continued disquisition and invention in the field of power transmission, aiming to produce further dependable and secure energy architectures for the future.

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EV INTEGRATION IN HOME LOAD ENERGY MANAGEMENT BY PARTICLE SWARM OPTIMIZATION

Dr.Gyan Ranjan Biswal, Sai Binayak Rout, Nitindra Kumar Sahoo, Akash kabi, Mohit Deviprasad, Lipun Bariha

Abstract—***This paper presents a novel approach to decentralized Home Energy Management System (HEMS) design, aimed at optimizing energy utilization according to predefined customer preferences, with a particular emphasis on leveraging the adaptability and mobility of home appliances, notably Electric Vehicles (EVs). Within this system, bidirectional EV flow integration enables the EV to serve both as a household load and a power source during peak demand periods. The study formulates the problem as a cost-minimization and load scheduling task, with the primary objective of minimizing the Peak-to-Average Ratio (PAR) while accommodating user preferences. Optimization is facilitated through the application of a particle swarm optimization (PSO) methodology. The central goal of HEMS implementation lies in reducing energy costs for end-users through efficient load management. By integrating EVs into HEMS, the system achieves enhanced flexibility and efficiency in energy resource management, contributing to load balancing and potential cost reductions during periods of peak demand. Additionally, the paper categorizes home appliances into fixed, generic schedule, and flexible schedule types, underscoring their role in shaping energy consumption patterns. Furthermore, the study provides a comprehensive overview of the Particle Swarm Optimization (PSO) algorithm, elucidating its components and iterative process, with a focus on tuning factors for balancing exploration and exploitation. Overall, this paper presents a unique framework for optimizing home energy management and integrating EVs into the system, offering promising avenues for cost reduction and enhanced energy efficiency***.

Keywords—HEMS, PSO, EV, PAR, Energy Management

1. INTRODUCTION

The integration of smart grid technology has transformed the traditional power grid by facilitating bidirectional power and information exchange between utility providers and consumers. This bidirectional flow improves the efficiency and flexibility of the power grid, addressing challenges posed by emerging technologies and diverse energy loads. With a heightened sensitivity to stability and cost considerations, smart home energy management has emerged as a vital component of the smart grid.

To enhance the efficiency of Home Energy Management Systems (HEMS), this study introduces a novel swarm-based meta-heuristic search approach. The primary focus lies in optimizing the scheduling of smart appliances within HEMS to minimize energy costs and accommodate the dynamic energy flow patterns of electric vehicles (EVs). The research is driven by the evolving landscape of smart home energy management, wherein the integration of EVs presents opportunities for improved energy utilization.

The proposed approach utilizes the State of Charge (SOC) level of the EV as a critical parameter for optimizing home appliance scheduling. Various factors, including energy thresholds and user preferences, are considered in this optimization process, ensuring a tailored approach to home load scheduling. The study's overarching objective is formulated using a meta-heuristic particle swarm optimization (PSO) technique, strategically applied to schedule both home loads and EV charging activities. The ultimate goal is to minimize the daily energy bill while enhancing the utilization of daily average power by mitigating the peak-to-average ratio, a critical consideration in smart home energy management.

2. HOME ENERGY MANAGEMENT SYSTEM

A decentralized Home Energy Management System (HEMS) has been devised, centered around predefined customer preferences and harnessing the flexibility of household appliances. The system primarily focuses on integrating Electric Vehicles (EVs) in a bidirectional capacity. Within this framework, the EV serves as a load within the household and can also function as a power source during peak periods. It is assumed that the EV battery maintains a nonzero State of Charge (SOC) upon returning home, allowing it to be connected in Vehicle-to-Home (V2H) mode. This configuration helps alleviate peak-time power surges and lowers overall energy costs. During off-peak hours, the EV is connected in Home-to-Vehicle (H2V) mode for charging purposes. The system's objective is formulated as a task to minimize costs and schedule loads while considering user preferences, with a focus on reducing the Peak-to-Average Ratio (PAR). Optimization is achieved through the utilization of particle swarm optimization techniques.

A. EV IN HEMS

In a Home Energy Management System, bidirectional Electric Vehicle (EV) flow refers to a setup enabling energy transfer not only from the grid to the EV for charging but also from the EV back to the home or grid. This bi-directional capability enhances flexibility and efficiency in energy resource management. During peak demand times or high electricity price periods, the EV can supply excess energy back to the home or grid, aiding load balancing and potentially reducing energy expenses. Conversely, in low-demand periods or when renewable energy generation is abundant, the EV can charge, storing energy for future use. Implementing bidirectional EV flow necessitates sophisticated control systems and smart charging infrastructure. It provides a dynamic and adaptable approach to home energy management while optimizing the utilization of renewable energy sources and grid assets.

Through a microcontroller for automation, contributing to a comprehensive overview of the field's moisture dynamics. By integrating this information into the webpage interface, farmers can remotely access and monitor soil moisture levels, enabling precise irrigation scheduling and preventing both overwatering and under-watering of crops. The utilization of soil moisture sensors in this venture underscores the significance of targeted data collection for sustainable and efficient agricultural practices. This technology empowers farmers to implement precise irrigation strategies, ultimately leading to improved crop health, resource conservation, and enhanced overall yield.

B. Types of Appliances

i. Fixed appliances

Fixed appliances, such as televisions, lighting systems, and refrigerators, operate continuously and consume a constant amount of power. They are considered non-schedulable due to their manual operation and immediate comfort they provide to users, making it difficult to delay their usage.

ii. Generic schedule appliances

Generic schedule appliances also maintain a consistent power consumption pattern but can be interrupted up to a certain point in their operation based on customer preferences. The controller can adjust their starting times; examples include washing machines, dishwashers, dryers, and induction cookers. The calculation pertains to these connected generic appliances.

iii. Flexible schedule appliances

Flexible schedule appliances within a home energy management system are devices that can adapt their operation timing or energy consumption based on various factors such as user preferences, energy costs, or overall demand on the electrical grid. These appliances are designed to be responsive to changing conditions, allowing homeowners to optimize energy usage, reduce costs, and contribute to a more efficient and sustainable energy consumption pattern. They are shift-able but can be interrupted and have multi-level energy consumption patterns. An example of such an appliance is an electric vehicle (EV), where the billing depends on its connection mode, whether it is connected as a load or in a bidirectional manner.

Its versatility and ease of programming make it an ideal choice for interfacing with the sensors and managing the communication between the field and the database. The microcontroller's open-source nature allows for flexibility in code development, enabling customization to suit the specific needs of the precision agriculture system. Its role in real-time data processing and transmission underscores the importance of a reliable and programmable microcontroller in enabling remote monitoring and data-driven decision support systems for precision agriculture.

C. PARTICLE SWARM OPTIMIZATION (PSO)

Particle Swarm Optimization (PSO) stands as a noteworthy computational intelligence technique initially proposed by Kennedy and Eberhart in 1995, finding its roots in swarm intelligence methods and belonging to the broader category of evolutionary computation—one of the foundational pillars of Computational Intelligence (CI). Inspired by the collective behavior observed in natural systems such as schools of fish or flocks of birds, PSO seeks to emulate the navigation and foraging patterns exhibited by these entities [5].

The fundamental premise of the PSO algorithm involves the deployment of a large population of entities known as particles, each acting as a potential solution within a multi-dimensional search space. In this context, particles navigate through the hyperspace with the collective goal of discovering the optimal solution. Each particle keeps track of its individual best location, assessed through a fitness function that measures its proximity to the optimal solution. Additionally, particles maintain awareness of their current movement direction and intensity, represented by their velocities. Furthermore, they are informed about the global best location, denoting the optimal position among all particles.

The iterative progression of the PSO algorithm involves particles continuously updating their positions and velocities based on historical information. At each iteration, particles adjust their velocities stochastically, taking into account their individual historical optimal positions as well as the historical global best position among all particles. This dynamic process ensures that particles collectively converge towards the optimal solution in the search space.

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \quad \text{.....(1)}$$

Here, x_{id}^{t+1} and x_{id}^{t} represent the next and current positions of the particle, respectively, and v_{id}^{t+1} is the velocity vector indicating the upcoming direction and intensity of movement.

The velocity update equation is given by:

$$V_{id}^{t+1} = w.V_{id}^{t} + c_1\, rand\,(0,1) \cdot \left(p_{id}^{t} - x_{id}^{t}\right) + c_2.\ rand(0,1).\left(p_{gd}^{t} - x_{id}^{t}\right) \quad \text{.....(2)}$$

Here, c1 and c2 are positive acceleration constants, rand1 and rand2 are weight factors in the range of [0, 1], and Pid and Pgd represent the individual and global best particle positions, respectively. The inertia weight Vid influences the impact of the particle's previous velocity on the update, with a value of one indicating the original PSO algorithm, and other values referring to the canonical PSO algorithm.
The iterative process continues until either a particle location close enough to the desired outcome is found, or the threshold of allowed iterations is exceeded. This amalgamation of historical information and dynamic movement strategies makes PSO a versatile and efficient optimization algorithm with applications across diverse domains.
The provided text outlines key components and considerations in the context of Particle Swarm Optimization (PSO) algorithms, specifically focusing on Equation (2) and its three distinct components: inertia, cognitive/individual, and social.

1. Inertia Component $w.V_{id}^{t}$:

This component, represented by the term $w.V_{id}^{t}$ is responsible for maintaining the current movement direction (velocity) of individual particle.

The inertia weight (w) is a crucial parameter influencing the balance between exploration and exploitation in PSO algorithms.

Typically, the inertia weight decreases linearly across iterations. Initially set at a high value (e.g., 0.9), it allows the swarm to move freely and quickly explore the search space.
As iterations progress, the inertia weight decreases, shifting the focus from exploration to exploitation, emphasizing the optimization of neighborhoods around individual and global optima.

2. Cognitive/Individual Component $c_1\, rand\,(0,1) \cdot \left(p_{id}^{t} - x_{id}^{t}\right)$:

This C_1 depicts the distance between each particle's current position and its own's best location found p_{id}^{t}.

c1 is a tuning factor for the cognitive component, influencing the impact of personal best information on the particle's movement.

rand(0,1) is a random parameter used to introduce stochasticity into the algorithm.

3. Social Component $c_2.\ rand(0,1).\left(p_{gd}^{t} - x_{id}^{t}\right)$:

This component calculates the distance between the particle's current position and the best position found by the entire swarm p_{gd}^{t} ie. global best.

c_2 is a tuning factor for the social component, determining the influence of global best information on the particle's movement.

rand(0,1) is a random parameter introducing randomness, contributing to the diversity of the swarm's search.
The text emphasizes the importance of tuning factors c_1, c_2, and the inertia weight (w) to modify the impact of cognitive and social components on velocity. It also highlights the linear decrease of the inertia weight across iterations to shift the algorithm's focus from exploration to exploitation.

In addition to these components, the text mentions the necessity of setting limits, such as maximum velocity and maximum aggregated acceleration constants, to ensure the convergence of the swarm. The provided flowchart (Figure 1) represents a simplified overview of the PSO algorithm's steps.

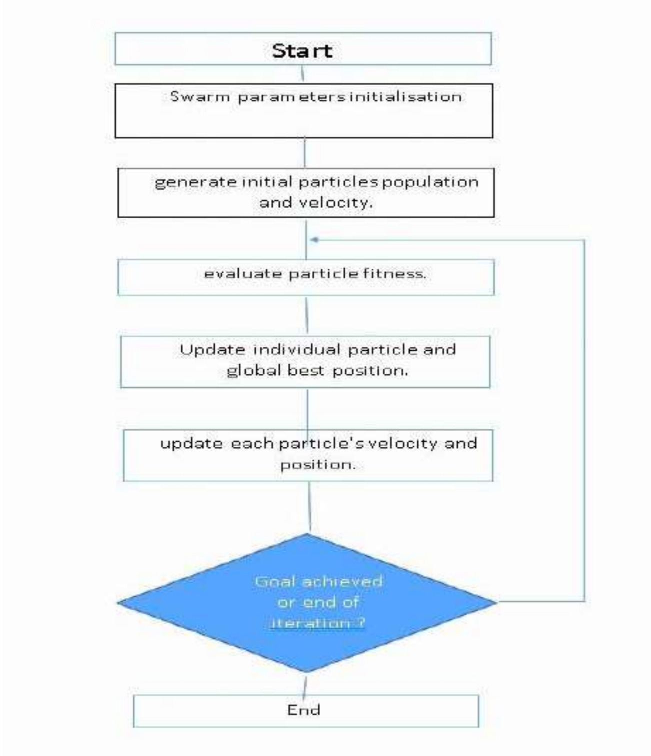

Fig.1Flow chart

D. PSEUDO CODE:

```
Initialize swarm of particles with random positions and velocities
Initialize personal best positions and fitness values for each particle
Initialize global best position and fitness value for the entire swarm

while (stopping criterion not met):
    for each particle in the swarm:
        Evaluate fitness of the current particle position using cost function (energy bill minimization)
        if current fitness is better than personal best fitness:
            Update personal best position and fitness for the particle
        if current fitness is better than global best fitness:
            Update global best position and fitness for the entire swarm
        Modify particle velocity and position with help of PSO update equation
       if EV integration condition is met:  # e.g., during specific time periods
            Implement particle swarm to exchange information about EV usage
            Update particle position based on the swapped information

# After optimization converges:
Implement the best solution found in the HEMS system for load scheduling
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E. Time of Use vs energy Cost:

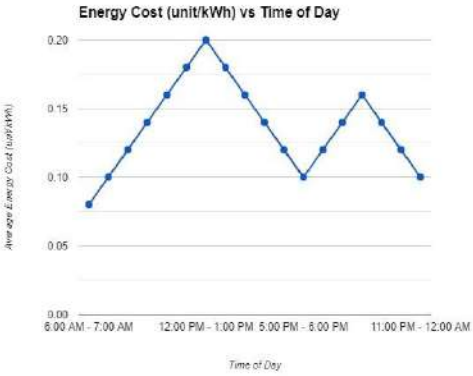

Fig.2 Time of use vs Energy cost

A TOU(Time-of-use) The cost profile, depicted in Figure 2 highlights the significance of Time of Use (TOU) pricing. TOU pricing offers the flexibility to adjust home appliance operating times strategically, empowering users to lower their utility bills effectively [6].

Result analysis

In Scenario 1, scheduling tasks involve regular household appliances, excluding Electric Vehicles (EVs). Users input their preferred operating times for these generic appliances before scheduling begins.

In Scenario 2, the scheduling framework revolves around the exclusive utilization of Electric Vehicles (EVs) for charging purposes. In this context, the EV is recognized as a flexible load seamlessly integrated into the scheduling mechanism. The amount of energy required for charging and the duration of charging are contingent upon the State of Charge (SOC) level of the EV battery. This dynamic aspect of scheduling enables optimized resource allocation and efficient energy management, catering to the varying needs of EV charging while ensuring minimal impact on the overall system.

Transitioning to Scenario 3, scheduling integrates both EV charging and discharging functionalities. The SOC level of the EV battery facilitates Electric Vehicle-to-Home (EV2H) mode, where surplus energy supports home loads via Vehicle-to-Home (V2H) connection during the evening return period, mitigating costs and peak surges. Off-peak hours are dedicated to charging the EV to its full capacity, with transitions between these states managed by the scheduler command signal within the smart home system.

This innovative approach aims to optimize energy consumption, minimize costs, and enhance the overall efficiency of the smart home. It demonstrates the adaptability and versatility of the Home Energy Management System (HEMS) in accommodating various scenarios and user preferences.

Appliances	**Power Rating(KWH)**	**Operating Hours**
Lights	0.7	12
TV/Entertainment	0.16	1
Water Heater	1.5	0.25
Refrigerator	0.35	24
Washing Machine	1.4	0.5
Air Conditioner(AC)	4.5	4
Fan	0.24	20
Induction Cooker	1.6	2

Scenario	PAR
Unscheduled	1.4
Scheduled Without EV	1.34
Scheduled with EV	1.3

Performance in different energy scenario

Unscheduled Load Profile:
In an unscheduled scenario, the electrical load undergoes natural fluctuations without specific management or optimization. Typically, the peak load exceeds the average load, resulting in a higher Peak-to-Average Ratio (PAR). This situation may lead to inefficient resource utilization and increased costs during peak demand periods.

Scheduled Load Profile without EV:
In a scheduled load profile without Electric Vehicle (EV) consideration, optimization efforts aim to reduce peak demand. By distributing energy-intensive activities and appliance usage, the scheduled load profile aims to align the peak load closer to the average load, resulting in a decreased PAR. This strategy helps minimize energy expenses and enhances overall grid stability.
Scheduled Load Profile with EV Charging:
Incorporating EV charging into the scheduled load profile may lead to a rise in peak load due to additional power requirements for charging. However, effective scheduling strategies can manage this increase in peak load reasonably. The PAR in this scenario might exceed that of the scheduled load without EV, contingent on charging patterns and needs.

In summary, the objective of load scheduling and EV integration is to minimize the PAR by optimizing energy consumption distribution over time. This approach not only reduces costs but also fosters efficient and sustainable electrical grid operation.

VIII. CONCLUSIONS

In conclusion, this study introduces efficient scheduling of different home appliances using particle swarm optimization technique to optimize the scheduling of smart appliances within Home Energy Management Systems (HEMs). The primary objective is to minimize energy costs by taking into account the energy flow dynamics associated with residential house and keeping the peak energy nearer to the average energy has been depicted.

The study's future scope includes integrating renewable energy with different energy sources (PV, wind, Biogas) and bidirectional Electric vehicle in home energy management system, for efficient and environment friendly use of energy.

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Hourly Photovoltaic Power Forecast by Long Short Term Memory Network for Land-based Data

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Abstract-In recent years, the world has vigorously promoted renewable energy and promoted global political, technological and economic progress. Distributed energy resources (DERs) are now an integral part of the grid, increasing resiliency and efficiency. Neural networks (NN) are used to address the unpredictability of data, specifically to predict solar power generation. The simplified Long Short-Term Memory (LSTM) is used to achieve this goal. LSTM networks use gates and devices like memory cells to manage the flow of information and adjust their weights through training to provide accurate predictions of renewable energy production. After rigorous data processing, model fitting, and cross-validation processes, the LSTM model demonstrated strong performance. It is particularly suitable for predicting slopes within an hour under various weather conditions.

I. INTRODUCTION

The increasing popularity of distributed energy resources implementations has a significant impact on the stability and operation of the grid. Accurate DER generation forecasts can help TSOs and DSOs optimize unit mix and regulate power quality and demand response activities. Nowadays, photovoltaic prediction research has become one of the main topics in the field of prediction research.

Solar powered control era estimating employments an assortment of calculations, counting numerical climate expectation (NWP), cloud symbolism, measurable time arrangement models, and fake neural systems (ANN), which have been recognized since the 1980s for their precision in anticipating photovoltaic control era. Particularly prevalent. Fake neural systems are characterized by their capacity to prepare nonlinear meteorological information and outflank factual strategies in complex scenarios [1]. In spite of the fact that single-layer counterfeit neural systems are broadly utilized, they frequently endure from complex information designs, driving to the advancement of different sorts of fake neural systems, such as multilayer perceptron (MLP), feedforward neural organize (FFNN), outspread Base Neural Organize (RBNN), Repetitive Neural Organize (RNN), Back Engendering Neural Arrange (BPNN), Generalized Relapse Neural Arrange (GRNN) and Versatile Neuro-Fuzzy Deduction Framework (ANFIS). MLP is an administered feedforward [2]. ANN that incorporates one or more layers between the input and yield layers and gives versatility to different complexities. Hidden layers in neural systems can be customized concurring to the complexity of the issue. Investigate appears that complex pictures occasionally require more than two covered up layers [3]. Feedforward neural systems (FFNN) take after a basic engineering where data streams unidirectionally from the input layer to the yield layer without the required for input circles. FFNN has applications in an assortment of forecast and design acknowledgment assignments. Spiral premise neural organize (RBNN) is as a rule a two-layer arrange, known for its effective learning handle and all-inclusive estimation properties, and has ended up the to begin with choice for photovoltaic control era expectation due to its straightforward structure [4]. Repetitive neural systems (RNNs) are characterized by learning complex connections in time arrangement information, in this manner minimizing forecast blunders compared to FFNNs. Backpropagation Neural Organize (BPNN) has a capable directed learning algorithm.

To combat the moderate meeting and wavering propensities of backpropagation neural systems (BPNN), analysts created an made strides BP organize. BPNN remains well known due to its nonlinear mapping capabilities, which is profitable for complex relapse problems [5]. Long short-term memory (LSTM) systems have appeared fabulous execution in anticipating sun-based vitality for the following day, particularly utilizing rectification strategies such as the discrete gray show (GDM). Moreover, the LSTM demonstrate with clarity record and K-means climate classification made strides the exactness, particularly on cloudy days. The Fractional Every Day Design Forecast (PDPP) system progresses the transient rectification rectification (TCM) in LSTM-RNN models [6]. Despite deficiencies such as overfitting, the streamlined one-day sun powered forecast strategy based on LSTM can optimize precision with constrained preparing information and successfully [7] and hence applied here for hour-ahead forecast of photovoltaic (PV) power.

II.METHODOLOGY

In recent years, the exploration and utilization of renewable energy has opened a new chapter in the development of energy policies, technologies, and business ecosystems in various countries. Distributed energy resources (DER) are primarily connected to the grid. Neural networks are used to predict data from unreliable sources. It proposes a simplified LSTM algorithm based on the architecture of a machine learning approach, as shown in Fig. 1, for predicting solar power generation a hour ahead. Through the steps of data processing and iterative adaptation, cross-validation, metric calculation, and hyperparameter optimization give an optimum LSTM network. Furthermore, the LSTM model will be ready for predictions of power for hourly increments for various weather scenarios.

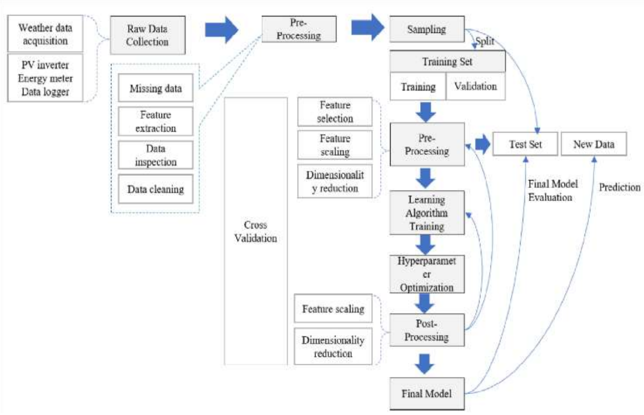

Fig. 1. Architecture of machine learning

LSTM systems are composed of different doors that contain data almost the past state. This data is either composed, put away, or perused from a memory unit.. It chooses on whether to store the approaching data, when it peruses, composes and deletes by means of the doors open and close. The inputs are passed as they possess sets of weights to yield layer through cover up layer in between. These weights are comparable to those that balance input and covered up states by altering through the network's preparing handle. Fig.2 appears the LSTM show including of input door, , i_t , yield entryway, o_t , disregard entryway, f_t and cell state c_t.

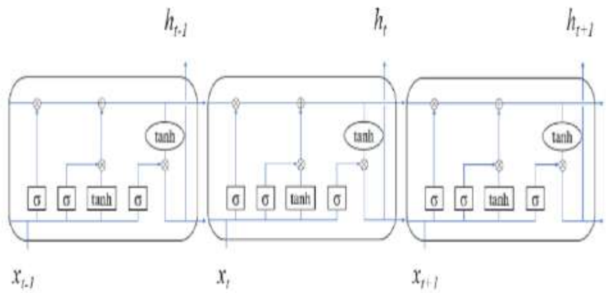

Fig.2 Overview of LSTM interactive layers

The disregard door f_t must choose what data to be saved and what data to be disposed of from the unit state c_t. The choice lies on the calculated work which yields an esteem between 0 to 1. An esteem of 0 implies to save and 1 implies to disregard whole data.

A. RMSE

The root-mean-square (RMSE) or root-mean-square deviation (RMSD) is a as often as possible utilized degree of the contrasts between values anticipated by a demonstrate or an estimator and the values watched. The RMSE serves to total the extents of the mistakes in expectations for different samples into a single degree of prescient control. The impact of RMSE is corresponding to the measure of the squared mistake; hence, bigger mistakes have an excessively expansive impact on RMSE. Subsequently, RMSE is touchy to outliers.

$$RMSE = \sqrt{1/n \sum_{i=1}^{n} (Y_i - Y_i')^2} \qquad (1)$$

Where Yi and Yi' carry are desired and calculated respectively for n samples. RMSE is continuously nonnegative, and a esteem of 0 (nearly never accomplished in hone) would demonstrate a idealize fit to the information. In common, a lower RMSE is way better than a higher one. Be that as it may, comparisons over distinctive sorts of information would be invalid since the degree is subordinate on the scale of the numbers utilized.

B. MAE

The mean absolute error (MAE) quantifies difference of quantity calculated by network from actual. It is a metric to check quality of forecast in time series regressions.

$$\text{MAE}= \frac{1}{n}\sum_{i=1}^{n} Y_i - Y_i' \qquad (2)$$

A lower MAE is better than a higher one.

C. R^2

R^2 is a insights that is a measurable degree of goodness of the relapse expectations to information. An R^2 of 1 demonstrates that the relapse expectations superbly fit the information.

$$R2 = 1 - \frac{RSS}{TSS} \quad (3)$$

RSS is aggregate of square of residuals

TSS is net aggregate of squares

R^2=goodness of fit

D. Train, validation, test

The dataset is used in part as illustrations utilized for learning of the LSTM to train it, then validate to adjust the network size and. unknown autonomous part for preparing the network to test and generalize.

The adjustment of network size fits LSTM for the particular dataset. Here, the number of nodes is fixed to 100 and node function is taken Relu..

IX.RESULTS AND DISCUSSIONS

The land-base and satellite dataset for the hourly predictions will be done for Cuttack, Odisha. For the training 90% and 95% of the entire available data respectively are taken in two observations.

The correlation graph is generated as shown in Fig.4 i.e., for the land-based data and Fig.5 i.e., for the satellite data for 10 months (April and September are unavailable due to some technical errors) in the year 2021. Based on this the non-dominant parameters like "module temperature" and "surface pressure" were dropped and network training is carried out using the rest of the parameters. Though some of the parameters could have been dropped, they are kept for providing essential information. We also need to find the parameters that are highly correlated with the power or the solar radiation to gain the knowledge whether the land base data and satellite data are having the same correlating parameter. In this project, we have taken the data of the year 2021 which is divided into a training to testing ratio of 90%:10% and 95%:5%.

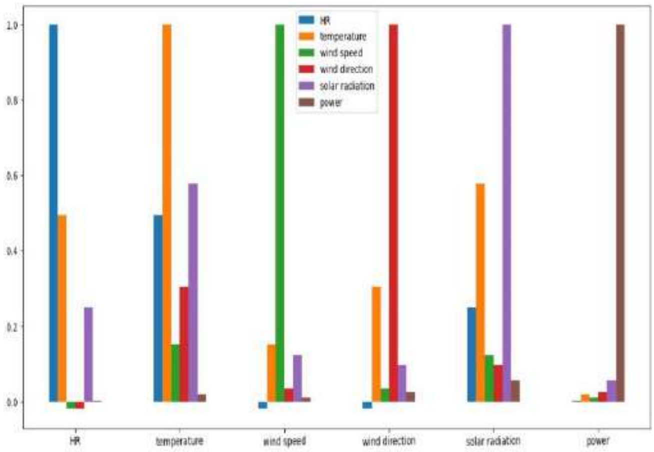

Fig.3. Pearson coefficient bar-plot for land base data

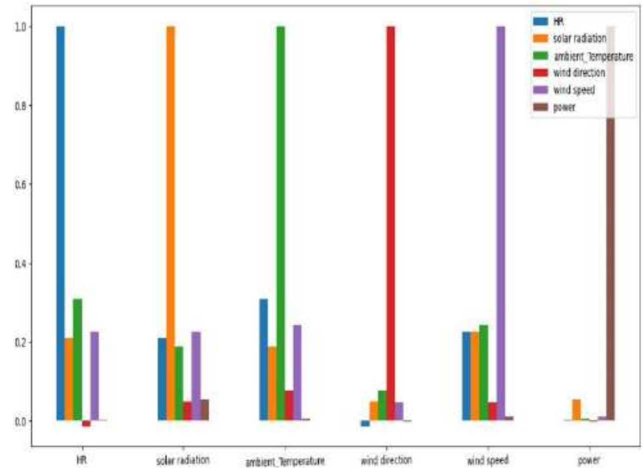

Fig.4. Pearson coefficient bar-plot for satellite data

TABLE I. COMPARISON OF CORRELATION COEFFICIENT

Parameters	**Land base dataset**	**Satellite dataset**
HR	0.001800	0.001800
solar radiation	0.054107	0.055732
ambient Temperature	0.006497	0.017355
wind direction	-0.003360	0.024094
wind speed	0.010583	0.010034

Therefore, the correlation coefficient calculation shown is evident that the output power is showing maximum correlation with solar radiation for the land base data and satellite data. The correlation for both the dataset is compared and is shown below in Table I.

Utilizing the dataset from the CSV record, a show has been made. Taking Adam as an optimizer, the number of ages utilized are 50 with a bunch measure of 512. In arrange to encourage rearrange the organize, diminish forecast time and preparing time we attempted to discover the overwhelming input among the 6 inputs given. This is done by finding the relationship of all inputs with each other. To discover the relationship, we utilized the Pearson Relationship equation. Control has the most elevated relationship with sun powered illumination (Fig.3 and Fig.4).
Later, alluding to Fig.3 (relationship of control with distinctive parameters), and past works the preparing is at that point done with 5 inputs as appeared and way better comes about were found by taking RMSE misfortune capacities. The relationship table is appeared in table 1. The information is isolated into preparing (90% and 95% individually) and testing (10% and 5% individually). The anticipated in comparison to real normalized control for a day is given for both the proportions and is appeared by Fig.5, Fig.6 and Fig.7, Fig.8 separately and for both the datasets.

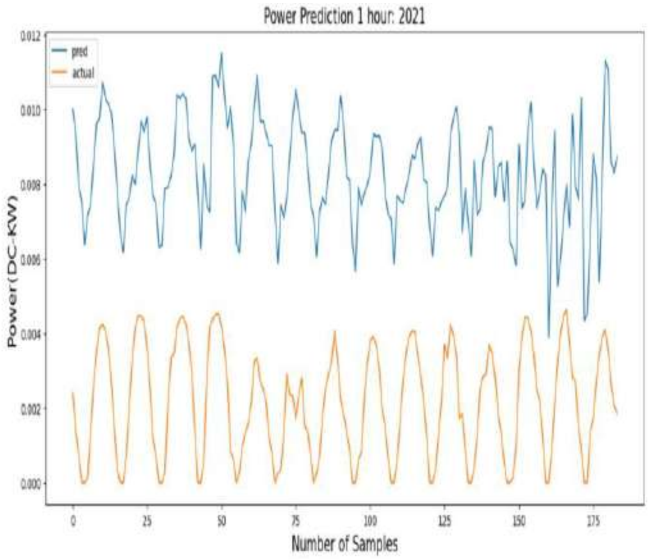

Fig.5. Power prediction plot of landbase data for train to test ratio of 95:5

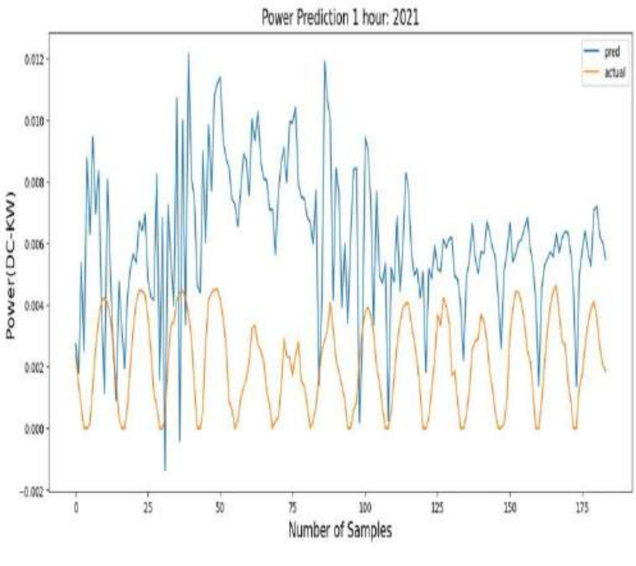

Fig.6 Power prediction plot of landbase data for train to test ratio of 90:10

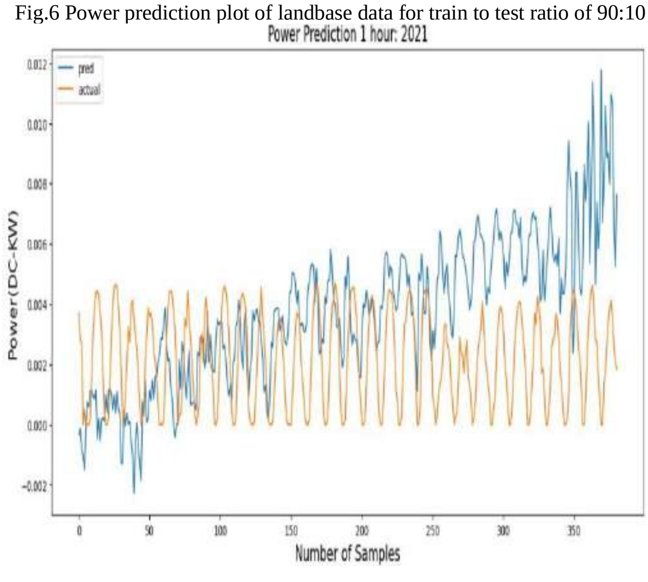

Fig.7. Power prediction plot of satellite data for train to test ratio of 95:5

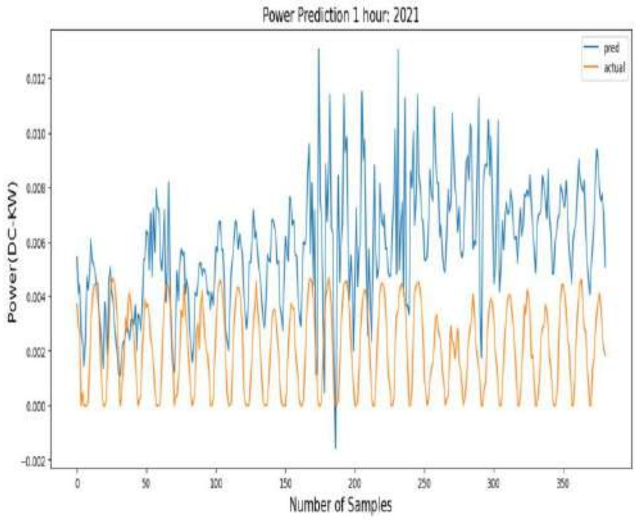

Fig.8. Power prediction plot of satellite data for train to test ratio of 90:10

X. CONCLUSION

In this project LSTM has been used. We used the network to predict the PV power generated and plotted the results for both datasets and compared. It is found that we got better results in prediction for 90:10 for data sampled in 1 hour intervals and longer dataset for short-term PV power prediction. The same network can be tested for consistency in other locations for global applicability. Further with reduction of weather variables the accuracy of the network can be studied.

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Frequency Regulation of microgrid with virtual inertia control

Dr.Bibhuti Prasad Sahoo, Chandan Kumar Dash, Dyutikrushna Dhal, A. Rohit, Kuldeep Gond

Abstract— The integration of renewable energy sources (RESs) in microgrids presents challenges in maintaining frequency stability due to variability and low inertia. To address this, a novel approach combines virtual inertia control, a Fractional order Proportional-Integral-Derivative (FOPID) controller, and the Aquila optimization algorithm. Virtual inertia control emulates additional inertia to compensate for reduced system inertia from high RESs penetration. The FOPID controller enhances adaptability and robustness by adjusting parameters to varying conditions. The Aquila algorithm fine-tunes FOPID controller parameters for optimal frequency stabilization, leveraging its efficient exploration of solution spaces. Simulation studies evaluate the integrated system across RESs variability and grid disturbances, using the Integral Time multiplied with Absolute Error (ITAE) as the objective function. Comparative analyses assess the effectiveness of the FOPID controller with Aquila optimization in enhancing microgrid stability. This research aims to advance control strategies for microgrids, tackling challenges of RESs integration to ensure reliable operation under diverse conditions.

Keywords—RES, frequency stability, Aquila optimization, controller

I. INTRODUCTION

The increasing global demand for energy, coupled with dwindling traditional resources and environmental concerns, has prompted a shift towards renewable energy sources. Microgrids (MGs) have emerged as a solution, utilizing local renewable and distributed energy resources to enhance power system reliability. Typically comprising distributed generations (DG), energy storage, and local loads, MGs leverage renewable sources like solar, wind, and bio-energy to generate green energy.

Load Frequency Control (LFC) is pivotal for ensuring stable and reliable electric power supply. It involves distributing load among generators, controlling tie-line power, and maintaining uniform frequency. A constant frequency signifies normal operation, but power generation fluctuates with load demand, necessitating effective control strategies to ensure reliable and economical power delivery while adhering to acceptable frequency and voltage limits.

System frequency is primarily influenced by load changes, with reactive power being less sensitive to frequency and more dependent on voltage magnitude variations. To maintain constant frequency, Fractional Order Proportional-Integral-Derivative (FOPID) controllers regulate turbines to minimize steady-state errors in system frequency. Algorithms such as the Aquila Optimization Algorithm (AOA) are utilized to optimize frequency control in microgrids.

This study aims to design an optimal LFC controller for a proposed MG, prioritizing the utilization of the best available renewable sources to mitigate the mismatch between load demand and generation. The project employs the Aquila Optimization, a novel nature-inspired meta-heuristic algorithm, drawing inspiration from the hierarchical and hunting behaviours of Aquila in nature. The algorithm mimics the pack hunting strategy of wolves to effectively optimize frequency control in microgrids.

II. PROJECT OBJECTIVES

1) To develop the model of the MG system consists of diverse energy sources.
2) Tuning of parameters of FOPID controller using Virtual inertia control with Aquila optimization algorithm

III.SYSTEM MODELLING

A. *The microgrid system employed in this study*

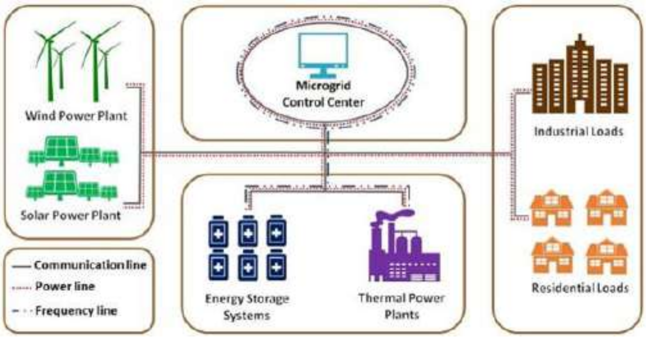

Figure-1

The study investigates a microgrid system incorporating renewable energy sources (RESs), as illustrated in Figure 1. This microgrid configuration comprises of various components: 20MW thermal power plant, 8.5MW solar power plant, 7.5MW wind power plant, 5MW residential load, 10MW industrial load, and a 4.5MW energy storage system (ESS). The system's base capacity is 15MW. It's noteworthy that the primary electrical system and energy distribution across units are decentralized in microgrid systems. Communication links (solid lines) facilitate data exchange and status monitoring among electrical equipment distributed in different locations. Additionally, control loops for primary and secondary regulation, along with inertia control, are managed via network communication (dash lined). The power network (dot lined) interfaces with the microgrid system to supply energy.

Figure 1 shows the dynamic model of the microgrid presenting block diagram for a typical frequency control analysis. This includes the Governor Rate Control (GRC) for the governor unit and rate limitations for turbine valve/gate opening or closing speed (V_U, V_L) within the turbine unit. The GRC, crucial for frequency regulation, is determined as 12% per unit megawatt per minute (p.u. MW/min) in this study. A dead-band limit of ±0.035 Hz (0.06%) and a time delay of 2 seconds are specified. The dynamic effects of generations, loads, as well as primary and secondary control mechanisms, are accounted for in the model, as depicted in Figure 1.

B. *Abbreviations and Acronyms*

ΔP_m - the change in the power produced by thermal power plant,

$\Delta P_{inertia}$ - the virtual inertia power change of the ESS,

ΔP_L - the overall load change of the system,

H - the corresponding system inertia

D - the comparable microgrid damping coefficient,

ΔP_G - the governor unit-based power variation of thermal power plant,

ΔP_{ACE} - the secondary control signal change,

ΔP_{RES} - the overall change in power provided by renewable energy sources,

ΔP_{PV} - the fluctuation of output electricity from solar power plant,

K_i - the secondary frequency controller,

ΔP_{wind} - the first power change due to wind speed,

ΔP_{solar} - the first shift in the solar radiation power,

ΔP_{SL} - the change in load of the residential area,

ΔP_{BL} - the change in load of the industrial area

C. ***Parameters(Table 1)***

<u>Parameters</u>	Value
System inertia, H	0.083
System damping coefficient, D (p.u. MW/Hz)	0.015
Virtual inertia value, $J_V\ I$ (s)	1.6
Virtual damping value, $D_V\ I$ (s)	1.2
Time constant of inverter-based ESS, $TESS$ (s)	10
Maximum capacity of ESS, $PESSmax$ (p.u. MW)	0.3
Minimum capacity of ESS, $PESSmin$ (p.u. MW)	-0.3

Droop constant R (Hz/p.u. MW)	2.4
Time constant of the governor T_g (s)	0.1
Time constant of a turbine T_t (s)	0.4
Frequency bias factor β (p.u. MW/Hz)	1.0
Integral control variable gain K_i (s)	0.05
Time constant of the wind turbine T_{WT} (s)	1.5
Time constant of the solar system T_{PV} (s)	1.85

D. *Equations*

The incremental change (ΔP_{TOTAL}) of the total power outputs is obtained as follow:

$\Delta P_{TOTAL} = \Delta Pm + \Delta P_{WT} + \Delta P_{SV} - \Delta P_{inertia} - \Delta P_L$ -(Eq 2.1)

The frequency and power variation of RESs system can be calculated as follow, considering the influence of the controllers and inertia control [1]:

$\Delta F = 1/ (2Hs + D)\ (\Delta P_m + \Delta P_{WT} + \Delta P_{SV} - \Delta P_{inertia} - \Delta P_L)$ - (Eq 2.2)

when,

$\Delta P_m = 1/ (1 + sT_t)\ (\Delta P_G)$ -(Eq 2.3)

$\Delta P_G = 1/ (1 + sT_g)(\Delta P_{ACE} - (1/R)\Delta F)$ -(Eq 2.4)

$\Delta P_{ACE} =(-K_i/s)/(\beta\Delta F)$ -(Eq 2.5)

$\Delta P_{RES} = \Delta P_{WT} + \Delta P_{PV}$ -(Eq 2.6)

$\Delta P_{WT} = 1/(1 + sT_{WT})(\Delta P_{wind})$ -(Eq 2.7)

$\Delta P_{PV} = 1/(1 + sT_{PV})(\Delta P_{solar})$ -(Eq 2.8)

$\Delta P_{PV} = \Delta P_{SL} + \Delta P_{BL}$ -(Eq 2.9)

E. *Structure of Virtual Inertia Control*

Virtual inertia control is a methodology employed within power systems to replicate the stabilizing impact traditionally provided by mechanical inertia from conventional generators. In contemporary power grids characterized by substantial integration of renewable energy sources (RES) like wind and solar, there is a decline in inherent inertia due to the intermittent and variable nature of these sources. Consequently, power systems become more vulnerable to frequency fluctuations and disturbances.

Virtual inertia control tackles this challenge by deploying control techniques that mimic the inertia effect using power electronic converters linked to energy storage systems or renewable generation sources. These systems have the capability to swiftly inject or absorb power to stabilize grid frequency during abrupt shifts in generation or load.

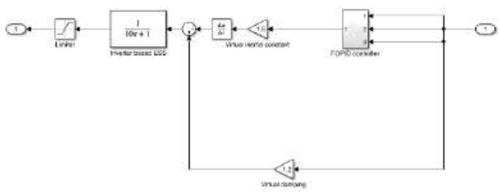

Figure-2 (Structural diagram of virtual inertia control)

IV. THE CONTROLLER AND OBJECTIVE FUNCTION

A. *FOPID Controller*

A "FOPID" controller stands for a Fractional Order Proportional-Integral-Derivative controller. Unlike the traditional PID (Proportional-Integral-Derivative) controller, which operates with integer order differentiation and integration, the FOPID controller utilizes fractional calculus principles, where the order of differentiation and integration can be fractional. The main idea behind using fractional calculus in control systems is to provide more flexibility and improved performance, especially in systems with complex dynamics, nonlinearity, or long-time delays. By allowing fractional orders for differentiation and integration, FOPID controllers can capture more intricate system behaviors and dynamics, potentially leading to better control performance.

$$C(s) = \frac{1}{s^{\lambda}} K_i + K_p + s^{\mu} K_d$$

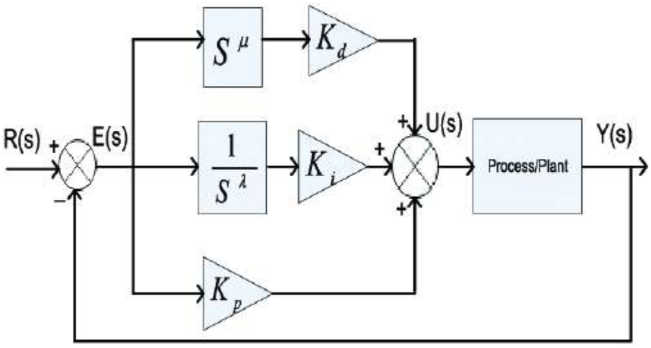

Figure-3 (FOPID Controller)

B. Objective Function

In this optimization process, parameters are adjusted using a designated objective function, typically derived from the integral of time multiplied absolute error (ITAE) criterion. ITAE, standing for Integral of Time multiplied by the Absolute Error, serves as a pivotal performance metric in the analysis and design of control systems. Widely utilized in assessing and comparing controller performance, ITAE evaluates how effectively controllers minimize error over time.

The ITAE criterion is computed as the integral of the product of time and the absolute value of the error signal across a predefined time interval. Mathematically, for a system's response to a step input, the ITAE can be expressed as follows:

$$ITAE = \int_0^{\infty} t.|e(t)|dt$$

where:

- e(t) is the error signal at time t.

- The integral is taken from 0 to infinity, representing the entire time response.

The use of ITAE as a performance criterion helps in quantifying how well a control system can track a desired setpoint or reference signal. Engineers and control system designers often use performance criteria like ITAE to assess and compare the effectiveness of different control strategies or tuning parameters. In control system design, the goal is often to minimize the ITAE value, as a lower ITAE generally indicates better tracking performance and reduced steady-state error. However, the choice of performance criteria can vary depending on the specific requirements and characteristics of the controlled system. Other commonly used criteria include Integral of Time multiplied by the Squared Error (ITSE) and Integral of Squared Error (ISE). The selection of a criterion depends on the specific goals and characteristics of the control application [8].

C. Optimization Algorithm

The Aquila optimizer (AO) is a novel metaheuristic optimization algorithm inspired by the hunting behavior of Aquila, a genus of eagles. Developed in 2021, AO has demonstrated effectiveness across various optimization problems. It operates through distinct phases, each mirroring a stage in the hunting process of an eagle:

1. High soar with vertical stoop: Similar to exploration phases in other metaheuristic algorithms, AO ascends above the search space, then executes a vertical stoop to identify potential prey regions.

2. Contour flight with short glide attack: Upon spotting potential prey, AO enters a contour flight phase, circling the prey while gradually lowering its altitude. This corresponds to the exploitation phase, where the algorithm refines its search around promising solutions.

3. Low flight with slow descent attack: As AO approaches the prey, it transitions to low flight, maintaining proximity to the ground and slowing its descent. This resembles the intensification phase, focusing the search on a small region of the search space.

4. **Swoop by walk and grab prey: Finally, AO swoops down to capture the prey, akin to the convergence phase where the algorithm zeroes in on the optimal solution.

AO has proven effective in tackling various optimization problems, including numerical, engineering design, and machine learning challenges. It excels in tasks such as function minimization, maximization, constrained optimization, structural, aerodynamic, and mechanical design, as well as feature selection, hyperparameter optimization, and model selection in machine learning. Overall, AO presents itself as a promising metaheuristic optimization algorithm with broad applicability across diverse optimization domains.

V.RESULTS OBTAINED

The system model depicted in Figure-1 is developed within the MATLAB/SIMULINK environment, accompanied by an optimization program written in a .m file. Subsequently, the developed model undergoes simulation in a separate program (.m file), wherein a 1% step loads perturbation is considered. The simulation process adopts a population size of NP=30 and a maximum number of iterations=50. These simulations are executed on a computer equipped with an Intel Core i5 9th gen CPU, operating at 2.4 GHz with 16 GB RAM, within the MATLAB (R2021a). The optimization routine is repeated 10 times, and the best final solutions among the 10 runs are selected as the optimal control parameters for all three conditions: i) Integral controller in ACE without virtual inertia control, ii) Integral control in ACE with virtual inertia control, and iii) Integral controller in ACE with virtual inertia control employing a FOPID controller.

The Load Frequency Control model of the Isolated Microgrid System utilizes system parameters outlined in Table-1. The Integral of Time multiplied by the Absolute Error (ITAE) values for all three conditions with controller gains tuned using AOA are presented in Table-2. Notably, the results indicate that AOA-based virtual inertia control employing a FOPID controller, with ITAE as the objective function, yields the lowest ITAE value (ITAE=0.2111) compared to the other conditions (ITAE=6.4246, ITAE=14.824). Furthermore, dynamic frequency change responses with optimal controller gains are illustrated in Figure-4.

From the analysis, it is evident that AOA-based virtual inertia control utilizing a FOPID controller outperforms the other configurations, demonstrating superior effectiveness in minimizing ITAE values.

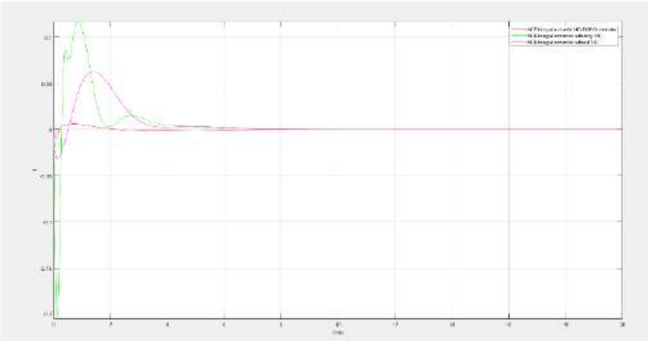

Figure-4 (Output result)

VI. CONCLUSION

This study focuses on implementing algorithms for virtual inertia control with a FOPID (Fractional Order Proportional Integral Derivative) controller for Load Frequency Control of Microgrid Systems. Specifically, the Aquila Optimization Algorithm (AOA) is employed in this context, aiming to optimally tune the parameters of the PD controller using the Integral of Time multiplied by the Absolute Error (ITAE) as the objective function. The simulations are conducted using MATLAB Simulink.

The simulation results indicate that virtual inertia control with a FOPID controller optimized through AOA exhibits superior performance in terms of achieving a lower ITAE value and improved dynamic responses compared to microgrid systems with only virtual inertia control or without virtual inertia control altogether.

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“Modern Control Engineering" fifth edition by Katsuhiko Ogata

Analysis and Prediction of Diabetes Using Machine Learning Techniques: A Review

Nayan Kajal Rout, Ph.D. Scholar

Abstract:- Diabetes is a metabolic disorder characterized by persistently high blood glucose levels due to the body's inability to utilize it effectively. This condition poses severe complications such as diabetic ketoacidosis, cardiovascular diseases, stroke, renal failure, retinal damage, and foot ulcers. With a significant rise in global diabetes cases, it has emerged as a major health concern worldwide. Diabetes, characterized by elevated blood glucose levels, poses significant health risks globally. Early detection is critical to mitigate complications. Machine learning, including algorithms like ANN, SVM, Naive Bayes, and deep learning, alongside data mining techniques, offer promise for diagnosis. However, current methods lack diversity in testing datasets, limiting practicality. This paper reviews these techniques, emphasizing challenges and suggesting avenues for improving prediction accuracy and treatment outcomes.

Index Terms- Machine learning (ML), Artificial Neural Network (ANNs), Support vector machine (SVM), Naïve Bayes, Deep learning, Data mining, Diabetes prediction

I. INTRODUCTION

Diabetes poses a significant health challenge globally, affecting both developed and developing nations [1]. In the United States, according to the National Diabetes Statistics Report 2020, approximately 34.2 million people, constituting 10.5% of the population, are diagnosed with diabetes [2]. Alarmingly, 7.3 million individuals are unaware of their diabetic status, indicating a substantial proportion of undiagnosed cases. Similarly, India ranks second globally in the number of diagnosed diabetes cases, with around 77 million people diagnosed in 2019 [3]. Diabetes manifests as persistently elevated blood sugar levels, either due to insufficient insulin secretion by the pancreas or the body's ineffectiveness in responding to insulin [4]. Insulin plays a vital role in facilitating glucose entry into cells, where it serves as a primary energy source [5]. The condition leads to both short-term complications such as dehydration and diabetic coma, and long-term complications including heart disease, blindness, kidney failure, stroke, and foot ulcers [6,7]. The classification of diabetes typically encompasses three main types: type 1 diabetes, type 2 diabetes, and gestational diabetes. Type 1 diabetes arises from the body's inability to produce insulin, often due to autoimmune destruction of pancreatic beta cells responsible for insulin secretion. Conversely, type 2 diabetes results from insufficient insulin production or the body's resistance to insulin's effects, accounting for the majority of diabetes cases worldwide [8,9].

Diabetes is a multifaceted condition with its primary cause still elusive. Various factors contribute to its onset, including genetic predisposition, obesity, high cholesterol, dietary habits, lack of physical activity, stress, hypertension, and infectious diseases [10]. Traditional methods of diabetes detection, such as glycated hemoglobin test, oral glucose tolerance test, and fasting plasma glucose test, are both time-consuming and costly, posing challenges, particularly in low-income countries. Given the significant number of undiagnosed cases globally, early detection holds paramount importance in mitigating severe complications. Automated computational prediction methods offer a promising solution to this dilemma. Machine learning techniques leverage existing data to predict diabetes, offering a quicker and cost-effective alternative to traditional diagnostic approaches. These methods enable patients to self-diagnose without medical intervention, reducing the time required for symptom processing and disease detection. Given the escalating prevalence of diabetes and its potential for severe complications over time, early detection emerges as a critical imperative in current epidemiology [11].

There's an urgent necessity to predict diabetes early in populations to initiate proper precautions and treatments, thus averting its worsening. Recently, there's been a shift in focus within the scientific community towards employing robust computational methods for accurate diabetes prediction. Artificial intelligence and soft computing techniques play a pivotal role in implementing these approaches, finding application not only in medical diagnosis but also in various health-related fields. It's imperative for these computationally intensive methods to exhibit high precision and undergo validation on diverse datasets representing different populations, considering the global nature of the disease. The current discussion revolves around various computational methods for diabetes prediction, along with suggestions aimed at enhancing their practicality.

II. RELATED WORK

Many studies have focused on using machine learning to detect diabetes, showing how important it is to address this health issue. In 1988, the ADAP algorithm, which used neural networks, was first used to predict diabetes in the Pima Indian community near Phoenix, Arizona. After this, many other predictive models based on neural networks were developed. One notable tool, the Diabetes Classifier, was made to be easy to use, allowing people to customize settings and access it through a simple interface on the web. Additionally, SVM, a popular method for recognizing patterns and sorting things into categories, was used to create models. These models were tested and validated using a method called 10-fold cross-validation.

M. Kalpana and A. Kumar [12] developed fuzzy expert systems for diabetes, using a large database called the Pima Indians Diabetes Database (PIDD). They converted clear-cut data into fuzzy data to better understand the dataset. This involved collecting data, creating a database, turning clear-cut data into fuzzy data, sorting fuzzy data, making rules based on the data, and getting a final result. This method was found to be more effective for predicting diabetes than previous methods.

K. Rajesh and V. Sangeetha [13] suggested a system using data mining to classify diabetes, also using the PIDD dataset. They first picked out the most important features for classification, ranked them based on their importance, and then tried different techniques to classify the data. One technique, called RND TREE, reached 100% accuracy, although it had a lot of rules and was prone to using too much data. Another technique, C4.5, a type of decision tree method, achieved around 91% accuracy and was considered the best out of the ten techniques they tested.

Anuja and Chitra [1] suggested using SVM to classify diabetes, training it with the PIDD dataset. SVM tries to minimize mistakes while maximizing the space between different groups. They used a specific type of SVM called Radial Basis Function (RBF) kernel to handle complex data. Patients were sorted into two groups: class 0 for negative tests and class 1 for positive tests, with an accuracy of 78%. Omar and Eman [5] introduced a hybrid algorithm for classifying type 2 diabetes, combining Least Squares-Support Vector Machine (LS-SVM) and Modified-Particle Swarm Optimization (MPSO) algorithms. LS-SVM was used to draw the best line between live and die groups, while MPSO helped pick the right attributes from the PIDD dataset. Their method had two steps: optimizing parameters and classifying. They achieved an accuracy of 97.833%, better than other methods used on the same dataset.

III. EXISTING METHODS

Machine learning is a field of computer algorithms that aims to imitate human intelligence by learning from the world around us [14]. It's all about recognizing patterns in data to understand things we didn't know before [15]. There are two main types: deductive learning, which predicts new things from what we already know, and inductive learning, which finds patterns without needing prior knowledge. Inductive learning is about spotting patterns in big sets of data to create computer programs [16]. Machine learning tries to make computers better by learning from experience, just like people do. It's used in lots of areas like seeing and understanding images, recognizing speech, detecting fraud, and much more. In machine learning, there are three main ways of learning: unsupervised, supervised, and reinforcement learning.

a) ANN: The neural network model is like a simplified version of the human brain's networks. It's used to figure out things based on a bunch of inputs we don't know much about [18]. It's made up of connected neurons, passing information between them. These connections have weights that change to get the right answers. Usually, there are three layers: the input layer, where information comes in from the outside world; the hidden layer, where neurons take in inputs from the input layer and send out information to the output layer, adjusting weights along the way; and the output layer, where neurons give out the final answers to the outside world.
b) Support vector machine (SVM): SVM is a type of learning method used for sorting things into groups based on certain rules. It's used for both figuring out patterns in data and making predictions. The idea is to find the best way to draw a line or boundary between different groups so that new things can be easily sorted [19]. Developed by Vapnik, SVM is famous for being really good at this. It tries to make as few mistakes as possible while making sure the gap between groups is as big as it can be. Think of it like drawing a line between different types of points in space, making sure there's a wide gap between them [20].
c) Bayesian network: A Bayesian network is like a map showing how different things are connected based on probabilities. It's a way to understand how one thing happening might affect another thing. It's kind of like a supervised learning method. It's good because it can deal with missing data by figuring out relationships between variables [21]. Also, it can help figure out cause and effect, which is useful for predicting what might happen if something changes.
d) Back propagation algorithm: The backpropagation algorithm was first made by Paul Werbos in 1974 and then found again by Rumelhart and Parker. It's a way to teach artificial neural networks to do certain jobs. It's usually used in networks where information moves in layers from the front to the back [18]. Backpropagation learns from examples of input and output data to figure out its mistakes. Its goal is to keep making fewer mistakes over time until it's really good at the tasks it's trained on.

e) Deep learning (DL): DL is now really important in computer learning. It works super well in lots of things like looking at pictures and videos, understanding speech, and predicting handwriting. DL models are really good at getting things right and doing it quickly in these areas. What's cool is that DL can be used in both types of learning problems: where the computer knows what the right answers are (supervised) and where it has to figure things out on its own (unsupervised). This shows that DL can be used for lots of different kinds of data and tasks.

IV. DISCUSSION

Predicting diabetes mostly uses data searching and computer learning tricks, using different sets of information to study. There are lots of different databases we can look at to figure it out. Among these, the PIDD dataset stands out as the most commonly utilized for machine learning-based predictions [22]. The datasets serve as valuable resources for developing computational methods aimed at early diabetes prediction. Scientists have used different computer learning methods like ANN, SVM, Bayesian methods, multilayer perceptron, backpropagation algorithm, modified-particle swarm optimization, and fuzzy-c mean clustering. Through experimentation, these methods have demonstrated promising accuracy in predicting diabetes onset. Utilizing new and rare machine learning methods in diabetes prediction is crucial, yet without addressing current issues and bottlenecks, progress remains limited. Recent studies have shown that implementing lesser-known machine learning methods did not improve accuracy compared to previous endeavors. An overarching trend in diabetes prediction indicates a progression from simpler neural network-based machine learning methods towards more advanced algorithms like deep learning, specifically convolutional neural networks, aimed at enhancing accuracy and robustness.

Initially, single machine learning algorithms were employed for prediction, but this evolved into the development of hybrid and combined models utilizing multiple algorithms to achieve higher accuracy. Notably, studies predominantly utilizing the PIDD dataset underscore the need for a data-independent machine learning algorithm to minimize reliance on specific datasets. Comparative analysis between single and hybrid model performances reveals that combinations such as SVM + ANN yield superior accuracies, surpassing 95%. Despite achieving remarkable accuracy rates, no diabetes prediction model claims universal applicability. The global nature of diabetes presents challenges due to lifestyle, race, and environmental factors influencing the disease. Integrating diverse datasets into machine learning models poses a significant challenge, as dataset features vary across populations. Reliability issues arise as most methods are trained and tested on single datasets, necessitating validation on diverse populations worldwide constructing a prediction model based on multiple datasets necessitates the fusion or merging of these datasets using data fusion methods prior to model training. Data fusion techniques, classified into three categories—data association, state estimation, and decision fusion—are employed based on the relationship between input sources, categorized as complementary, redundant, or cooperative. Dasarathy's common data fusion system, tailored to the nature and type of input and output, provides a framework for implementing these techniques effectively [23].

Table 1: Values of important machine learning based prediction methods

Sl. no	Year	Methods	Accuracy (%)
1	2013	SVM [1]	78
2	2014	Neural Network [24]	81
3	2014	ANN [25]	82
4	2015	Decision Tree [26]	73
5	2018	Naïve Bayes Algorithm [27]	79
6	2016	Probabilistic neural network [28]	81
7	2017	Gaussian process [29]	88
8	2016	SVM+ANN [30]	96
9	2015	MLP +Bayes net [31]	82

V. CONCLUSION

The aim of this study is to present a comprehensive overview of various machine learning techniques applicable to automatic diabetes prediction. Recent advancements in machine learning and data mining techniques for classification are explored, each demonstrating varied accuracy on distinct datasets. While initial focus was on achieving higher prediction accuracy, the primary objective has shifted towards ensuring greater reliability for application across global populations. Despite this, only a limited number of methods have been developed and tested on multiple datasets. Given the worldwide prevalence of diabetes, there's a pressing need for a method capable of predicting diabetes across diverse populations. People are talking about and suggesting a plan for computer programs to help scientists make better prediction tools for finding diabetes early.

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