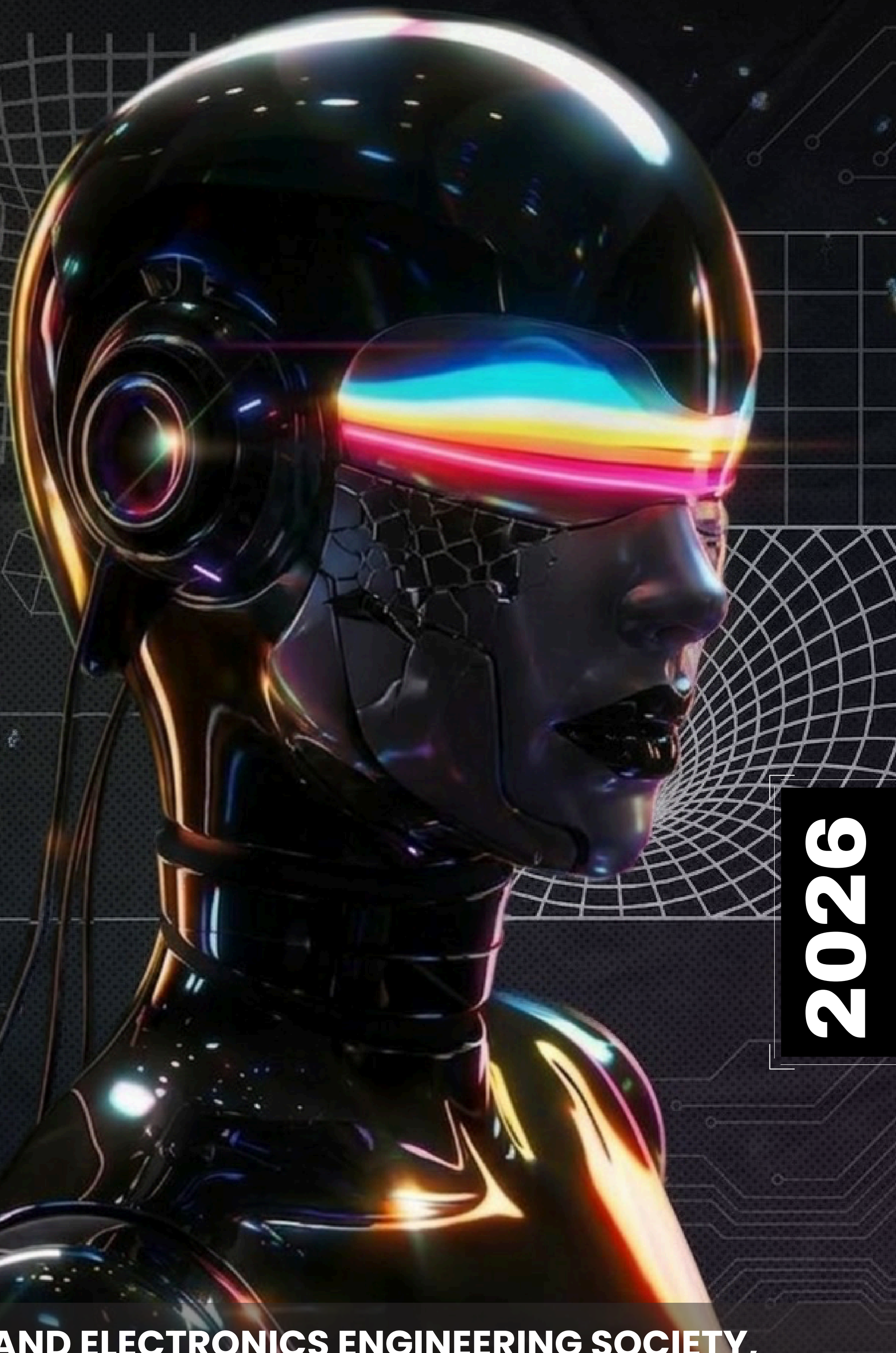
VEER SURENDRA SAI UNIVERSITY OF TECHNOLOGY

ConnEEEct

4th Edition

SPECTRUM



2026

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

FACULTY AND STAFF

From Left to Right: Dr. S Sahu, Er. P.K. Rath, Er. D.P. Jena, Dr. B.P. Sahoo, Dr. L. Dora, Dr. S. Garnaik, Dr. Sasmita Behera, Dr. G.R. Biswal (HoD), Prof. R.K. Sahu, Dr. Shanti Behera, Er. P.K. Parida, Mrs. T.S. Das, Er. N. Rout, Er. N. Suhashini, Er. R. Fathima,Mr. K. Khadia

BATCH OF 2026

Preface

It is a pleasure to present Spectrum, a compilation that reflects the curiosity dedication and creativity of the students of the Department of Electrical and Electronics Engineering. This volume continues our effort to bring together the research work and innovative ideas developed by our students. It serves as a platform where learning exploration and academic curiosity come together in a meaningful way. Through this collection we aim to highlight the enthusiasm of students who are eager to question learn and contribute their ideas to the growing field of engineering.

The preparation of this publication has been a collective effort built on teamwork commitment and enthusiasm. Students faculty members and coordinators have worked together to make this compilation possible. We extend our sincere gratitude to our faculty members and mentors for their constant guidance support and encouragement throughout this journey. Their mentorship has helped students refine their ideas and present them as thoughtful academic contributions.

The abstracts included in this volume represent a range of ideas and perspectives within the field of electrical and electronics engineering. Some explore theoretical concepts while others focus on practical applications and emerging innovations. Each contribution reflects the curiosity dedication and willingness of students to explore new topics and think beyond the boundaries of the classroom.

We hope that Spectrum not only showcases the academic efforts of our students but also inspires readers to explore new ideas and possibilities. May it encourage curiosity meaningful discussions and a continued interest in the ever evolving world of engineering and technology.

With warm regards,
Team Spectrum

Editorial Team

Sonalika Patel
Suparna Mallick
Disha Darshita
Pratyush Kumar Dash
Paila Devi Vara Prasad
Samarpita Hota
Swagatika Dikshit
Rishika Kumari Behera
Riya Mishra
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Bishwaranjan Mohapatra
Om Prakash Patra
Siddharth Singh
Chinimya Rout
Shreya Panigrahi
Bhabani Sankar Behera
Anuraag Bisoyi

About Electrical and Electronics Engineering Department

Every great journey begins with a single step and ours began in 2010. What started as a shared dream within the walls of VSSUT Burla has grown into a proud and independent department since 2020. Today, Electrical and Electronics Engineering is more than a programme; it is a vibrant community of thinkers, builders and problem solvers.

From B.Tech. to Ph.D., we offer academic pathways that shape not only engineers but future visionaries. With over ₹70 lakhs in funded research supported by CPRI, the Ministry of Power, NPIU MHRD and ANRF-PAIR along with a landmark MoU with CPRI for next-generation GIS sensor development, our work creates impact far beyond the classroom.

Our students do not simply earn degrees; they earn their wings. Our laboratories thrive on curiosity, our research groups work with purpose and our Innovation Centre turns ideas into reality. This commitment is reflected in our outcomes with over 80 percent of graduates stepping into roles at leading organisations such as L&T, TCS, Adani and Infosys.

Our students have also proven their talent on prestigious platforms including IITs, ISRO, BARC, HAL and international arenas. A departmental patent, published books and faculty honoured by IEI, ISTE India and IEEE USA further reflect the excellence within the department.

We do not just teach engineering; we ignite passion for it. Guided by the belief that great engineering changes lives, we continue to nurture talent, advance impactful research and build solutions that matter.

About SPECTRUM

The Annual Symposium Spectrum, the student society of the Department of Electrical and Electronics Engineering, emerged as one of the most engaging academic events of the year. The symposium brings together students, faculty members and young innovators and creating a space where ideas, knowledge and creativity can come together and grow.

The event encourages students to step beyond classroom learning and explore real world technological challenges. Participants share their research work, innovative projects and technical ideas from different fields of electrical and electronics engineering. It provides budding engineers with a platform to express their thoughts, exchange knowledge and learn from one another in a supportive and collaborative environment.

Technical presentations, discussions and interactive sessions forms the heart of the symposium. Students show great enthusiasm while presenting their work, which reflects their curiosity and dedication toward engineering and technological progress. The event also gives them the opportunity to interact with faculty members and experts and receive valuable insights along with constructive suggestions on their ideas.

From the Vice Chancellor‘s Desk

There are moments in academic life that rise above the ordinary, moments where ambition, intellect and creativity come together to create something truly meaningful. SPECTRUM is one such moment. What makes it genuinely special is not just the scale of the programme but the sincere effort of the student organizers who bring it to life with passion and purpose. Their dedication, team spirit and pursuit of excellence reflect the vibrant academic culture that this institution proudly nurtures.

SPECTRUM, the flagship technical fest of the Electrical and Electronics Engineering Society, has grown into a valued platform where curious minds meet, ideas are explored and refined through open dialogue and emerging technologies are examined with enthusiasm and depth. At its heart, it is a celebration of the potential of young minds and a reaffirmation of the values that define this department.

I deeply appreciate the organizing team for the thought and care they have put into every aspect of the event, the maturity with which they have handled challenges and the determination that has guided them throughout this journey. To every student who has worked behind the scenes and to every participant who joins with a willingness to learn, connect and grow, this symposium belongs to you. Make the most of it with confidence and enthusiasm.

I extend my heartfelt congratulations and warmest wishes for a successful and memorable SPECTRUM 2026.

Prof.(Dr.) Dipak Kumar Sahoo
Vice-Chancellor
VSSUT, Burla

Message

With great pride and delight, I extend my warmest greetings to all students, faculty and guests on the occasion of SPECTRUM 2026, the annual technical and cultural fest of the Department of Electrical and Electronics Engineering. SPECTRUM has always been a proud confluence of innovation, intellect and creativity and this year it continues that legacy with even greater enthusiasm. From technical competitions and research paper presentations to vibrant cultural performances, SPECTRUM 2026 promises to be a truly enriching experience for everyone involved.

The significance of SPECTRUM goes far beyond a single day's celebration. It is a platform where young minds transform classroom learning into real world solutions. I especially encourage every student to participate in project exhibitions and paper presentations, as it is through these endeavours that one truly understands the depth of engineering. Working on a project nurtures patience, teamwork and problem-solving virtues that no textbook alone can impart.

As the Head of the Department, I take immense pride in the dedication of our student organizers and faculty coordinators for bringing SPECTRUM 2026 to life. I wholeheartedly encourage every student to step forward and participate with full enthusiasm. Let this fest be more than just an event, let it be a memory you carry with pride throughout your professional journey. My warmest wishes to all participants for a grand and successful SPECTRUM 2026.

Dr. Gyan Ranjan Biswal
Head of the Department, EEE

Message

“The spirit of innovation is fostered when ideas are encouraged and opportunities are created.”
Watching SPECTRUM 2026 take shape has been a genuinely proud moment. As the annual technical symposium of the Electrical Engineering Society, SPECTRUM has always been more than just an event, it is a space where students discover their potential, sharpen their thinking and grow in ways that no classroom alone can offer.
What makes SPECTRUM truly meaningful is the culture it builds, one rooted in curiosity, collaboration and a genuine love for engineering. It is heartening to see so many young minds come together with such energy and purpose.
My sincere appreciation goes to the organizing team for their hard work and commitment in bringing this vision to life. To every participant, walk in with confidence, engage with an open mind and make the most of every moment this symposium has to offer. Wishing everyone a wonderful and successful SPECTRUM 2026.

Dr. Sarmila Garnaik
Faculty Advisor,
EEE Society

From the Editor's Desk

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Sonalika Patel
Editor,
ConnEEEct SPECTRUM

FACULTY PROFILE

PROF. RABINDRA KUMAR SAHU

Professor

Professor Rabindra Kumar Sahu is a distinguished scholar in power system engineering with more than 23 years of experience in teaching and research. He obtained his Ph.D. from IIT Madras. His research focuses on modelling and simulation of power systems, automatic generation control FACTS devices, deregulation of power systems and the application of soft computing techniques in electrical engineering.

He has earned global recognition for his research contributions and has been ranked among the Top 2% of Most Cited Scientists in the World by Stanford University and Elsevier for three consecutive years 2021, 2022 and 2023. His achievements also include the IEEE Best Paper Award in 2013 and the MHRD Government of India Scholarship during both his M.E. and Ph.D. studies. He also served as a Session Chair at the International Conference on Computational Intelligence in Data Mining in 2017.

Professor Sahu is a Fellow of the Institution of Engineers India and a Life Member of ISTE. Through his research guidance, academic leadership and dedication to teaching he continues to inspire students and contribute to the advancement of electrical and electronics engineering.

FACULTY PROFILE

DR. GYAN RANJAN BISWAL

Associate Professor

Dr. Gyan Ranjan Biswal is an Associate Professor and Head of the Department of Electrical and Electronics Engineering at VSSUT, Burla. He obtained his B.E. in Electronics Engineering from Pandit Ravishankar Shukla University (1999), M.Tech. (Honors) in Instrumentation & Control Engineering from Chhattisgarh Swami Vivekananda Technical University (2009), and Ph.D. in Electrical Engineering (Power System Automation) from IIT Roorkee (2012).

With over 20 years of academic experience, he joined VSSUT in December 2016 and currently serves as HOD (EEE), PIC Electrical Maintenance, and Coordinator of the Centre of Excellence in Electric Vehicles. His expertise includes generator cooling systems, process C&I, sensor design, smart sensors, LiFi, power system automation, and hydrogen-based energy systems.

Dr. Biswal has over 90 international publications, 3 patents, and has edited an Elsevier-published book. He has secured research funding of USD 320,000 (INR 264 lakhs) and consultancy projects worth INR 70 crores. He has supervised 2 PhDs, 9 Master's theses, and is guiding 3 ongoing collaborative PhD projects.

He has received several honors including the Best Faculty Award (2021–22, VSSUT), INSA CICS travel grant (USA), MHRD Fellowship, and Gopabandhu Das Scholarship. He is a Fellow of IE (India), Senior Member of IEEE (USA), and Life Member of ISTE. He actively contributes as a reviewer for IEEE, IFAC, ISA, and has been part of IEEE-SA working groups (P1876, P21451-001, P1415, P1451.5, PC37.1.3).

He contributes to academia through invited lectures and key institutional roles, including PIC Security, IDP member (Govt. of Odisha), and Founding Coordinator of the EV Centre of Excellence. He served as HOD from 2020 to 2023 and continues to lead academic and research development.

FACULTY PROFILE

DR. SANTI BEHERA

Associate Professor

Dr. Santi Behera is a distinguished academician and Associate Professor in the Department of Electrical and Electronics Engineering at VSSUT with over 24 years of teaching and research experience. Her research focuses on Power System Stability Voltage Stability Optimization Techniques Renewable Energy Systems Power Quality THD analysis and intelligent techniques applied to power systems. She holds a B.Tech from C.E.T OUAT Bhubaneswar (1995), an M.TECH in Power System Engineering from Sambalpur University (1999) and a Ph.D from NIT Rourkela (2016).

Dr. Behera has received several recognitions for her contributions to research and engineering education. She received the Institution Prize in 2019 for her work on Power Quality Analysis of Hybrid SPV Wind Integrated Systems. She was also honored with the Institution Award in 2020 for Fault Detection in Distributed Generation Systems using Neuro Fuzzy Techniques. Earlier she received the Institution Award at the 46th Annual Technical Session of the Institution of Engineers India Odisha in 2005. Received Banabhari Memorial Award at 64th Annual Technical Session ,OSC, Bbsr in 2025.

Successfully completed her tenure as HOD,EEE, from 2023-2025. She is a Life Member of ISTE and a Member of the Institution of Engineers India. Dr. Behera continues to contribute actively to engineering education research and student mentorship. Her work includes research on hybrid renewable energy systems and advanced fault detection methods in distributed generation. Performed her duty as Member Academic Council, member Moderation committee, member conducting board, member SMCC, Member ICC during her work as assistant Professor and Associate Professor.

FACULTY PROFILE

DR. SARMILA GARNAIK

Assistant Professor

Dr. Sarmila Garnaik has been serving as an Assistant Professor in the Department of Electrical and Electronics Engineering at VSSUT Burla since 2011. She completed her B.Tech in Electronics and Telecommunication Engineering from Utkal University in 2001 and her M.Tech in Communication System Engineering from UCE Burla in 2008. She earned her Ph.D. from VSSUT Burla in 2023 in the area of VLSI Signal Processing. With more than a decade of academic experience she has been actively involved in teaching and guiding students while helping them build strong foundations in core engineering concepts.

Along with her teaching responsibilities Dr. Garnaik has contributed significantly to academic administration. She served as the Head of Programme of the department and played an important role in academic coordination and curriculum development. She currently serves as the Faculty Advisor of the Department where she mentors students in organizing technical events competitions and academic activities. Under her guidance students are encouraged to participate in research discussions, collaborative learning and innovative technical initiatives that enrich their academic experience.

FACULTY PROFILE

DR. LINGRAJ DORA

Assistant Professor

Dr. Lingraj Dora is a dedicated academician in engineering education who is known for simplifying complex technical concepts and creating an engaging learning environment for students. He completed his B.E. in Electronics and Telecommunication Engineering from UCE Burla in 2006, M.Tech in Communication System Engineering from VSSUT in 2010 and Ph.D. from VSSUT in 2019.

His areas of specialization include Medical Image Processing, Pattern Recognition and Communication Systems Engineering. Through his teaching and research he encourages students to develop innovative thinking, analytical ability and strong technical foundations.

Dr. Dora is actively involved in teaching research and student mentorship. Through his academic contributions and guidance he continues to promote innovation research culture and technical excellence at VSSUT Burla.

FACULTY PROFILE

DR. SASMITA BEHERA

Assistant Professor

Dr. Sasmita Behera has 26+ years of professional experience spanning industry and academia. She holds a B.E. (2000) from UCE Burla, M.E. (2003) from BPUT Rourkela and Ph.D. (2017) from VSSUT. Her research interests include power systems, renewable energy, soft computing and ML applications.

She is the recipient of the Best Faculty Award (2022–23) and the Best Paper Award (2023–24). She was also selected for INAE-INFOSYS CEEE mentoring program in Domain 2 (Electrical, Electronics and Instrumentation Engineering), held at IIT Kharagpur in June 2025. She has also led research projects funded under TEQIP (MHRD) and OURIIP (OSHEC), related to microgrids, hybrid energy systems, photovoltaic power forecasting and membrane technology for air purification.

Dr. Behera actively contributes to academic administration as NBA Co-Coordinator, NEP Coordinator, Dept. Time Table Coordinator and AICTE Coordinator. She also serves as Professor-in-Charge of the CADEA Lab and Department Seminar Hall and mentors' students as Faculty Advisor for Team of Sustainable Energy (ToS).

FACULTY PROFILE

DR. BIBHUTI PRASAD SAHOO

Assistant Professor

Dr. Bibhuti Prasad Sahoo is an Assistant Professor in the Department of Electrical Engineering at VSSUT Burla with specialization in Measurement and Instrumentation. He obtained his B.Tech from NIT Rourkela in 2007, M.Tech from IIT Roorkee in 2011 and Ph.D. from VSSUT in 2022. With more than a decade of experience in teaching and research he is committed to nurturing technical curiosity and analytical thinking among students.

His research focuses on soft computing applications in power system control for renewable energy based microgrids along with power electronics. He is also engaged in signal processing research including medical image processing, face recognition and image fusion.

At the university Dr. Sahoo teaches courses such as Electronic Circuits Microprocessors Digital Image Processing and Communication Systems. Along with his teaching and research responsibilities he actively contributes to academic administration as Assistant Comptroller of Examination and NSS Programme Officer.

FACULTY PROFILE

ER. PRASANTA KUMAR PARIDA

Assistant Professor

Er. Prasanta Kumar Parida is a faculty member in the Department of Electrical and Electronics Engineering at VSSUT Burla. He completed his B.Tech in 2007 and M.Tech in 2012 from VSSUT with specialization in Communication Systems. Over the years he has remained dedicated to strengthening the learning experience of students and helping them develop a strong foundation in core engineering principles.

His teaching interests include Digital Circuits Control Systems and Electromagnetics. He is known for his clear teaching approach and supportive nature which helps students understand complex technical concepts with ease. Through his classes he encourages students to connect theoretical knowledge with practical applications and to explore innovative ideas in engineering.

Er. Parida also served as the Faculty Advisor of the EEE Society where he guided students in organizing technical events, competitions and collaborative academic activities. Through his mentorship and commitment to academic excellence he continues to motivate students to pursue knowledge innovation and professional growth in the field of electrical and electronics engineering.

Pre-final year 2025 - 2026

Second year 2025 - 2026

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DYNAMIC PRICING-BASED SMART EV CHARGINGUSING AI + IOT

RUDRAMANI JENA, ADITYA RANJAN NAYAK, SHIVANGI SAHU, AVINASH MOHANTA, TADVAB PRADHAN

OBJECTIVE

The objective of this projectis to design an intelligent EV charging system that optimizescharging cost and energy utilization using real-time data and machine learning techniques.

Specific objectives:

- Measure electrical parameters such as voltage, current,power, and energyconsumption using sensorsand energy meters.
- Acquire real-time data through an ESP32 microcontroller with IoT connectivity.
- Develop a machine learningmodel to predictoptimal charging price based on time, demand,energy use, and grid load.
- Transmit sensor data to a cloud server and receivepricing decisions in real time.
- Automatically controlcharging using a relay module.
- Provide user feedback via a display showing status and pricing.
- Improve energy efficiency and reduce peak grid load.

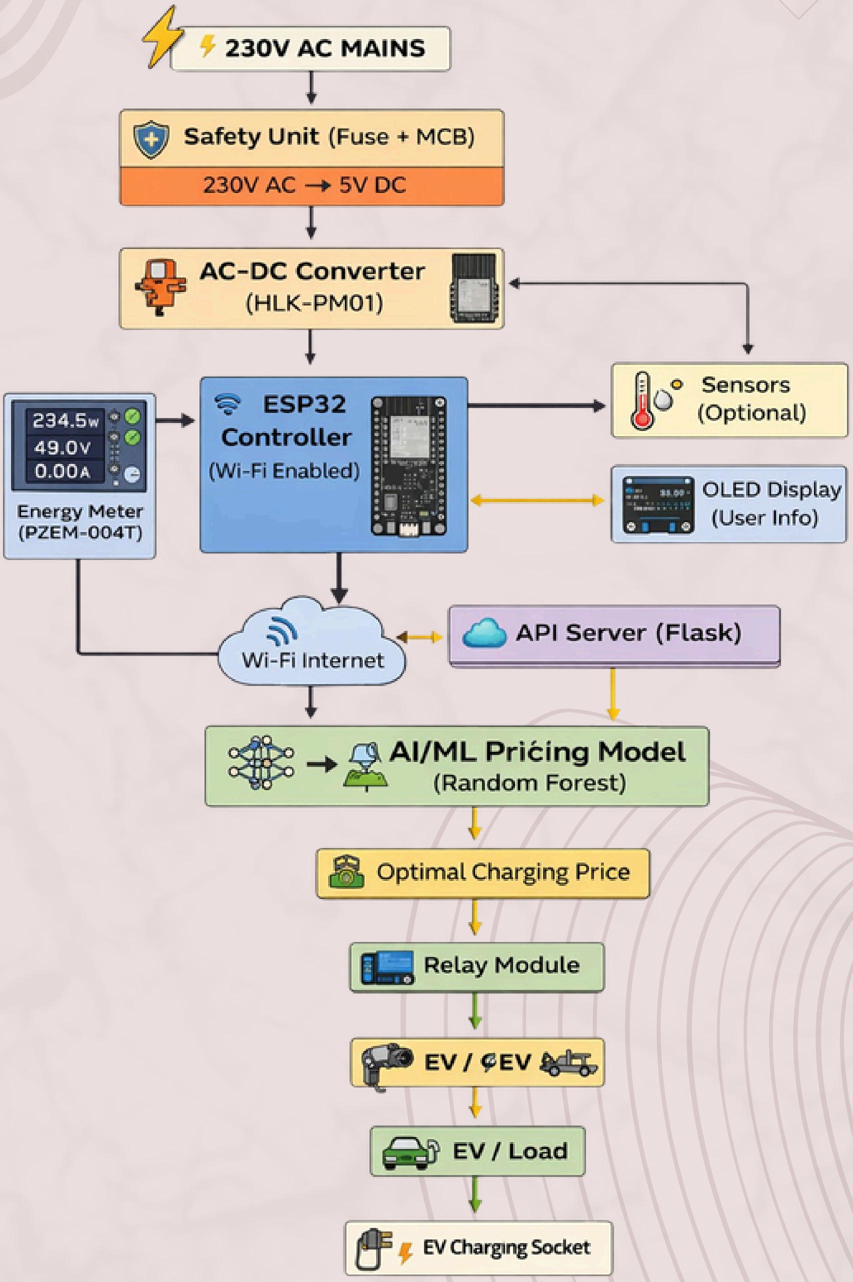
WORKING

The system integrates IoT-based monitoring with AI-driven decision-making to enable efficient and intelligent EV charging.

- Data Monitoring: Sensors continuously measure key electrical parameters such as voltage, current, and power. An ESP32 microcontroller collects this data in real time.
- Data Transmission: The collected data is transmitted via Wi-Fi to a cloud server for further processing and analysis.
- AI-Based Pricing: An AI model processes inputs including time of day, user demand, energy availability, and grid load conditions to determine the optimal charging price dynamically.
- Charging Control: The computed price signal is sent back to the charging station, where a relay mechanism regulates the charging process accordingly.
- User Display: Important information such as charging status, energy consumption, and current pricing is displayed to the user through an LCD or OLED interface.
- Energy Optimization: The implementation of dynamic pricing incentivizes users to charge during off-peak hours, thereby reducing grid stress and enhancing overall energy efficiency.

BLOCK DIAGRAM

The proposed system includes a power supply unit, sensingmodule, IoT-enabled microcontroller, communication interface, machine learning server, and control unit for charging management.



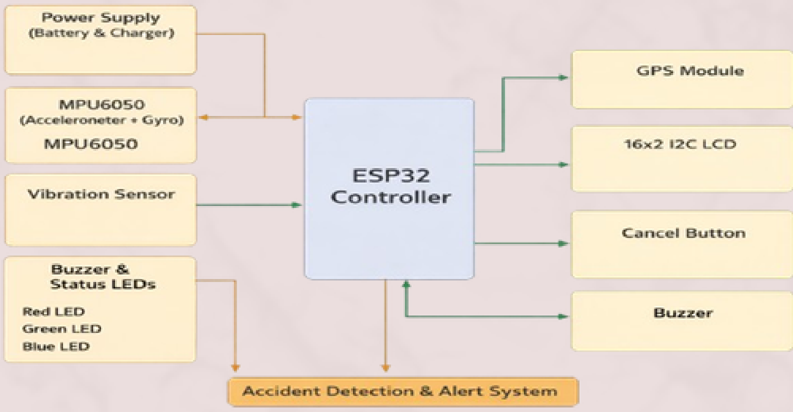
ACCIDENT DETECTION AND EMERGENCY ALERT SYSTEM

ARMAAN MISHRA, AYUSH MOHANTY, HAREKRUSHNA DASH, PARSURAM NATH, RAHULDEV SAMAL

OBJECTIVE

Design a smart accident detection system using ESP32 and sensors that automatically identifies accidents and sends the victim's location to emergency contacts for quick response. It includes a manual cancel feature to prevent false alerts and ensure reliable operation

BLOCK DIAGRAM



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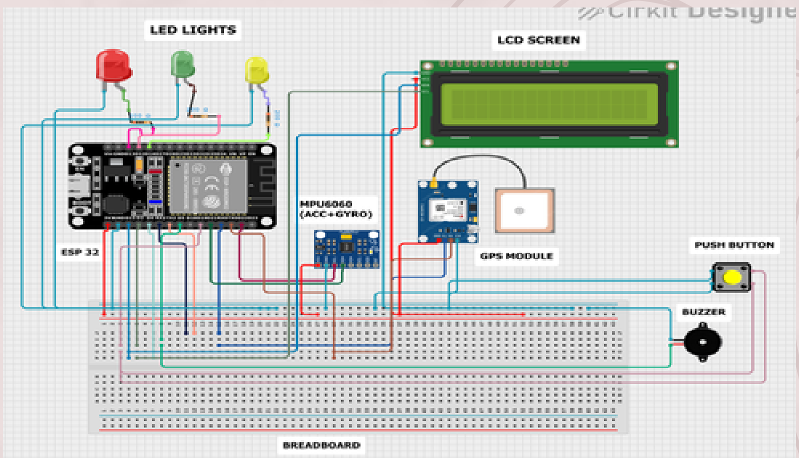

WORKING

The system uses a battery and charger to provide a stable power supply to the ESP32 and all connected components. The ESP32 acts as the main controller, continuously monitoring data from the MPU6050 and vibration sensor. The MPU6050 detects sudden tilt or abnormal acceleration, while the vibration sensor senses strong shocks during a crash. When these values exceed a preset threshold, the system identifies a possible accident. Once detected, a buzzer is activated and a timer starts, allowing the user a few seconds to cancel the alert using a button. If cancelled, the system returns to normal operation. If not, the ESP32 reads the current location from the GPS module and prepares the data for alert transmission (GSM can be added later). The LCD displays system messages, and LEDs indicate different states, ensuring quick detection and response.

AUTOMATIC RAILWAY TRACK CRACK DETECTION SYSTEM

SHIMRAN JEET PRADHAN, PRIYANKA RANA, OUMPRIYA DHARUA, KORUKONDA PAWAN KUMAR, ASHUTOSH DASH, ROJALIN SAHOO

OBJECTIVE

- To detect railway track cracks automatically
- To prevent accidents and improve safety
- To send real-time alerts to authorities upon crack detection

•To develop a low-cost and reliable system

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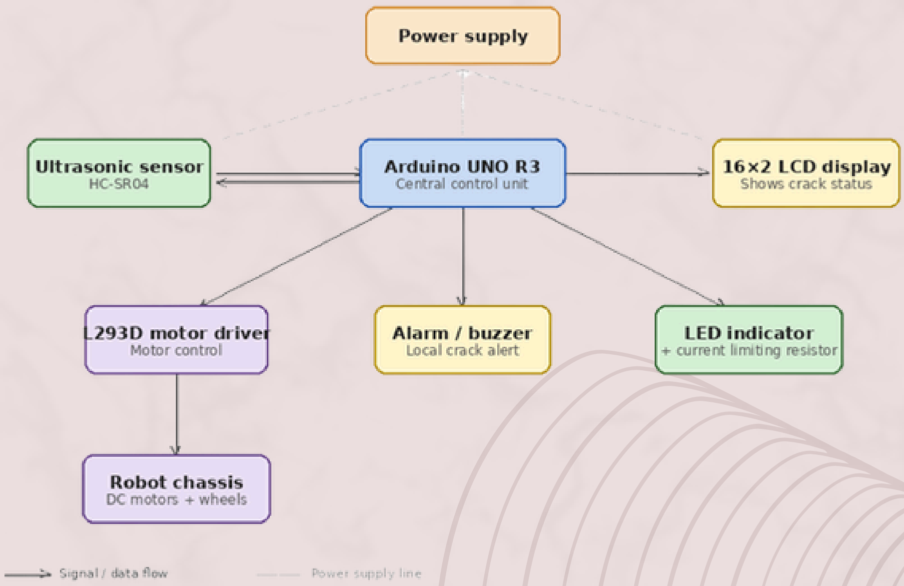

WORKING

The automatic railway track crack detection system operates on the principle of ultrasonic sensing and real-time data processing using an Arduino UNO R3 as the central controller. An Ultrasonic Sensor HC-SR04 continuously transmits ultrasonic waves toward the railway track surface while the system moves along the track. These waves reflect back to the sensor, and the time taken for the echo to return is used to calculate the distance between the sensor and the track. Under normal conditions, this distance remains nearly constant; however, when a crack or gap appears, the distance changes significantly, which is detected by the system as a fault.

The Arduino processes this variation by comparing it with predefined threshold values. When the detected value exceeds the normal range, it identifies the presence of a crack and immediately triggers alert mechanisms. A buzzer and LED provide a local warning signal, while the status is displayed on a 16×2 LCD Display for real-time monitoring. The entire system is mounted on a moving robot controlled by an L293D Motor Driver, which drives the motors and allows continuous scanning of railway tracks. This integrated working ensures early detection of cracks and enables timely action to prevent accidents.

SMART STREET LIGHT WITH VEHICLE DETECTION AND INTENSITY CONTROL

ARCHANA MAHARANA, SWATI SUBHRA SAHOO, SAMANGYA DASH, OM PRAKASH NAYAK, SATYA NARAYAN PATRA, IPSITA SAMAL

OBJECTIVE

The main objective of this project is to design a smart street lighting system that can automatically control the brightness of street lights based on environmental conditions and vehicle movement. The system aims to reduce energy consumption by keeping the lights off during day time and maintaining low intensity at night when no vehicles are present. It also focuses on improving efficiency and automation by increasing the brightness of lights only when required, thereby ensuring proper illumination and energy saving.

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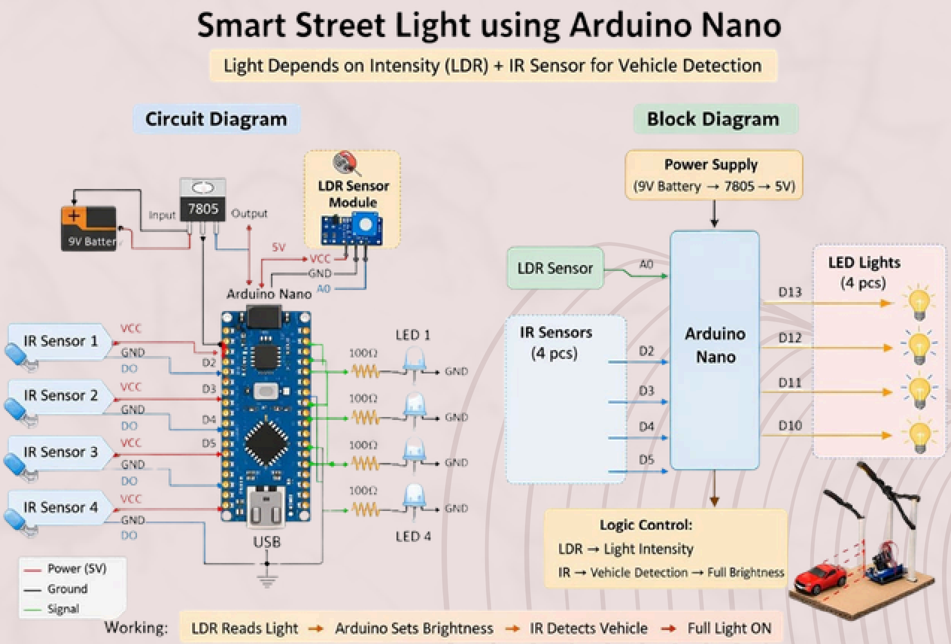

WORKING

The working of this system is based on sensors and a microcontroller. A light sensor (LDR) is used to detect whether it is day or night. During daytime, the street lights remain switched off. At night, all the street lights glow with low intensity to conserve energy. Infrared (IR) sensors are used to detect the presence of vehicles or objects on the road. When a vehicle passes near a particular street light, that light glows with full intensity. As the vehicle moves forward, the next street light becomes bright while the previous one returns to low intensity. This continuous process ensures that only the required lights operate at high brightness, leading to efficient energy utilization.

2-AXIS SOLAR PANEL WITH SOLAR TRACKER

OM PRAKASH SAHU, SIDHANT SEKHAR BOHIDAR, ABHISHEK AGRAWAL, SIBANANDA MISHRA, SIBASHISH PANDA

OBJECTIVE

The primary objective of this project is to develop a low-cost, dual-axis solar tracking system that increases the energy output of a photovoltaic panel by 20–35% compared to fixed-position panels. Using an Arduino UNO microcontroller and four LDR sensors arranged in a cross pattern, the system intelligently detects sunlight intensity to keep the panel aligned perpendicular to the sun. The design aims to maximise solar energy capture by precisely adjusting both azimuth and tilt using servo motors, providing an efficient, lightweight solution suitable for academic and small-scale renewable energy applications without requiring complex MPPT systems.

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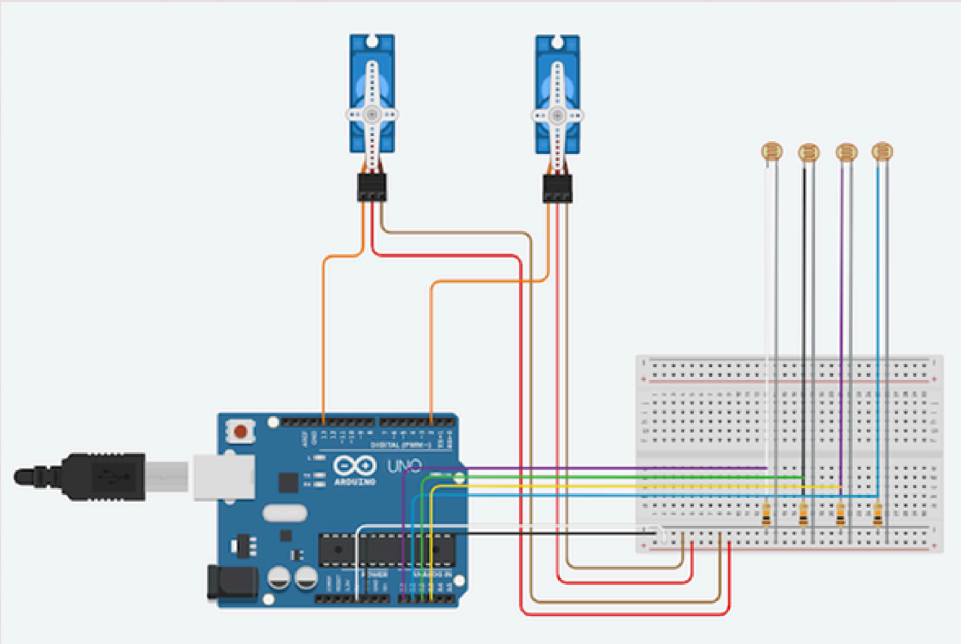

WORKING

A 2-axis solar tracker operates by continuously aligning the solar panel toward the sun. Four LDR sensors placed in a cross pattern detect the intensity of sunlight from different directions. When the light is uneven, the sensors produce voltage differences, which are processed by a microcontroller. The controller then drives two motors—one for horizontal rotation and one for vertical tilt—to reposition the panel until all LDR readings are balanced. This indicates that the panel is directly facing the sun. The process repeats throughout the day, ensuring maximum sunlight exposure and improved energy output.

REAL-TIME DETECTION OF NEUTRAL AND EARTHING FAULTS IN RESIDENTIAL ELECTRICAL SYSTEMS

BISHWARANJAN MOHAPATRA, SHRABAN KUMAR PRUSTY, SWASTIK SENAPATI

OBJECTIVE

The objective of this project is to design a low-cost, easy-to-install household safety device capable of detecting neutral open or high-impedance conditions in single-phase electrical systems. It aims to continuously monitor variations in Neutral–Earth voltage to identify abnormalities that may indicate faults such as missing or improper earthing. The system is intended to enhance electrical safety by providing real-time fault indication through visual alerts using LEDs and audible alerts via a buzzer, enabling users to quickly recognise and respond to potentially hazardous conditions.

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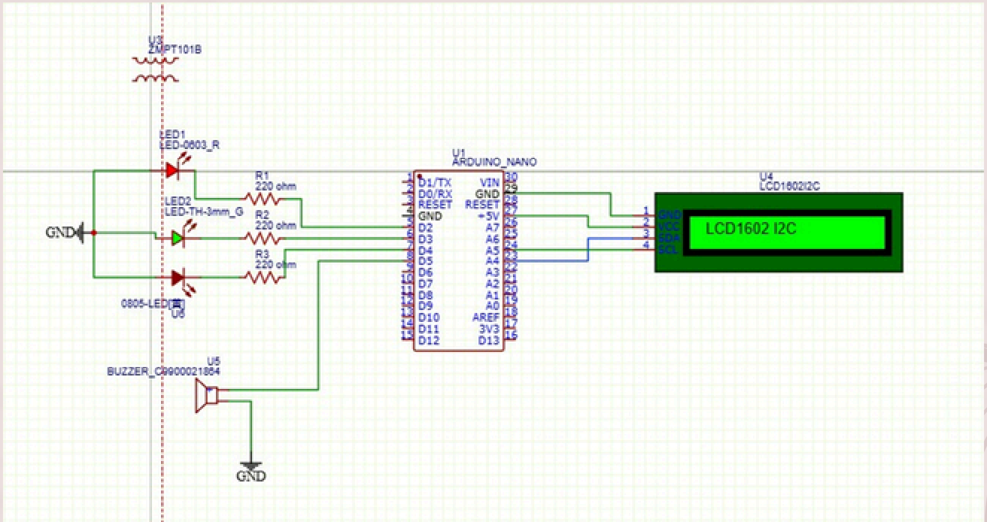

WORKING

The system continuously monitors Phase–Neutral and Neutral–Earth voltages using voltage divider circuits. The sensed analog voltages are fed to a microcontroller (Arduino/STM32) through ADC channels. Under normal conditions, Neutral–Earth voltage remains within a safe limit (near zero). If a neutral fault occurs, the Neutral–Earth voltage rises significantly. Similarly, if the earthing connection is missing or unstable, abnormal voltage behaviour is detected. The microcontroller compares measured values with predefined threshold levels. If fault conditions are detected, the system activates corresponding LED indicators and a buzzer to alert the user in real time.

SELF BALANCING BOT

DIBYAJYOTI SAMAL, DIBYA AAHWAN MISHRA, AYUSH KUMAR BAITHALU, ADARSH RAJ, SOMESH BISWAL, SUMIT KUMAR NAND

OBJECTIVE

The main objective of this project is to design and develop a two-wheeled self-balancing robot that can maintain its upright position automatically using real-time feedback control. The system aims to demonstrate the implementation of control system techniques such as PID control, along with sensor integration and embedded programming.

Additionally, the project serves as a foundation for advanced applications in robotics, including autonomous vehicles, defence surveillance systems, agricultural robots, and warehouse automation, where stability and precise motion control are essential.

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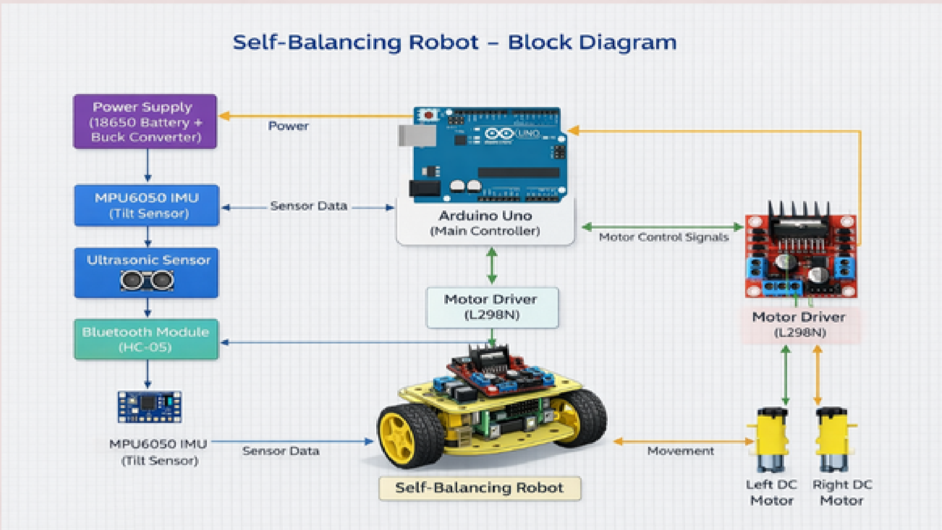

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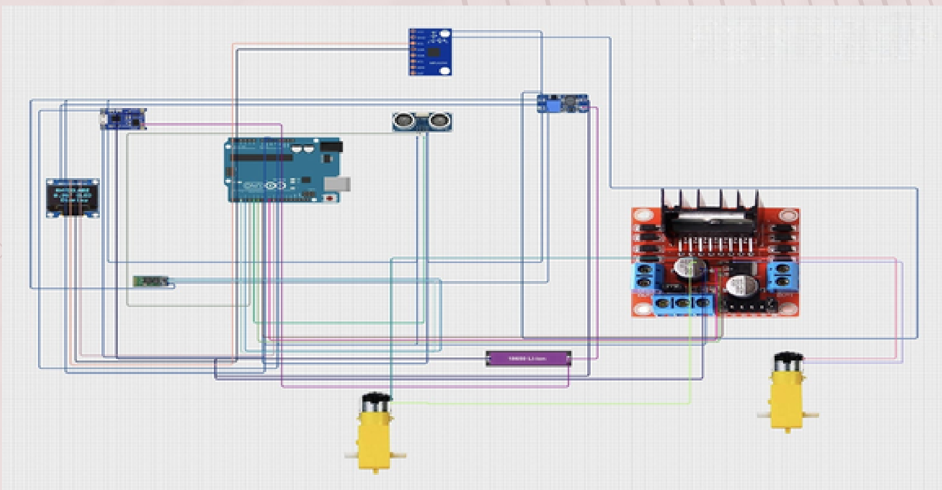


WORKING

The self-balancing robot works on the principle of an inverted pendulum, where continuous correction is required to maintain stability.

- The robot is powered by batteries, and a regulated voltage is supplied to all components.
- The MPU6050 sensor measures the tilt angle and angular velocity of the robot.
- The Arduino reads this sensor data and determines the current orientation.
- The controller compares the measured angle with the desired vertical position (setpoint).
- The error between the actual and desired position is calculated.
- A PID control algorithm processes this error to determine the required correction.
- Based on the PID output, control signals are sent to the motor driver.
- The motor driver controls the direction and speed of the motors.
- The motors rotate the wheels forward or backward to restore balance.
- This process repeats continuously in a feedback loop, allowing the robot to remain stable.

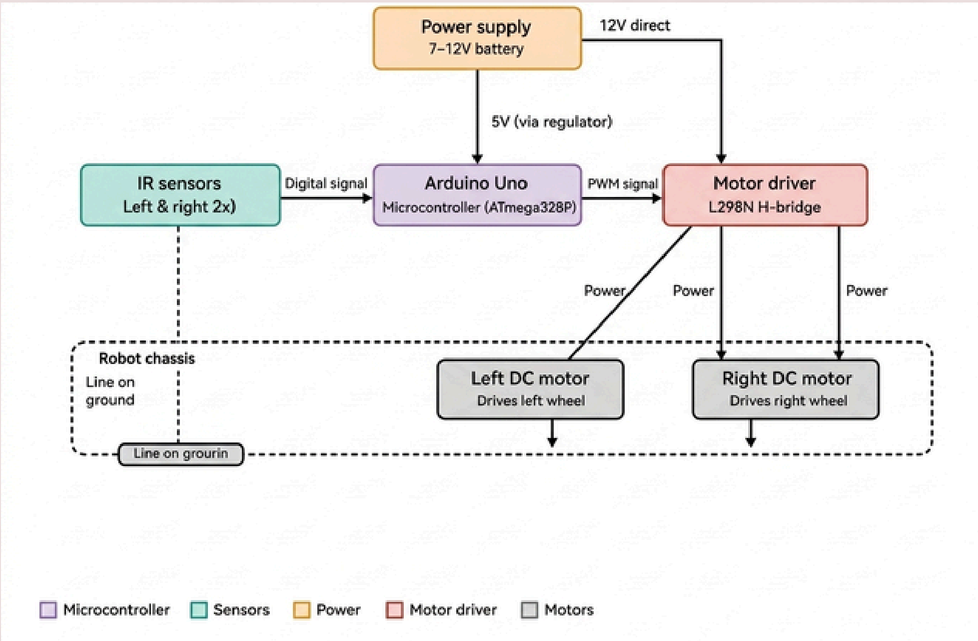
LINE FOLLOWING ROBOT

PULLAK MOHAPATRA, SUBHASARTHAK SAHOO, SRINAYA JENA, SHREYA PANIGRAHI, ASUTOSH BEHERA

OBJECTIVE

- To design and build a robot that follows a predefined line path on a surface.
- To implement infrared (IR) sensor-based line detection for real-time path tracking.
- To enable motor control and directional correction using an L293D motor driver.
- To develop a low-cost and energy-efficient autonomous navigation system.

BLOCK DIAGRAM



The line following robot operates on the principle of infrared (IR) sensing and real-time feedback control using an Arduino UNO R3 as the central microcontroller. Two IR sensors are mounted at the front of the robot, facing downward toward the surface. These sensors continuously emit infrared light and detect the reflected signal. A dark-colored line (typically black tape on a white surface) absorbs IR radiation and reflects less light back, whereas the surrounding white surface reflects more. This contrast in reflected signal allows the sensors to distinguish between the line and the background.

The Arduino continuously reads the sensor outputs and makes navigation decisions based on predefined logic. When both sensors detect the white surface, the robot moves straight ahead. If the left sensor detects the line (black), the robot steers left to re-center itself. Similarly, if the right sensor detects the line, the robot steers right. This feedback loop ensures the robot remains on track at all times.

UG CABLE FAULT DISTANCE LOCATOR USING ARDUINO MICROCONTROLLER

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Abstract

This report presents an automated system for the precise detection and location of faults in urban underground electrical cables. The proposed system leverages the fundamental principle of Ohm's law, applying a low DC voltage to the cable through a series resistor to measure the resulting current, which varies proportionally with the distance to the fault. The system is architected around an Arduino microcontroller, which processes data from a current detection circuit via an Analog-to-Digital Converter (ADC). The microcontroller calculates the fault's distance from the base station in kilometers and displays this information on a 16x2 LCD screen. For immediate notification, the system is equipped with a GSM module that automatically sends an SMS message detailing the fault's location to a central station, alongside an integrated buzzer for an audible on-site alert. The system's functionality is validated using a set of switches and relays to simulate fault conditions across various cable lines.

Keywords

Arduino microcontroller, Ohm's law, cable fault detection, UG cables, GSM, ADC, monitoring.

1. Introduction

1.1 Background: The transition from overhead to underground electrical cables in urban areas offers enhanced grid reliability and immunity to adverse weather conditions. However, detecting the precise location of a fault in a buried cable is a complex and resource-intensive process that typically results in extensive excavation.

1.2 Literature Review: Traditional methodologies for cable fault location, such as the Murray Loop test and Time Domain Reflectometry (TDR), require specialized, expensive equipment and significant human intervention [1-3]. The most significant evolution is the integration of wireless communication, such as GSM modules, to transmit fault data via SMS to a control room, minimizing the gap between fault occurrence and the dispatch of repair crews [4].

1.3 Objectives

- To design a digitized, automated system for the precise localization of short-circuit (Line-to-Ground) faults in underground cables.

- To capture changing voltage profiles using an Analog-to-Digital Converter (ADC) and algorithmically determine the exact distance to the fault in kilometers via a programmed Arduino microcontroller.

2. Methodology

- The operation of the underground cable fault detection system is based on the principle of Ohm's Law and the Voltage Divider Rule.
- It utilizes the electrical principle that the longer a cable is, the higher its electrical resistance.

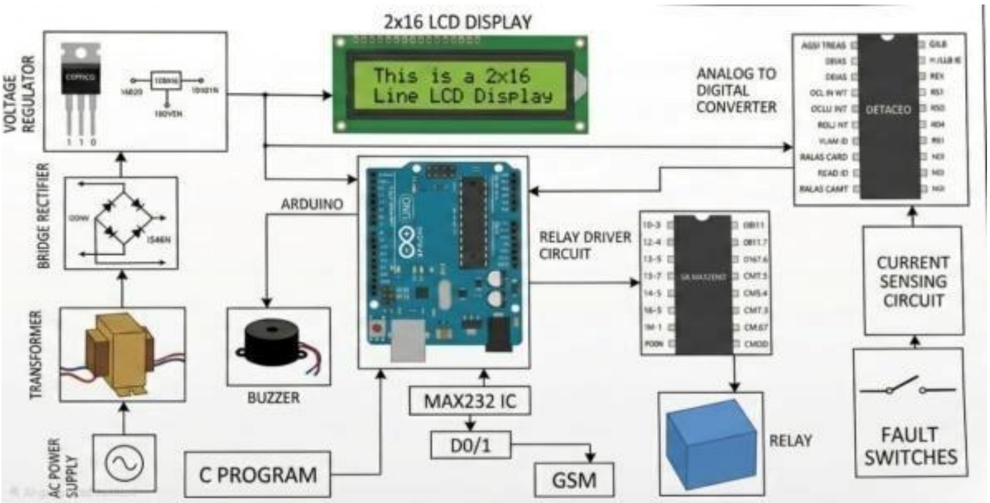

Fig 1. Schematic diagram

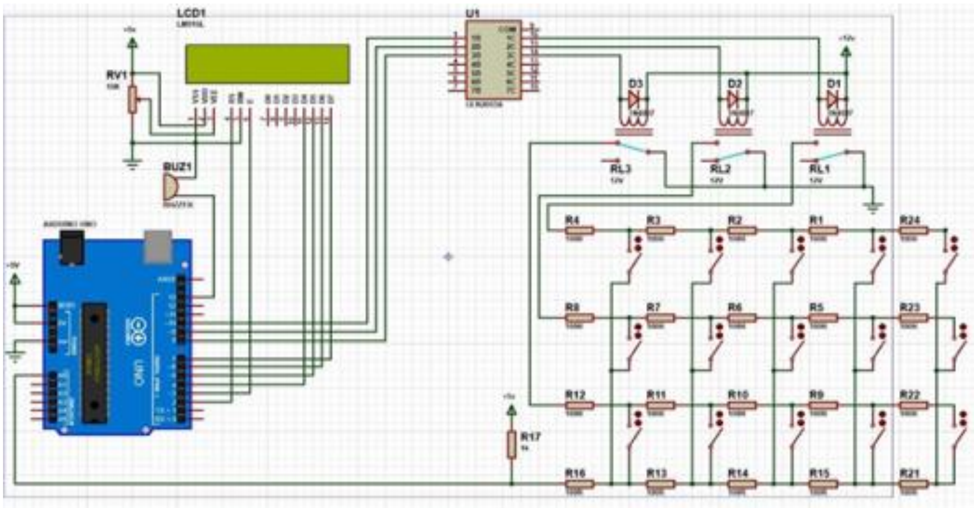

Fig 2. Layout of the Network.

3. Results and Discussion

- The simulation successfully validated the Ohm's law-based distance calculation, confirming that the output matched the injected fault switches based on calibration.
- **Normal Condition:** When all switches were open, the Arduino read the maximum voltage, and the LCD displayed "NF" (No Fault) for the R, Y, and B phases

Case 3.1 (R-Phase): A fault was simulated at a 1 km distance in the R-Phase. The voltage divider network created a potential drop resulting in the Arduino reading and outputting the exact corresponding location.

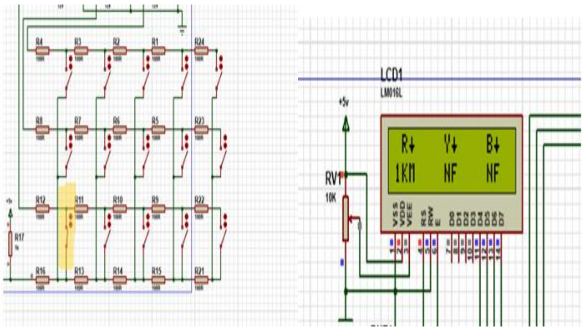

Fig 3. Fault in A-Phase

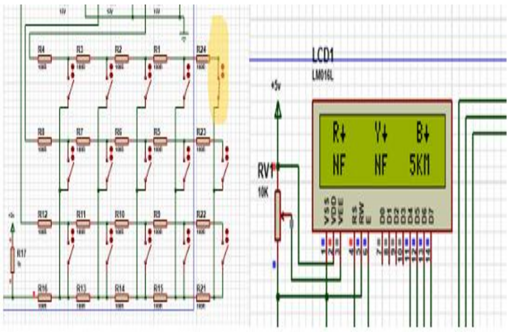

Fig 4. Fault in B.Phase

Case 3.2 (B-Phase): A short circuit was simulated further away in the B-Phase. The system detected the resistance path and outputted a distance of 5 km on the LCD.

Case 3.3 (Multi-Phase Capability): Three switches were closed simultaneously across the three phases. The system effectively detected and outputted the distances as 4 km for R-Phase, 5 km for Y-Phase, and 1 km for B-Phase, proving its ability to handle multi-phase line faults

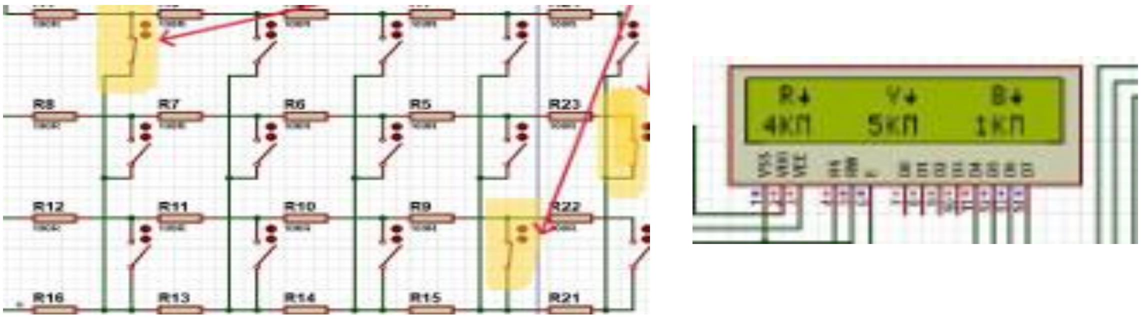

Fig.5 Multi-phase fault

Table.1 Fault detection results for three cases.

Fault	Distance	Display	Observed
In the R-Phase	1 km from R-Phase	Fig.3.1	correct
in the B-Phase	5 km from the B-Phase	Fig.3.2	correct
In the R, Y, B - Phases	4 km for 5 km for Y-Phase, and 1 km for B-Phase R-Phase	Fig.3.3	correct

4. Conclusion

- The Arduino-Based Underground Cable Fault Distance Locator successfully addresses the difficult and time-consuming nature of identifying faults in subterranean power networks.

- By utilizing an Arduino microcontroller interfaced with a resistance measurement circuit, the system accurately calculates and displays the specific fault distance in kilometers.
- The reliance on precise measurement of cable resistance up to the point of the fault prevents unnecessary and costly excavation, drastically reducing manual effort.
- The integration of a local buzzer alarm and remote GSM communication ensures that personnel are immediately notified regardless of their proximity to the feeder, facilitating a swift and proactive response to electrical failures.

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IOT-BASED SMART SOIL ANALYSIS AND CROP-SPECIFIC FERTILIZER & IRRIGATION RECOMMENDATION SYSTEM

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Abstract

This project presents the design and development of an IoT-based Smart Soil Analysis and Crop-Specific Fertilizer and Irrigation Recommendation System aimed at improving agricultural productivity and resource efficiency. The system utilizes an integrated soil sensor capable of measuring key soil parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), pH value, and temperature. These parameters are acquired in real time and processed using a microcontroller-based platform. The measured soil data is compared with predefined optimal requirements of selected crops such as rice, rose, and strawberry, which are stored in a structured dataset. Based on this comparison, the system identifies nutrient deficiencies and calculates the precise amount of fertilizers required per square meter, including commonly used fertilizers such as urea, DAP, and MOP. Additionally, the system estimates the water requirement per square meter by considering crop-specific needs and current soil moisture conditions. The proposed system provides output through a user interface or mobile platform, enabling farmers to make informed decisions regarding crop selection, fertilizer application, and irrigation management. This project integrates concepts from embedded systems, IoT, and agricultural engineering, and offers a cost-effective and scalable solution for precision farming. It has the potential to be extended with advanced features such as machine learning-based crop prediction, automated irrigation control, and cloud-based data analytics for large-scale agricultural applications.

Keywords

Smart Agriculture, Soil Analysis, NPK Sensor, Soil pH Measurement, Precision Farming, Fertilizer Recommendation System, Irrigation Management, Internet of Things (IoT), ESP32 Microcontroller, RS485 Communication, Modbus Protocol, Nutrient Deficiency Detection, Crop Recommendation, Sustainable Agriculture

1. Introduction

1.1 Background

Agriculture plays a crucial role in food production and economic development. Traditional farming methods often rely on manual assessment of soil conditions, leading to inefficient use of fertilizers and water. With the advancement of technology, IoT-based smart agriculture systems have enabled real-time monitoring of soil parameters, improving decision-making and resource utilization. The use of sensors and microcontrollers such as ESP32 allows efficient data collection and processing for precision farming applications [1].

1.2 Literature Review

Sharma and Kumar [1] developed an IoT-based agriculture monitoring system using ESP32 for real-time data acquisition and remote monitoring. Navulur et al. [2] proposed a system using wireless sensors and IoT to enhance agricultural management through continuous monitoring. Ramesh and Rajesh [3] focused on real-time soil nutrient analysis using NPK sensors, highlighting their importance in fertilizer management.

However, most existing systems focus on monitoring or irrigation individually. An integrated system that provides crop-specific fertilizer and irrigation recommendations based on soil parameters is required, which is addressed in this work.

1.3 Objectives

- To develop a smart system capable of measuring soil parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), and pH using integrated sensors and embedded technology.
- To design an algorithm that analyzes soil data and recommends suitable fertilizers and their required quantity per square meter for selected crops.
- To estimate and provide crop-specific irrigation requirements based on soil conditions, enabling efficient water usage and supporting precision agriculture practices.

2. Methodology

2.1 System Overview

The proposed system is designed to analyze soil parameters and provide crop-specific recommendations for fertilizer application and irrigation. The system consists of a multi-parameter soil sensor, a microcontroller unit (ESP32), communication modules, and a decision-making algorithm. The sensor measures key soil properties such as Nitrogen (N), Phosphorus (P), Potassium (K), and pH value. These values are transmitted to the microcontroller, where they are processed and compared with predefined crop requirements.

2.1.1 Soil Parameter Acquisition

A multi-parameter soil sensor is used to measure NPK values, pH, and temperature. The sensor communicates using RS485 protocol, and a MAX485 module is used to interface it with the ESP32 microcontroller. The microcontroller sends Modbus commands to the sensor and receives real-time data, which is then decoded into meaningful values such as mg/kg for nutrients and pH levels.

2.1.2 Data Processing and Analysis

The acquired soil data is processed within the microcontroller. The measured values are compared with a predefined dataset containing optimal soil conditions for selected crops such as rice, rose, and strawberry. Based on this comparison, the system identifies nutrient deficiencies or excess levels in the soil.

2.1.3 Fertilizer Recommendation Algorithm

The system calculates the required amount of fertilizers based on nutrient deficiency. The difference between the required nutrient level and the available nutrient level is computed. This deficit is then converted into fertilizer quantity per square meter using standard nutrient composition values of fertilizers such as Urea (Nitrogen source), DAP (Phosphorus source), and MOP (Potassium source).

2.1.4 Irrigation Requirement Estimation

The system estimates the water requirement for the selected crop based on its standard water needs and current soil conditions. Soil moisture and crop-specific water demand are used to calculate the required water per square meter. This helps in optimizing irrigation and preventing overwatering or underwatering.

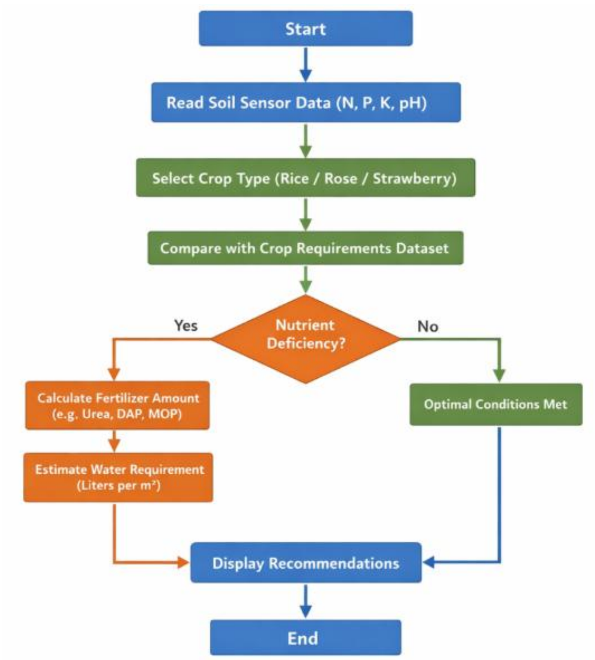
2.1.5 User Input and Output Interface

The user selects the desired crop (e.g., rice, rose, or strawberry) through a user interface such as a mobile application or serial input. The processed results, including soil status, recommended fertilizers, and irrigation requirements, are displayed on the interface or transmitted via IoT platforms for remote monitoring.

2.1.6 System Integration and Workflow

The complete system operates in a sequential manner starting from soil data acquisition, followed by data processing, comparison with crop requirements, and generation of recommendations. The integration of sensors, microcontroller, and communication modules ensures real-time monitoring and efficient decision-making for precision agriculture.

2.2 Flowchart



3. Results and Discussion

The proposed system was tested using simulated soil parameter values obtained from a controlled test environment. The simulation and validation of the system were carried out using MATLAB, where different soil conditions were modeled to analyze the performance of the fertilizer and irrigation recommendation algorithm. A single set of soil sensor readings was considered, and crop-specific recommendations were generated for three different crops: Strawberry, Rose, and Maize.

3.1 MATLAB Simulation

MATLAB was used to simulate soil parameter inputs such as Nitrogen (N), Phosphorus (P), Potassium (K), and pH values. The developed algorithm was implemented to compute nutrient deficiencies and generate fertilizer and irrigation recommendations. The simulation execution time was recorded for each case to evaluate computational efficiency.

3.2 Common Soil Sensor Readings

Parameter	Value
Nitrogen(N)	40 mg/kg
Phosphorus(P)	25 mg/kg
Potassium(P)	60 mg/kg
pH Value	6.7

3.3 Case 1: Strawberry

3.3.1 Fertilizer and Irrigation Requirement

Simulation Time: 0.42 seconds

Parameter	Value
Urea (g/m^2)	10
DAP (g/m^2)	6
MOP (g/m^2)	0
Water Requirement ($L/m^2/day$)	3.0

3.4 Case 2: Rose

3.4.1 Fertilizer and Irrigation Requirement

Simulation Time: 0.47 seconds

Parameter	Value
Urea (g/m^2)	6
DAP (g/m^2)	12
MOP (g/m^2)	15
Water Requirement ($L/m^2/day$)	4.2

3.5 Case 3: Maize

3.5.1 Fertilizer and Irrigation Requirement

Simulation Time: 0.51 seconds

Parameter	Value
Urea (g/m²)	18
DAP (g/m²)	5
MOP (g/m²)	8
Water Requirement (L/m²/day)	5.5

4. Conclusion

This project presents an IoT-based system for analyzing soil parameters such as NPK and pH to provide crop-specific fertilizer and irrigation recommendations. The system processes real-time sensor data and compares it with predefined crop requirements to generate accurate outputs. The proposed system reduces manual effort, minimizes excessive fertilizer use, and supports water conservation. It offers a cost-effective solution for precision agriculture and can be further enhanced with machine learning and automated irrigation for improved performance and scalability.

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MODIFIED DEEP LEARNING FRAMEWORK FOR ALZHEIMER'S DISEASE CLASSIFICATION

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Abstract

Alzheimer's disease (AD) is a brain disorder. Its early diagnosis is important for effective treatment. Recently, deep learning (DL) methods are showing robust performance in medical image analysis. In this paper a modified DL framework is presented for classification of AD using magnetic resonance imaging (MRI) samples. In this work, a modified convolutional neural network (CNN) model is developed to learn and extract features in an automatic way. The modified CNN is trained using a patch-based learning approach. For training and validation, a subset of MRI samples from Kaggle dataset is utilized. The results illustrate that the modified model achieves better performance compared to other methods. The model offers a reliable and efficient approach for AD detection and can assist medical experts in early treatment.

Keywords
Alzheimer's disease, Deep learning, Convolutional neural network, Magnetic resonance imaging.

1. Introduction

AD is a progressive brain disorder. It causes progressive impairment of brain activity, affecting memory and judgment-making skills. It is the main reason of dementia. It contributes to around 60-70% of dementia cases around the globe [1]. Thus, it is one of the leading public health concerns worldwide. Early as well as accurate detection of AD is a critical step in clinical practice. It enables to perform timely treatment planning. Thereby, helping in delaying the disease progression. Conventional clinical evaluation involves the utilization of neuroimaging techniques such as MRI. MRI aids in capturing significant structural information in the brain, including cortical atrophy and hippocampal shrinkage. These features are the key indicators for the AD diagnosis. However, manual interpretation of MRI is time-consuming, and the decision completely relies on the expertise of clinicians. Thus, manual interpretation may lead to diagnostic error [2].

Recently, advancements in artificial intelligence, and DL frameworks have shown significant impact in the field of medical image analysis. In the domain of DL, one of the powerful tools for automatic feature extraction. CNN is capable to obtain hierarchical attributes from images as well as performing classification tasks. It is witnessed that many CNN-based models are reported in literature, showing remarkable performance (accuracy more than 90%) in AD detection. Thereby, highlighting its potential in assisting clinical decision-making [3][4]. Despite of the remarkable performance, CNNs suffer from critical limitations [5]. In medical applications, these limitations in CNNs pose a significant challenge. Clinicians require a clear as well as reliable automated system which can be trusted. Hence, there is a growing need for solutions capable of providing accurate predictions. The work in this paper focuses on the development of a modified CNN for AD classification using MRI samples. The work aims to combine high classification accuracy with enhanced interpretability. Thereby, providing reliability as well as clinical applicability of DL-based diagnostic models.

The remainder of this paper is organized as follows. Section 2 provides a comprehensive review of related work in AD detection as well as highlights the role of DL frameworks. Section 3 describes the methodology, including the architecture of the CNN. Section 4 presents the experimental setup and results, demonstrating the performance of the approach. Finally, Section 5 concludes the paper and outlines directions for future research.

2. Background

Particularly in AD, the integration of advanced techniques into medical imaging has significantly improved the diagnosis of neurological disorders. In between the available imaging techniques, MRI is important for identifying the structural brain abnormalities, such as cortical thinning and hippocampal atrophy. However, traditional analysis of images largely depends on feature extraction and expert evaluation by making them time intensive and susceptible to inconsistencies [2]. To address these challenges, researchers have progressively adopted machine learning (ML) and DL techniques for the automated classification of AD. Earlier ML techniques used manually designed features along with different classifiers. The results of these methods are considerable but not very good at generalizing to new data. With the development of DL, manual feature extraction is no longer needed as the models can directly learn important attributes from MRI samples [3].

Several studies have shown that CNN based models work well for classifying the diseases. For example, deep CNN architectures have achieved accuracies above 90% in distinguishing Alzheimer's patients from healthy individuals [3][4]. Further, with the use of advanced architectures such as DenseNet and ResNet helps to improve feature learning and reduce issues like vanishing gradients by making the models more reliable for multi class classification tasks [4]. Additionally, CNNs are combined with traditional ML methods to further improve accuracy and make the models more stable [2].

Nowadays, researchers have started using the integration of feature selection methods and transformer based models to better understand the overall patterns. However, one major challenge in DL is that the models are difficult to interpret. Most of them work like black box giving accurate results but not clearly explaining how decisions are made. This makes it harder to use them in clinical settings, where understanding the reasoning behind a diagnosis is very important. To solve this, methods like gradient-weighted class activation mapping (Grad-CAM) have been developed. grad-CAM helps highlight the important brain regions that influence the model's decision, making the results easier to understand and more useful in medical practice [5].

3. Methodology

The methodology established in this paper concentrates on development of a modified CNN for AD classification using MRI samples. The overall working of the methodology includes pre-processing, model training, and classification. Initially, MRI samples of AD and normal subjects are collected. These samples are then passed through pre-processing steps such as intensity normalization and removal of non-brain structures. The pre-processing step ensures uniformity across the samples. In addition, it limits the variability caused by the imaging conditions as well as enables the model to learn meaningful patterns. After pre-processing, a modified CNN framework is trained using a patch-based learning approach. Instead of processing the entire MRI, the image is divided into small 2D patches. The model is allowed to capture the local features using the patches. This scheme aids in improving sensitivity to subtle structural changes that may not be available at global level. The model is then used to generate patch-wise disease probability maps across the entire MRI sample. Thereby, highlighting the regions with higher likelihood of AD. To manage the computational complexity, only the most significant features are selected from the generated probability maps. Thereby, reducing redundancy and improving computational efficiency. Finally, a multilayer perceptron classifier is used for classification. The classifier learns from the features derived from the preceding stage. Thereby, enhancing predictive performance.

The model architecture is designed using different operational layers. The operational layers such as convolution, max-pooling, and fully connected layers are used. These layers are effective in extracting attributes as well as in performing classification. At first, an input sample is given to a convolution layer operated using 32 number of kernels. The output of this layer is applied to a max-pooling layer to reduce the dimension while preserving the details. Then the resulting output is passed through a second convolution layer containing 64 number of kernels. To further reduce the dimension next pooling is again applied. The output feature map is then applied to a third convolution layer containing 128 number of kernels followed by max-pooling operation. The final multi-dimensional output is converted into one-dimensional using flattening operation. This one-dimensional vector is channel through dense layers for classification.

Table 1. Architecture of the model

Layer(type)	Output Shape	Parameter
Layer – 1 (convolution)	126 × 126 × 32	896
Layer – 2 (max-pooling)	63 × 63 × 32	0
Layer – 3 (convolution)	61 × 61 × 64	18,496
Layer – 4 (max-pooling)	30 × 30 × 64	0
Layer – 5 (convolution)	28 × 28 × 128	73,856
Layer – 6 (max-pooling)	14 × 14 × 128	0
Flattening	25088 × 1	0
Dense Layer – 1	128	3,211,392
Dropout	128	0
Output Layer	2	258

4. Results and discussion

A standard Alzheimer's MRI images dataset is utilized and is selected from Kaggle [17]. The dataset consists of 305 images categorized into two classes, namely AD and normal control (NC). For the training process, to ensure efficient parameter updates, Adam optimizer is applied with a learning rate of 0.001. Due to its suitability for the classification problems loss function cross-entropy is used. Additionally, to maintain a balance between computational efficiency and training stability a batch size of 32 is selected. 25 to 30 epochs is utilized to achieve robust performance. Then, the performance of the classification model on the test set is measured using four different metrics such as accuracy, recall, precision, and F1-score.

As presented in Table 2, the model achieves an overall accuracy of 92.50%, indicating the model's generalization as well as effectiveness in correctly classifying most MRI images. The precision value of 92.20% demonstrates that the model has a low rate of false positives. A recall value of 93.80% signifies the models capability of detecting the majority of actual instances. Furthermore, the F1-score of 91.49% provides a comprehensive measure of the models performance by balancing both precision and recall. These performance metrics collectively shows the models robustness.

Table 2. Performance metrics obtained using the model

Metric	Values
Accuracy	92.50%
Precision	92.20%
Recall	93.80%
F1-score	91.49%

In Table 3, the model is compared with several state of-the-art techniques which employ custom features and various classifiers. The results clearly show that our model performs better compared to other state-of-the-art methods for AD classification. In particular, the model achieves superior accuracy by indicating its enhanced capability. This improvement highlights the robustness as well as effectiveness of the model when compared to other conventional approaches.

Table 3. Comparison of the model DL-based methods

Model	Accuracy
Ensemble learning [13]	81.17%
Regression Tree [14]	91.08%
SVM [15]	68.39%
XGBoost [16]	88.20%
Modified DL model	**92.50%**

5. Conclusion

The modified deep learning framework provides an effective solution for the classification of AD using MRI images. In the study CNN model is developed with improved architectural design. And an optimized training strategies selects to automatically extract more representative and discrimative features from brain scans, enabling effective classification of subjects into AD and NC categories. The model shows superior performance, achieving an accuracy of 92.50%, precision of 92.20%, recall of 93.80%, and an F1-score of 91.49% on the selected dataset. These results suggest that the model can serve as a reliable and supportive tool for clinicians in the early prediction and diagnosis of AD. Furthermore, the generalizability of the classifier can be further assessed by evaluating it on larger and more datasets. Further research may also explore on advanced model architectures and multi-class classification.

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ON-OFF + P CONTROLLER FOR ELECTRIC VEHICLE COOLING SYSTEM

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Abstract

Charging of electric vehicle (EV) battery packs generates heat, which can accelerate degradation, reduce efficiency, and compromise safety if not properly managed. This project presents a hybrid ON–OFF and Proportional (P) control strategy to regulate coolant flow and maintain optimal battery temperature. The ON–OFF controller ensures energy-efficient activation of cooling at threshold temperatures, while the proportional controller improves system response by regulating the cooling effort according to temperature variation. A laboratory-scale EV cooling model is developed to evaluate performance under normal charging conditions. Results demonstrate that the proposed approach provides effective temperature control and stable cooling performance, offering a cost-effective solution for EV battery thermal management systems.

Keywords

ON-OFF Controller, P Controller, Electric Vehicle, Charging

1. Introduction

Effective thermal management is essential for ensuring the safety, reliability, and lifespan of lithium-ion batteries in electric vehicles (EVs). During charging, battery packs generate heat, which can lead to temperature rise and possible degradation if not properly controlled. Conventional air-cooling methods are often inadequate, making liquid-cooling systems necessary to maintain battery temperature within the optimal 25–40 °C range [1]. Previous studies have highlighted the importance of proper thermal management techniques for EV batteries. Cooling systems combined with controller-based regulation can significantly improve temperature stability and system reliability [2]. Control strategies such as proportional control are commonly used to regulate cooling systems and improve temperature response. In addition, tuning methods such as the Ziegler–Nichols (ZN) method are widely applied to determine suitable controller parameters for achieving improved system performance and stability [3].

Among different control strategies, ON–OFF control is simple and robust but can cause temperature oscillations and slower response. In contrast, proportional control improves thermal regulation by enabling a smoother response and better adjustment of cooling effort according to temperature variations. The objectives of the work are

- To study ON–OFF + P controller for the cooling system of EV.

- To analyse the effect of proportional gain on: battery pack temperature, pump power, refrigerant power.

2. Methodology

2.1 System Modelling and Simulation

The Battery Thermal Management System (BTMS) is developed using MATLAB–Simulink R2024a to replicate realistic battery operating conditions as in Figure 1. To evaluate thermal performance, a normal charging current profile is applied to the battery thermal model. During charging, heat generation occurs within the battery pack, requiring effective cooling to maintain the temperature within the safe operating range.

2.1.1 Controller design

To manage the heat generation, a hybrid ON–OFF + Proportional (P) control strategy is implemented for regulating coolant flow. The ON–OFF controller activates the cooling system when the battery temperature exceeds a predefined threshold. Once activated, the proportional controller adjusts the cooling effort based on the temperature difference between the actual battery temperature and the desired reference temperature. This approach improves thermal response and ensures stable temperature regulation.

2.1.2 Controller Tuning using ZN Method

The controller is tuned using the ZN closed-loop method. The system is driven to sustained oscillations to determine the ultimate gain and oscillation period. These parameters are then used to calculate suitable proportional gain values for the controller. The range used for Kp is 0.6-1.6.

2.1.3 Performance Evaluation

Different proportional gain values are evaluated to analyse their impact on system performance. Lower gains provide a smoother response with lower energy consumption, while higher gains produce faster cooling but require more power.

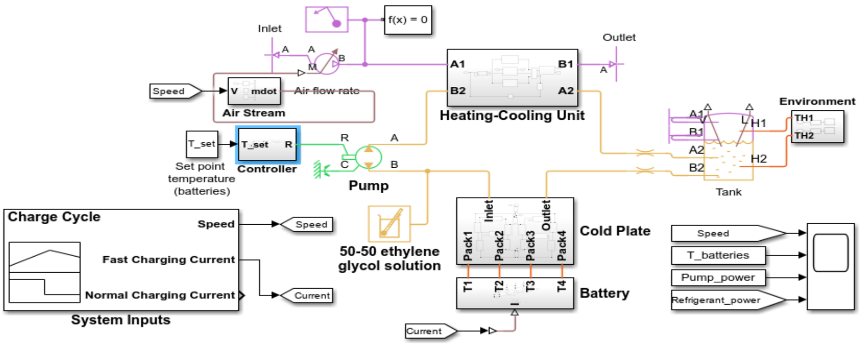

Figure 1. Block diagram of EV battery cooling system using ON–OFF + P controller

3. Result and Discussion

The Figure 2 illustrates the variation of battery pack temperature during normal charging for different proportional gain values (P = 0.6 to 1.6), selected using the ZN tuning method. Initially, the battery temperature is approximately 50°C for all cases. As charging progresses, the temperature decreases due to reduced heat generation with declining current.

It is observed that the proportional gain significantly influences the cooling performance of the thermal management system. At a lower gain (P = 0.6), the response is slow, with the temperature remaining above 39°C even after 500 seconds. With a moderate gain (P = 1.0), cooling improves, reducing the temperature to around 30°C. For higher gains (P = 1.4 and P = 1.6), the controller responds more aggressively, achieving faster heat dissipation and lowering the temperature to approximately 22°C, within a safe operating range.

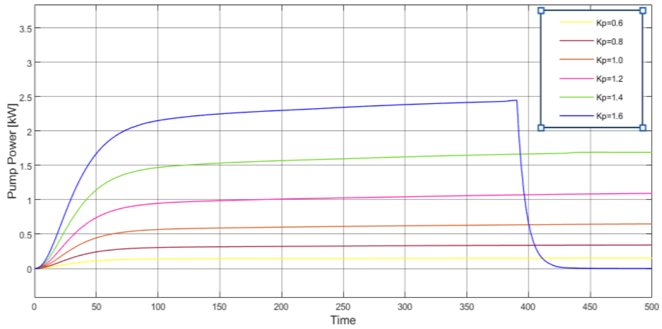

Figure 2. Battery pack temperature of P gain for various ranges

This demonstrates that increasing the proportional gain enhances system responsiveness and accelerates cooling, leading to more effective and reliable thermal management during normal charging.

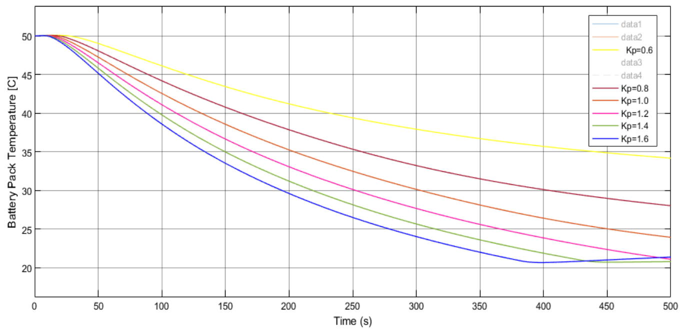

Figure 3. Pump power of P gain for various ranges

The graph in Figure 3 shows how coolant pump power varies during normal charging for different proportional gains (Kp). Higher Kp values lead to a faster and stronger controller action, causing higher pump power consumption initially to quickly remove heat. For instance, Kp =1.6 reaches the highest peak power (>2.4 kW), whereas Kp = 0.6 settles at a much lower level (~0.3 kW). After about 400 s, the power drops sharply as the battery temperature approaches the desired operating range and cooling demand reduces. Overall, increasing Kp enhances cooling performance but also increases energy usage, indicating the need to choose an optimal gain that balances temperature control and power efficiency.

Figure 4 shows how refrigerant power changes during normal charging for various proportional gains (Kp). At the start, all curves rise sharply because the controller responds to high battery temperature with strong cooling demand. Higher proportional gains result in a more aggressive response: Kp = 1.6 produces the highest peak (≈65 kW), while Kp = 0.6 has the lowest peak (≈25 kW). After the initial peak, the refrigerant power gradually decreases as the battery cools down and the required cooling effort reduces. Around 400 seconds, the refrigerant power for higher gain cases drops sharply, indicating that the battery has reached safe operating temperatures and only minimal cooling is needed.

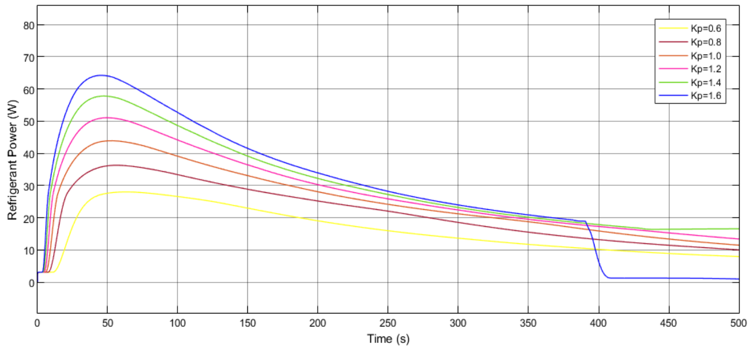

Figure 4. Refrigerant power of P gain for various ranges

The simulation results highlight that proportional gain selection plays an important role in achieving efficient thermal management of the battery pack. Higher proportional gains improve cooling performance and reduce battery temperature more rapidly, but they also increase pump and refrigerant power consumption. Lower gain values reduce energy usage but lead to slower cooling response. Therefore, selecting an appropriate proportional gain is necessary to balance temperature control and power efficiency. Overall, the results confirm that ON–OFF + P controller directly influences both thermal response and system energy consumption.

4. Conclusion

This work demonstrates that an optimized thermal management strategy using a hybrid ON–OFF + P controller is effective for maintaining battery temperature within a safe operating range during charging. Simulation results show that proportional gain significantly affects temperature reduction rate and cooling system power consumption. Higher gains improve cooling performance but require greater pump and refrigerant power. Among the tested cases, P = 1.6 provides the best cooling performance by achieving faster temperature reduction while maintaining stable operation. The proposed control strategy therefore improves battery safety, reliability, and efficiency in EV battery thermal management systems.

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MACHINE LEARNING-BASED SURROGATE MODEL FOR CELL-LEVEL PERFORMANCE PREDICTION USING LIBERTY FILES

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Abstract

Accurate estimation of delay and power is a critical requirement in modern VLSI design. Conventional approaches, such as SPICE simulation and Static Timing Analysis are computationally intensive and limit rapid design exploration. This work proposes a machine learning-based surrogate model for predicting cell-level delay directly from Liberty (.lib) files. A structured dataset is generated by parsing the Nangate Open Cell Library, extracting parameters such as input slew, output load, supply voltage, and temperature. Gradient boosting (XGBoost) is employed to model nonlinear relationships between input features and target outputs. The proposed model achieves a Mean Absolute Percentage Error (MAPE) of 2.80% for delay prediction, significantly outperforming a baseline model (16.81% MAPE). To evaluate generalization, a holdout-cell strategy is used, where unseen cell types are excluded during training. The initial holdout error of 15.22% is reduced to 2.42% after data refinement, highlighting the importance of preprocessing and feature consistency. The results demonstrate that machine learning surrogates can provide fast and accurate performance estimation, making them suitable for early-stage electronic design workflows.

Keywords
VLSI, Liberty Files, PPA Prediction, XGBoost, Surrogate Modeling, Timing Analysis

1. Introduction

1.1 Background

Accurate estimation of delay and power is a fundamental requirement in digital circuit design. These parameters directly influence system performance, power efficiency, and reliability. Conventionally, delay and power estimation are performed using SPICE simulations and Static Timing Analysis (STA), which provide highly accurate results but require significant computational resources. As circuit complexity continues to increase, these traditional methods become time-consuming and limit rapid design space exploration. This creates a need for faster estimation techniques that can provide reasonably accurate predictions with reduced computational cost. In this context, machine learning-based surrogate models have emerged as a promising alternative, enabling fast approximation of circuit behavior.

1.2 Literature Review

Recent studies have explored the use of machine learning techniques for timing and power prediction in VLSI systems. Raslan et al. [1] demonstrated that deep learning models can effectively approximate cell delay behavior, achieving high prediction accuracy compared to traditional methods. Similarly, Zhao et al. [2] proposed a machine learning-based framework for multi-corner timing prediction, allowing efficient estimation under varying process, voltage, and temperature (PVT) conditions. Further advancements were made by Xu et al. [3], who incorporated statistical variations into

timing prediction using deep learning approaches. These works highlight the growing relevance of machine learning in Electronic Design Automation (EDA).
However, most existing approaches focus primarily on model accuracy under standard datasets and do not adequately address practical challenges such as data extraction from Liberty files, handling real-world library structures, and evaluating model performance on unseen cell types. This gap limits their applicability in realistic design scenarios.

1.3 Objectives

Motivated by these limitations, this work aims to develop a practical machine learning-based surrogate model for predicting delay using Liberty file data. The objectives of this study are:

- To develop machine learning models for delay prediction
- To compare baseline models with advanced approaches such as XGBoost
- To evaluate model performance using both random split and holdout-cell validation

2. Methodology

The proposed methodology follows a structured pipeline beginning with Liberty file parsing and ending with machine learning-based prediction of delay. The Nangate Open Cell Library [4] is used as the primary data source, from which timing and power tables are extracted and converted into a structured dataset. Relevant input features such as input slew, output load, supply voltage, temperature, and cell characteristics are then used to train regression models. The trained models are evaluated using both random split validation and holdout-cell testing to assess accuracy and generalization capability.

2.1 Schematic Diagram

As illustrated in Fig 1, the process begins with parsing the Liberty (.lib) file to extract timing and power data corresponding to different operating conditions. The extracted data is organized into a structured CSV format, enabling efficient preprocessing

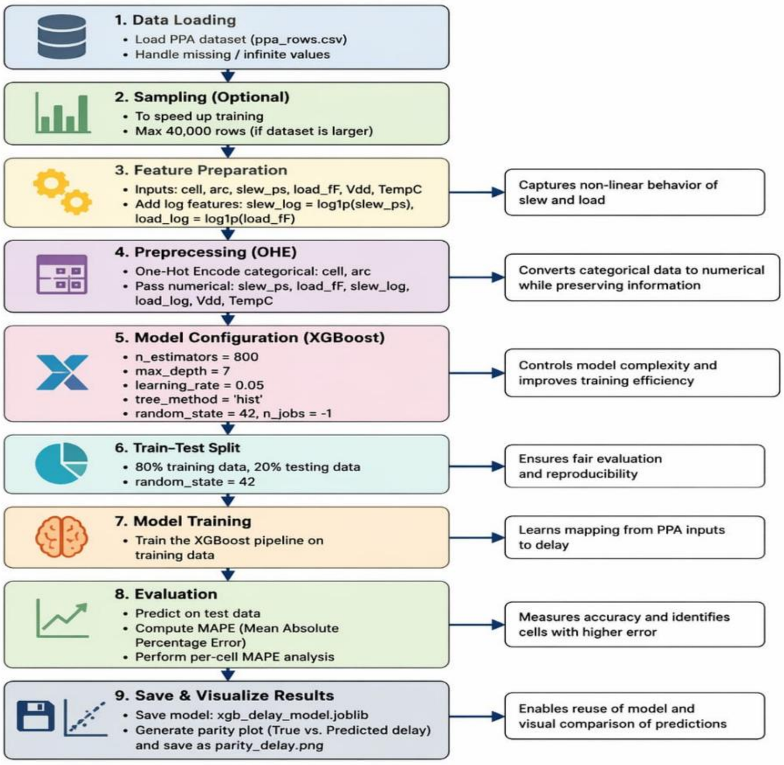


Fig 1. Methodology Flowchart

and feature selection. The feature engineering stage involves selecting key electrical and environmental parameters such as slew, load, voltage, and temperature, which significantly influence delay and power behavior. The processed dataset is then used to train machine learning models, including a baseline Random Forest model and an advanced XGBoost model. These models learn the nonlinear relationships between input features and target outputs. Finally, the trained models are evaluated using Mean Absolute Percentage Error (MAPE) and parity plots to assess prediction accuracy and generalization performance.

2.2 Random Forest

The Random Forest model is used as the first approach for delay prediction. The dataset obtained from the Liberty file is loaded and cleaned by removing rows with missing or invalid values. The required input features, such as cell, arc, slew, load, voltage, and temperature were selected, and additional logarithmic features for slew and load were created to better represent their behavior. Since the model requires numerical inputs, the categorical features (cell and arc) were converted using one-hot encoding, while the numerical features were used directly. All these steps were combined into a single pipeline. The model is configured with 200 trees and a maximum depth of 12, and the data is split into training and testing sets using an 80:20 random split. The model is then trained on the training data and used to predict delay values on the test set, and the results were evaluated using MAPE.

2.3 MAPE

The performance of the model is evaluated using MAPE, which measures the average percentage difference between the predicted and actual values. It provides an intuitive understanding of how far the predictions deviate relative to the true values, making it suitable for regression tasks where the scale may vary. MAPE is defined as

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_p}{y_i}\right| \times 100$$

Where y_i represents the actual value, y_p is the predicted value, and n is the total number of samples. A lower MAPE indicates better prediction accuracy, as it reflects smaller relative errors between predicted and actual values.

2.4 XGBoost Model

XGBoost (Extreme Gradient Boosting) [5] is a machine learning algorithm based on an ensemble of decision trees, where multiple trees are built sequentially to improve prediction accuracy. Each new tree focuses on correcting the errors made by the previous ones, allowing the model to learn complex patterns in the data. It is widely used for regression problems due to its ability to handle nonlinear relationships, control overfitting through regularization, and efficient training. This model is then used to improve prediction accuracy over the baseline model. The same dataset, preprocessing steps, feature selection, and train-test split were retained, so no additional data preparation is required. The main difference lies in the model configuration, where an XGBoost regressor was used with 800 trees, a maximum depth of 7, and a lower learning rate of 0.05 to allow more gradual learning. The histogram-based tree construction method was used to improve training efficiency. After training, predictions were generated on the test data and evaluated using MAPE per-cell. The trained model is saved for later use, and a parity plot is generated to visually compare predicted and actual delay values.

To test how well the model performs on unseen data, a holdout-cell approach is introduced. Instead of randomly splitting the dataset, around 10% of unique cell types were selected and completely excluded from training, and the model was evaluated only on these unseen cells. This is different from the earlier random split, where similar cell types could appear in both training and testing. The purpose of this step is to check the model's ability to generalize to new cell structures rather than relying on previously seen patterns, making the evaluation more realistic. After obtaining the initial holdout results, an additional analysis step is performed to improve the reliability of the evaluation. In this stage, predictions were generated again using the trained model, and rows containing missing values in either the actual or predicted outputs were removed before calculating performance metrics. This ensured that only valid predictions were considered, avoiding incorrect error calculations. Along with overall MAPE, per-cell error values were computed and saved, and a parity plot is generated to visualize the results. This step helped provide a more accurate and stable estimate of model performance on unseen cells.

Finally, a detailed holdout evaluation is carried out to store prediction results and enable further analysis. In this step, the same holdout-cell approach is used, but predictions along with actual values were saved into CSV files for inspection. Additional outputs, such as per-cell MAPE and parity plots, were also generated. Similar to the previous step, invalid rows were filtered out to ensure consistency in evaluation. This step is mainly included to create a complete record of predictions and errors, making it easier to analyze model behavior across different cell types and support the results presented later.

3. Results and Discussion

The performance of the proposed surrogate model is evaluated for delay prediction using Mean Absolute Percentage Error (MAPE). The baseline Random Forest model provided an initial reference with a delay MAPE of 16.81% under a random train–test split. While the model is able to capture general trends, the relatively high error indicated limitations in modeling the nonlinear relationships present in the data.

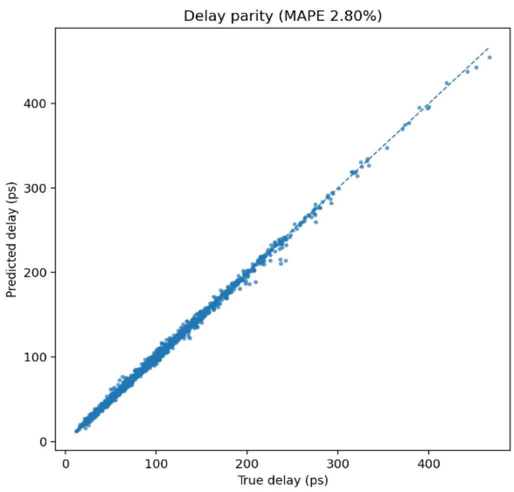
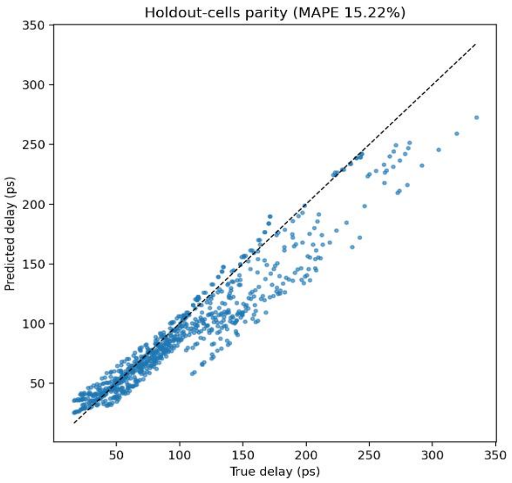
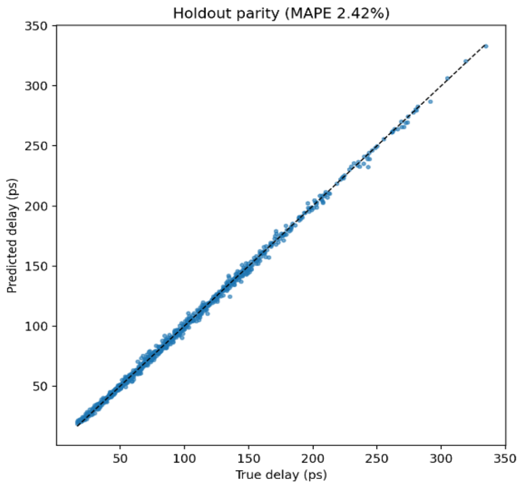


Figure 2. Delay parity plot showing predicted versus actual delay values (MAPE = 2.80%)

The use of XGBoost significantly improved prediction accuracy, reducing the delay MAPE to 2.80% on the same random split. The dataset consisted of 7448 valid rows after preprocessing, which were divided into training and testing sets in an 80:20 ratio, resulting in 5958 rows used for training and the remaining rows for testing. This improvement demonstrates the ability of gradient boosting to effectively learn complex relationships between input features such as slew, load, voltage, and temperature, and the resulting delay values. The corresponding parity plot in Fig.2 shows a strong alignment between predicted and actual values, indicating high in-domain accuracy. To further evaluate the model's generalization capability, a holdout-cell validation approach is used. In this setup, approximately 10% of unique cell types were excluded from training and used only for testing, resulting in 6664 rows for training and 784 rows for evaluation on unseen cells. Under this stricter condition, the model achieved an MAPE of 15.22%, showing a noticeable drop in performance compared to the random split. The corresponding parity plot in Fig.3 (a) reflects a wider spread of predictions, indicating the increased difficulty of predicting unseen cell behavior.





(a) **(b)**

Figure 3 (a). Holdout-cell parity plot showing prediction performance on unseen cell types (MAPE = 15.22%). (b) Refined holdout parity plot after data cleaning, showing improved prediction accuracy (MAPE = 2.42%).

To obtain a more reliable estimate of performance, a refined evaluation is performed by removing rows containing invalid or missing values in either the actual or predicted outputs. A total of 49 such rows were filtered out, leaving 784 valid rows for final evaluation. After this cleaning step, the model achieved a significantly improved MAPE of 2.42%, indicating that the earlier higher error is largely influenced by noisy or inconsistent data rather than model limitations. The refined parity plot in Fig.3(b) shows a much tighter clustering of points along the diagonal, confirming improved prediction consistency.

Table 1. Performance Comparison of Models

Model	Evaluation Type	MAPE (%)
Random Forest	Random Split (80:20)	16.81
XGBoost (Delay)	Random Split (80:20)	2.80
XGBoost (Delay)	Holdout Cells (90:10)	15.22
XGBoost (Refined)	Clean Holdout (90:10)	2.42

The overall comparison of model performance across different evaluation strategies is summarized in Table 1. The results clearly show that XGBoost provides highly accurate predictions under standard conditions and that evaluation methodology significantly impacts the observed error. The difference between holdout and refined holdout results highlights the importance of data quality in ensuring reliable model assessment.

Further analysis of prediction errors shows that certain cell types, particularly clock-gating cells and high-drive buffers, exhibit higher deviations. This suggests that these cells have more complex behavior that may not be fully captured by the current feature set. Incorporating additional parameters such as drive strength or internal characteristics could further improve model performance. Overall, the results demonstrate that the proposed approach achieves high accuracy while maintaining simplicity and efficiency.

4. Conclusion

This work demonstrates a machine learning-based approach for predicting cell-level delay using data extracted from Liberty files. A Random Forest model is first used as a baseline, followed by XGBoost, which significantly improved accuracy, achieving a MAPE of 2.80% under random split conditions. To evaluate generalization, a holdout-cell approach is applied, where unseen cell types were tested, resulting in a higher error of 15.22%. After removing invalid data points, the refined evaluation achieved a MAPE of 2.42%, highlighting the importance of data quality. Overall, the results show that the proposed method provides accurate and efficient delay prediction, making it suitable for early-stage design analysis.

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BREAST CANCER CLASSIFICATION USING CNN AND VISION TRANSFORMER

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Abstract

Breast cancer continues to be a major cause of death among women globally, highlighting the importance of early detection and accurate diagnosis in improving survival rates. This project aims to develop a breast cancer classification system using a Convolutional Neural Network (CNN) based on histopathology images, designed to help medical professionals identify cancerous patterns more efficiently and reliably. The system uses the VGG16 model, a pre-trained deep learning network known for its strong performance in image classification. This allows the model to make use of previously learned features, reducing the time needed for training and improving accuracy, even with smaller datasets. To enhance data quality and model effectiveness, preprocessing steps like image resizing, normalization, and data augmentation are applied, which help in reducing noise, improving generalization, and preventing overfitting. The model is trained and tested on labelled histopathology datasets, achieving high classification accuracy and showing strong performance across a variety of samples, effectively differentiating between benign and malignant tissues. Overall, this project demonstrates the strong potential of CNN-based models as computer-aided diagnosis (CAD) tools. These models support clinicians in making faster and more accurate decisions, ultimately contributing to early breast cancer detection and better patient outcomes.

Keywords
CNN, Vision transformer, Classification, VGG16

1. Introduction

Breast cancer is one of the most common and dangerous diseases among women worldwide. Early and accurate diagnosis is essential for increasing survival rates. Traditional methods depend heavily on manual evaluation of medical images, which can be time-consuming and prone to human error. With the advancement of artificial intelligence, deep learning methods like Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) have shown great promise in automating medical image analysis and enhancing diagnostic accuracy.

1.1 Literature Review

CNN-based models such as ResNet and VGG are effective in extracting local features from histopathological images [1]–[3], but they often struggle to capture long-range dependencies. Vision Transformers (ViTs) overcome this limitation by using self-attention to model global relationships [4]. Hybrid approaches combining CNNs and ViTs further enhance performance by leveraging both local and global feature representations, particularly in medical imaging tasks such as breast cancer detection using the BreakHis dataset [5].

1.2 Objectives

- To develop a hybrid model that combines CNN and Vision Transformer for accurate breast cancer classification.

- To enhance classification performance by capturing both local and global image features.
- To reduce misclassification and assist in reliable early diagnosis of breast cancer.

2. Methodology

The methodology involves developing a hybrid deep learning model that integrates Convolutional Neural Networks (CNN) and Vision Transformer (ViT) for the classification of breast cancer. The process includes data collection, preprocessing, feature extraction, model integration, and evaluation.

2.1 Data Collection and Preprocessing

Breast cancer image datasets, such as histopathological or mammogram images, are collected from trusted sources. The images are resized to a standard size, such as 224x224 pixels, and normalized to ensure uniformity. Data augmentation techniques like rotation, flipping, and zooming are used to increase the diversity of the dataset and reduce overfitting.

2.2 Feature Extraction using CNN

A pre-trained CNN model, specifically VGG16, is used to extract local features from the input images. These models help in recognizing important patterns such as edges, textures, and shapes related to cancer detection.

2.3 Vision Transformer Implementation

The extracted features are transformed into patches and input into the Vision Transformer. The self-attention mechanism in ViT captures global dependencies and relationships within the image, enhancing the overall understanding.

2.4 Model Training and Evaluation

The combined model is trained using labelled data with appropriate loss functions and optimizers. Performance is evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure reliable classification results.

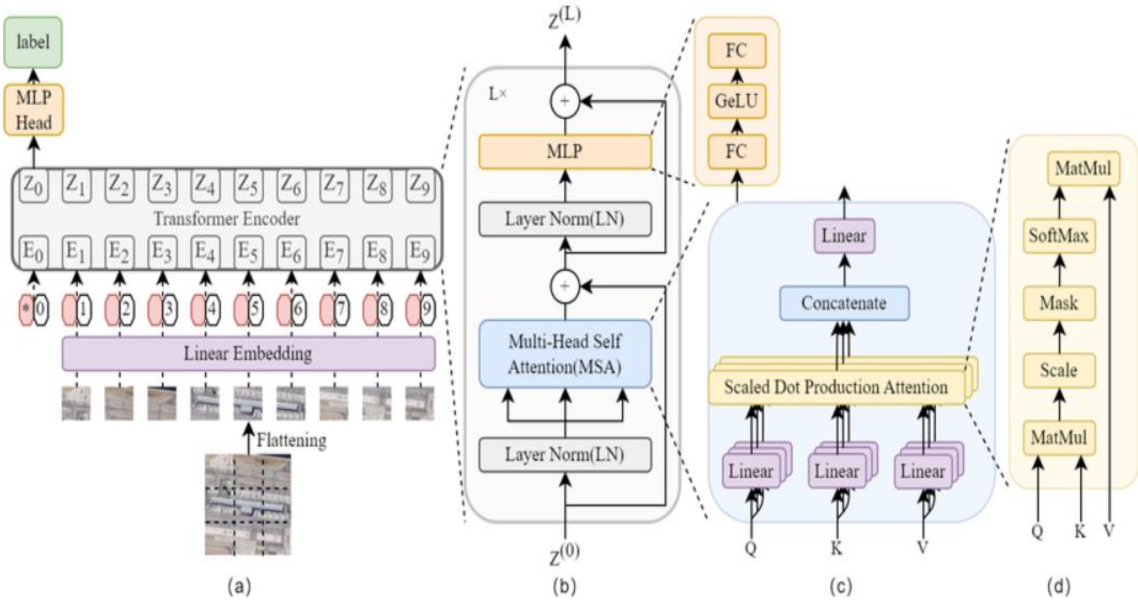

Fig. 1. Vision Transformer (ViT) Architecture [4]

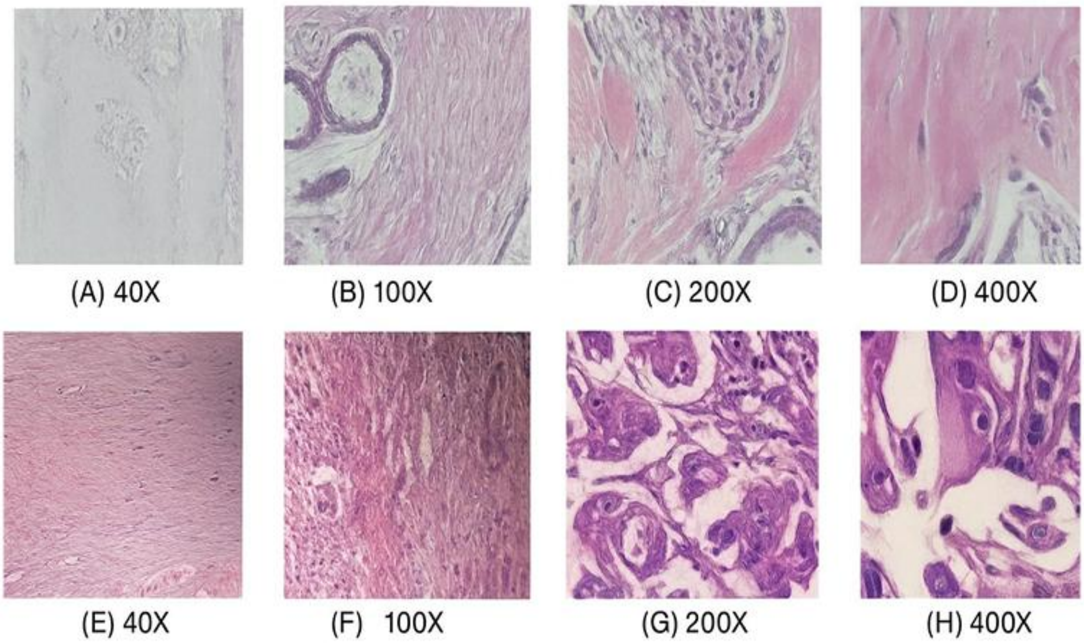

Fig. 2. Dataset (BreakHis) [5]

3. Results and Discussion

3.1 Results

Total number of images taken for testing: 1000

$$500(Benign) \ \& \ 500(Malignant)$$

The performance of the proposed CNN model is evaluated using the following metrics:

Accuracy = (TP + TN) / N

Precision (PPV) = TP / (TP + FP)

Recall (Sensitivity) = TP / (TP + FN)

F1 Score = 2 × (Precision × Recall) / (Precision + Recall)

Where **TP** denotes true positives (correctly identified malignant cases), **TN** denotes true negatives (correctly identified benign cases), **FP** refers to false positives, and **FN** indicates false negatives. Based on the confusion matrix, a high detection rate (sensitivity) is observed, suggesting that the proposed CNN model performs effectively in recognizing malignant breast cancer instances. A limited number of false positives are also present, which may lead to slight overdiagnosis. This can be further minimized through model fine-tuning and enhanced data augmentation techniques.

Table 1. Comparison of performance metrics of purposed Hybrid CNN+ViT with Base model

Model	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1-Score
CNN (Standard)	0.878	0.853	0.306	0.332	86%	85%	84%	85%
Inception V3	0.983	0.995	0.047	0.016	95%	94%	95%	94%
SE-ResNet	0.954	0.962	0.114	0.106	94%	94%	93%	93%
Hybrid (CNN + ViT)	**0.952**	**0.940**	**0.120**	**0.210**	**94%**	**95%**	**94%**	**94%**

3.2 Discussion

The proposed hybrid CNN-Vision Transformer model demonstrates significant potential in improving breast cancer classification accuracy. By combining CNN's ability to extract local spatial features with ViT's strength in capturing global dependencies, the model provides a more comprehensive understanding of medical images. This hybrid approach helps in identifying subtle patterns that may be overlooked by traditional methods or standalone models. Experimental results indicate that the model achieves higher accuracy and better generalization compared to conventional CNN-based approaches. The use of data augmentation further enhances model robustness and reduces overfitting. Additionally, evaluation metrics such as precision, recall, and F1-score confirm the reliability of the classification outcomes, particularly in distinguishing between benign and malignant cases.

4. Conclusion

The study presents a hybrid approach that combines Convolutional Neural Networks (CNN) and Vision Transformer (ViT) for effective breast cancer classification. By integrating CNN's capability to extract local features with ViT's strength in capturing global dependencies, the model achieves improved accuracy and a deeper understanding of medical images. This approach reduces reliance on manual diagnosis and improves the detection of complex patterns in histopathological data. The evaluation metrics demonstrate the reliability and robustness of the proposed system. While the model requires high computational resources and high-quality datasets, its performance highlights strong potential for real-world implementation. Overall, the proposed method can significantly assist medical professionals in early and accurate breast cancer detection, contributing to advancements in AI-based healthcare solutions.

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DESIGN AND ANALYSIS OF SRF-PLL SYNCHRONIZATION TECHNIQUES FOR GRID-CONNECTED VSI USING OPTIMUM SETTING ALGORITHM TUNING

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Abstract

The rapid integration of renewable energy systems heavily relies on robust synchronization methods for voltage-sourced converters (VSCs) tied to the electrical grid. Inaccurate phase estimation can trigger dangerous cross-coupling between active and reactive power, compromising system stability. This paper investigates the comprehensive modelling, control design, and phase-locking dynamics of a three-phase grid-integrated VSC subjected to diverse grid anomalies. The mathematical foundation employs space-phasor theory and synchronous reference frame (dq-frame) transformations to decouple the active and reactive current control loops, managed by proportional-integral (PI) controllers. A critical component of this control scheme is the Synchronous Reference Frame Phase-Locked Loop (SRF-PLL), which directly dictates the accuracy of grid synchronization. To enhance the transient stability of the SRF-PLL, this study contrasts two distinct PI tuning methodologies: the traditional Symmetrical Optimum (SO) technique and the advanced Optimum Setting Algorithm (OSA). Using MATLAB/Simulink, the dynamic responses of both tuning strategies were evaluated under steady-state startup, step frequency deviations, and sudden phase angle shifts. Simulation findings indicate that while the analytical SO method ensures a stable phase margin, it suffers from sluggish convergence and high overshoots during fast transients. Conversely, the OSA-optimized PLL demonstrates superior dynamic tracking, minimized overshoot, and accelerated synchronization recovery. This research confirms that optimization-driven loop filter tuning significantly bolsters VSC reliability, making it highly suitable for utility grids experiencing frequent condition variations.

Keywords

Voltage-Sourced Converter, Synchronous Reference Frame Phase-Locked Loop, Optimum Setting Algorithm, Symmetrical Optimum, Grid Synchronization.

1. Introduction

The transition toward sustainable energy networks necessitates the extensive use of distributed generation and high-voltage direct-current systems, fundamentally driven by voltage-sourced converters (VSCs) [1, 2]. To effectively manage these converters in isolated or weak AC networks [2, 3], linear proportional-integral (PI) regulators are typically deployed within a synchronously rotating reference frame (dq-frame) [4], which simplifies time-varying sinusoidal signals into manageable steady-state direct current (DC) equivalents [2]. However, this strategy's efficacy depends entirely on the Synchronous Reference Frame Phase-Locked Loop (SRF-PLL) to continuously provide an accurate grid voltage phase angle [5]. Misalignments in phase tracking induce severe cross-coupling between the active (i_d) and reactive (i_q) current control channels, potentially leading to undesirable current injection or total system instability during grid faults, voltage sags, or frequency jumps [1, 3].

Traditionally, the SRF-PLL is calibrated using the Symmetrical Optimum (SO) method, an analytical approach that ensures guaranteed stability margins [6] but often results in conservative, heavily damped transient responses under fast-changing conditions. Recent advancements emphasize optimization-driven techniques to overcome these limitations, including adaptive frequency-tracking PLLs [7], extended-state-observer (ESO)-based loop filters [8], and meta-heuristic strategies like the Aquila-Optimizer [9]. Hybrid analytical-optimization strategies like the Optimum Setting Algorithm (OSA) [10] have emerged as promising alternatives to minimize settling times and suppress overshoots under fluctuating network conditions.

Objectives

- To mathematically formulate the grid-tied VSC and SRF-PLL systems utilizing space-phasor concepts and dq-frame transformations.
- To implement and analyse a decoupled current control architecture within the MATLAB/Simulink platform.
- To comparatively benchmark the dynamic performance of SO and OSA tuning strategies during frequency variations and phase steps.

2. Methodology

2.1 Coordinate Transformations and Space Phasors

The voltages of the 3-Φ grid are stated as:

$$V_a = V_m \sin\theta \tag{1}$$

$$V_b = V_m \sin\left(\theta - \frac{2\pi}{3}\right) \tag{2}$$

$$V_c = V_m \sin\left(\theta + \frac{2\pi}{3}\right) \tag{3}$$

To simplify the control of the three-phase VSC, the time-varying AC phase signals are translated into a singular rotating complex vector. This space phasor f(t) for a balanced system is mathematically defined as:

$$\vec{f} = \frac{2}{3}\left[f_a(t) + e^{j\frac{2\pi}{3}} f_b(t) + e^{j\frac{4\pi}{3}} f_c(t)\right] \tag{4}$$

Using the Clarke transformation, this three-phase vector is mapped onto a stationary two-axis reference frame ($\alpha\beta$-frame):

$$\begin{bmatrix} f_\alpha \\ f_\beta \end{bmatrix} = \frac{2}{3}\begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix}\begin{bmatrix} f_a \\ f_b \\ f_c \end{bmatrix} \tag{5}$$

To eliminate steady-state errors when using linear PI controllers, these components are further projected onto a synchronously rotating dq-frame via the Park transformation. Assuming the rotation angle ρ aligns with the grid frequency, the transformation is:

$$\begin{bmatrix} f_d \\ f_q \end{bmatrix} = \begin{bmatrix} \cos(\rho) & \sin(\rho) \\ -\sin(\rho) & \cos(\rho) \end{bmatrix}\begin{bmatrix} f_\alpha \\ f_\beta \end{bmatrix} \tag{6}$$

In this perfectly synchronized dq-environment, active (P) and reactive (Q) powers are decoupled and directly proportional to their respective axis currents:

$$P(t) = \frac{3}{2} v_d i_d \tag{7}$$

$$Q(t) = -\frac{3}{2} v_d i_q \quad (8)$$

2.2 VSC Dynamic Modeling and Decoupled Control

The plant dynamics of the grid-connected VSC equipped with an interface reactor (L) and parasitic resistance (R) reveal an inherent cross-coupling between the d and q axes. The coupled differential equations are expressed as:

$$L\frac{di_d}{dt} = v_{td} - v_{sd} - Ri_d + \omega L i_q \quad (9)$$

$$L\frac{di_q}{dt} = v_{tq} - v_{sq} - Ri_q - \omega L i_d \quad (10)$$

To achieve independent axis regulation, feed-forward decoupling algorithms are introduced into the control references (v_{td}^* and v_{tq}^*) to neutralize the cross-coupling voltages ($\omega L i_q$ and $\omega L i_d$) and reject grid disturbances (v_{sd} and v_{sq}):

$$v_{td}^* = u_d - \omega L i_q + v_{sd} \quad (11)$$

$$v_{tq}^* = u_q + \omega L i_d + v_{sq} \quad (12)$$

2.3 SRF-PLL Loop Filter Tuning

The SRF-PLL utilizes the q-axis voltage as a phase error indicator. For small deviations, the error is approximated by $v_q \approx V_s(\theta_{grid} - \rho)$. The estimated frequency ω_{est} is generated by passing this error through a PI loop filter:

$$\omega_{est} = \omega_{ff} + K_p v_q + K_i \int v_q dt \quad (13)$$

The closed-loop transfer function mapping the estimated angle to the actual grid angle forms a characteristic second-order system:

$$H_{PLL}(s) = \frac{\rho(s)}{\theta_{grid}(s)} = \frac{V_s K_p s + V_s K_i}{s^2 + V_s K_p s + V_s K_i} \quad (14)$$

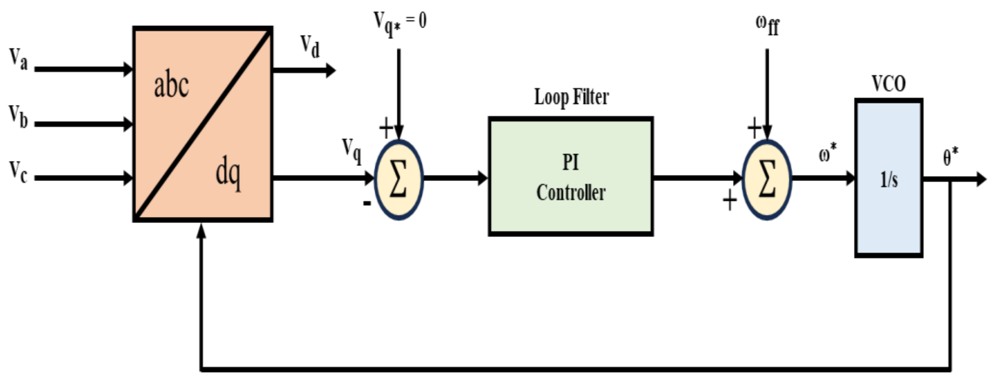

Fig. 1 Mathematical control framework of Three-phase SRF PLL system

2.3.1 Symmetrical Optimum (SO) Method

The analytical SO approach centers the maximum phase margin at the crossover frequency. By defining a design constant $a = 1 + 2\zeta$ (where $\zeta = 0.707$) and accounting for system delays (T_m), the PI gains are calculated as:

$$K_p = \frac{1}{aT_m K_g} \quad (15)$$

$$T_i = a^2 T_m \quad (16)$$

2.3.2 Optimum Setting Algorithm (OSA)

The OSA minimizes the time-weighted Integral of Squared Time-weighted Error (ISTE) to enhance transient responsiveness. The primary cost function is:

$$J_n(\theta) = \int_0^{\infty} t^n e(\theta, t)^2 \, dt \tag{17}$$

By approximating the PLL as a First-Order Plus Dead-Time plant and utilizing a relay-autotuning technique to identify the critical gain (K_c) and critical period (T_c), the optimized PI parameters are directly derived:

$$K_p = \alpha \, K_c \tag{18}$$

$$T_i = \beta(k) \, T_c \tag{19}$$

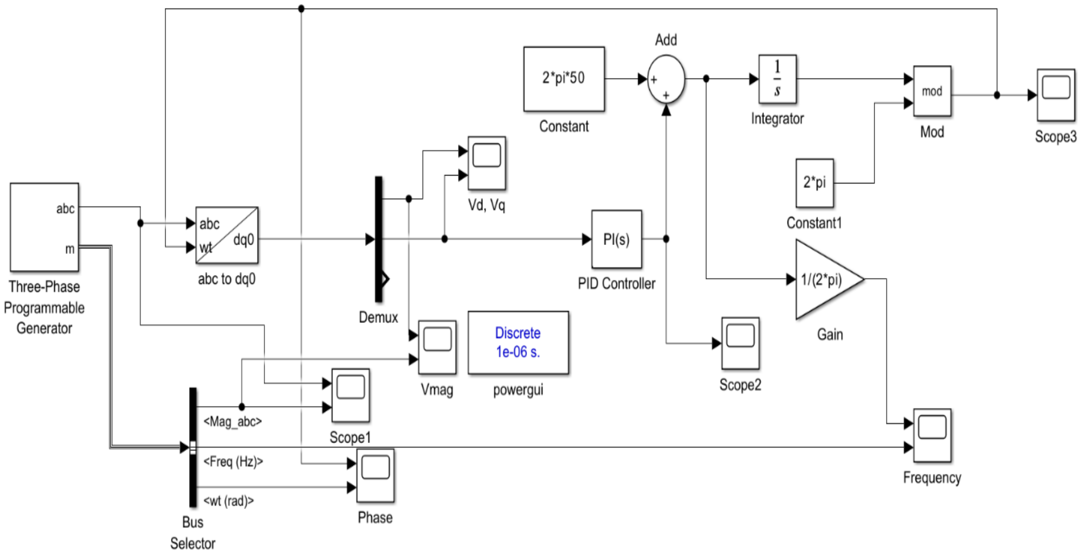

Fig. 2 Simulink implementation of the Synchronous Reference Frame Phase-Locked Loop (SRF-PLL)

3. Results and Discussion

Comprehensive testing was conducted in MATLAB/Simulink to benchmark the dynamic tracking capabilities of both tuning architectures under various grid anomalies.

Table 1. Optimum PI parameters for SRF-PLL tuning

Techniques	**Proportional Gain K_P**	**Integral Gain K_I**
SO	0.7545	59.8809
OSA	0.5690	60.2490

Case 3.1 Startup and Steady-State Alignment

Under normal grid conditions, both tuning methodologies successfully aligned the d-axis with the supply voltage. The measured q-axis voltage remained effectively at 0 V, confirming that accurate frame synchronization can be achieved by both configurations without steady-state lag.

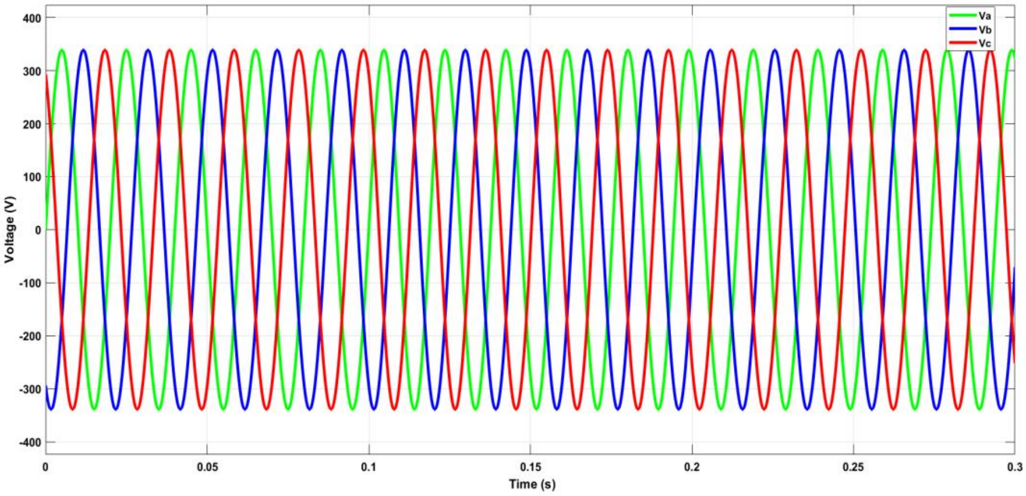

Fig. 3 Grid Voltage signals (under normal condition)

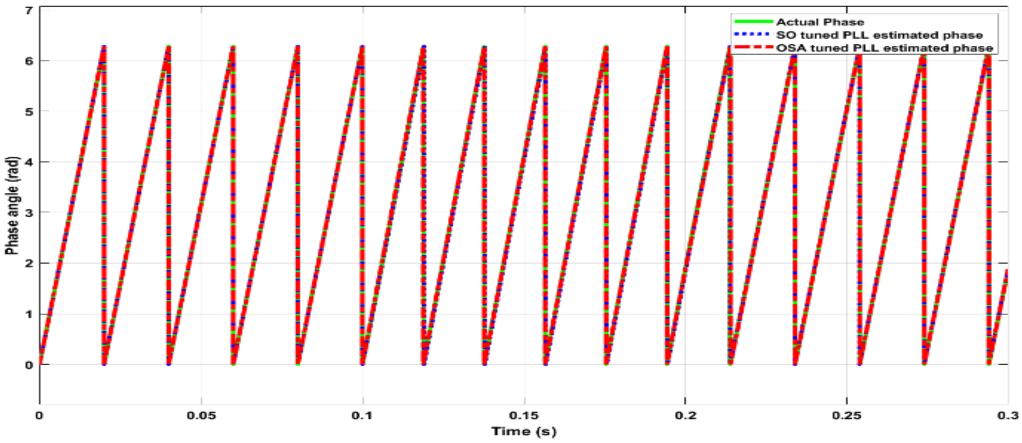

Fig. 4 PLL extracted Phase angle (under normal condition)

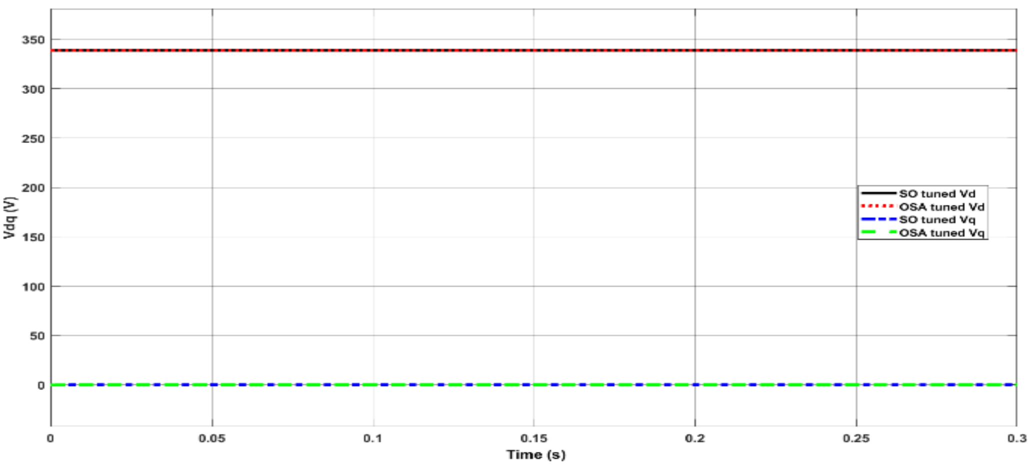

Fig. 5. V_d, V_q (under normal condition)

Case 3.2 Dynamic Response to Frequency Deviations

To test tracking agility, a 3 Hz step change (50 Hz to 53 Hz) was introduced. The SO-calibrated loop filter registered a significant overshoot, peaking above 53.5 Hz before slowly damping to the reference. In contrast, the OSA-tuned PLL managed the transition with drastically reduced overshoot and accelerated stabilization. This superior recovery was identically mirrored when the frequency was stepped back down to 50 Hz.

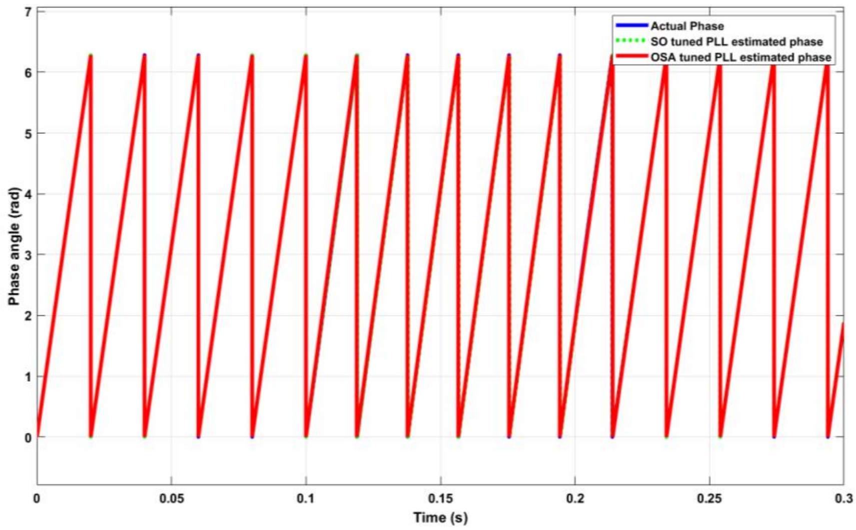

Fig. 6 PLL extracted Phase angle (under step change of frequency)

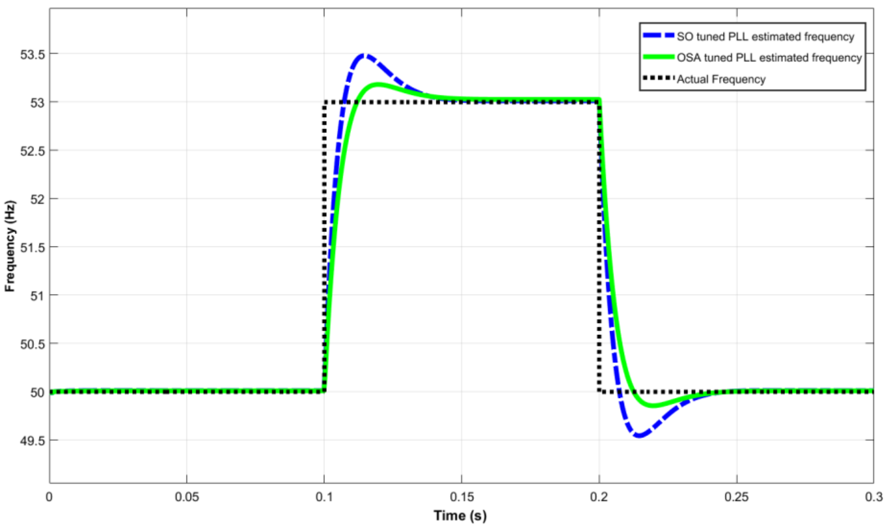

Fig. 7 PLL extracted frequency (under step change of frequency)

Case 3.3 Dynamic Response to Phase Angle Shifts

When subjected to a sudden +30° phase angle shift, both systems experienced immediate frequency spikes as the phase detectors reacted. The SO method once again demonstrated a prolonged, high-amplitude transient deviation. The OSA configuration rapidly suppressed the perturbation and restored stable phase-locking in a fraction of the time, highlighting its exceptional disturbance rejection capabilities.

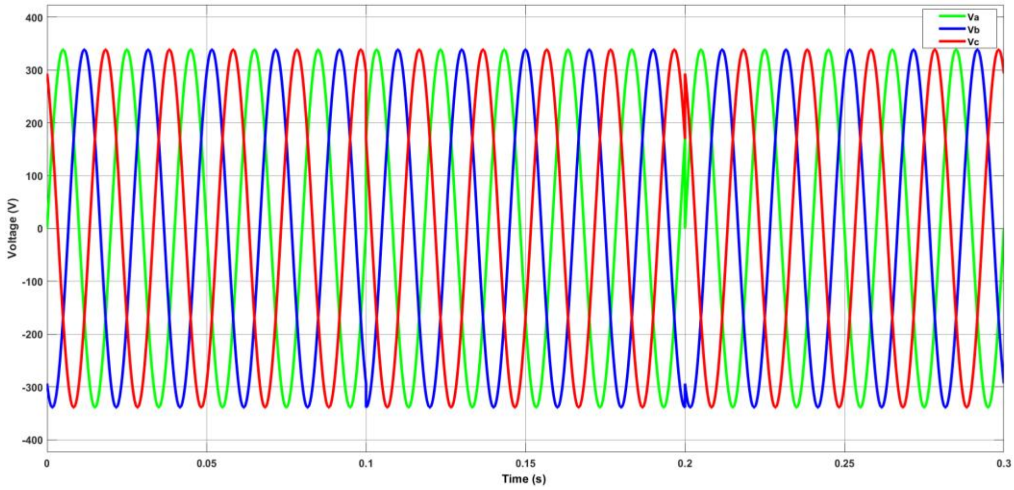

Fig. 8 Grid Voltage signals (under step change of phase)

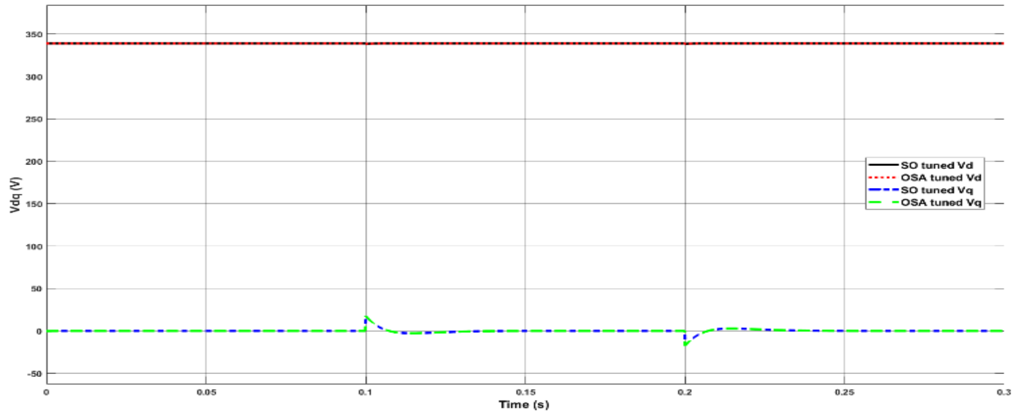

Fig. 9 V_d, V_q (under step change of phase)

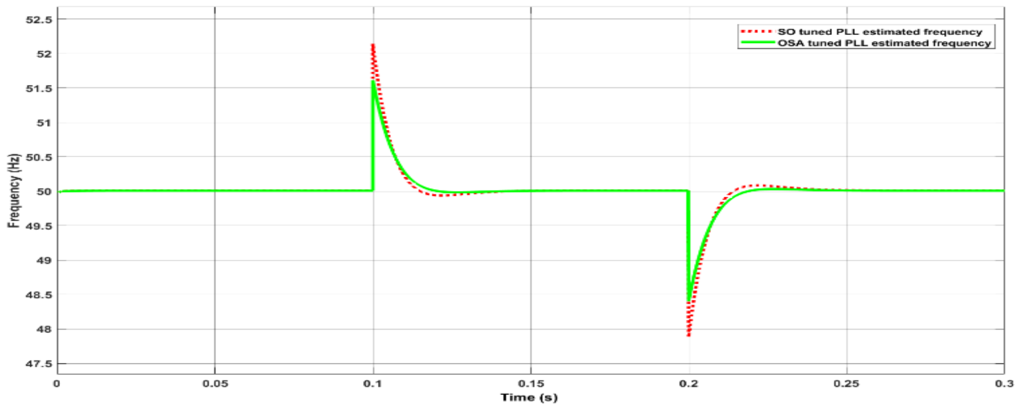

Fig. 10 PLL extracted frequency (under step change of phase)

4. Conclusion

This study systematically detailed the mathematical abstraction and control synthesis required for grid-tied Voltage-Sourced Converters. Through rigorous dq-frame modeling, decoupled current loops were designed to ensure independent real and reactive power regulation. A critical comparative analysis of SRF-PLL synchronization revealed that while traditional Symmetrical Optimum (SO) tuning guarantees analytical stability, it suffers from sluggish, heavily oscillating transient responses during grid fluctuations. Conversely, the Optimum Setting Algorithm (OSA) effectively minimizes time-weighted errors, yielding a phase-tracking mechanism that drastically reduces overshoot and accelerates recovery during frequency and phase step anomalies. Consequently, OSA-optimized synchronization is far better suited for the harsh dynamics of modern, distributed utility networks. Future investigations will target Hardware-in-the-Loop (HIL) validation to confirm these algorithmic benefits in real-time embedded environments.

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OQSM AND OFDM-BASED OPTICAL COMMUNICATIONS USING DEEP LEARNING APPROACH

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Abstract

This paper uses deep learning algorithms to discuss Optical Quadrature Spatial Modulation (OQSM) and orthogonal frequency division multiplexing (OFDM)-based optical networks. The Generalised-OQSM (GOQSM) and multiple-input multiple output (MIMO) method play a significant role in telecommunication systems. We need to estimate error spread and noise increase by using ML-MRC data-driven detection technique. For OFDM and GOQSM-based communication systems, we should prefer DNN-enabled signal detection technique. We must measure the edge of deep learning-based approaches OFDM and GOQSM schemes for faster speed MIMO optical communication systems. The optimal estimation parameters in optical networks include BER and SNR, with simulation results obtained using MATLAB.

Keywords

Optical communications, Deep learning, Orthogonal frequency division multiplexing, Optical quadrature spatial modulation, Signal-to-noise ratio, Bit error rate.

1. Introduction

Optical communication and networks are crucial, data is sent via light pulses through optical fiber George, N. (2002, May). Visible light is a carrier signal i.e., modulated to carry information in optical networks. High-speed and long-distance services are an essential advantage of optical fiber communication and networks. Optical networks are widely applicable in the development of telecommunication systems with bigger bandwidth, higher resistance, greater security, greater flexibility, and Improved latency. In recent years, optical network technologies have maximized faster in mobile data traffic. The major estimating parameters are visible light, infrared, and ultraviolet spectrum. For optical communication and networks, the data rate is limited due to the low bandwidth of the fiber-optic components in the transmitter section. Light-emitting and photodiodes contain a cut-off frequency between -3 dB to 3 dB. To boost the spectral efficiency and capacity of optical networks by using multiple-input multiple-output (MIMO), orthogonal frequency division multiplexing (OFDM), and optical spatial modulation (OSM) schemes Christian. (2020, November). The optical spatial modulation contains a single optical transmitter is utilized for symbol modulation and transmission spatial index symbols. The major advantages of optical spatial modulation are minimal crosstalk, efficient power use, and low complexity. In optical spatial modulation (OSM) schemes, the attainable spectral efficiency is constrained due to the optical transmitters. To propose a generalized OSM (GOSM) technique, for maximizing the spectral efficiency and spatial index symbols. Also, we choose multiple transmitters for transmitting the constellation symbol and higher spatial bits. In optical quadrature spatial modulation, the spatial mapping is applied to both I/Q components. The GSM, QSM, GQSM, and GOQSM techniques are applicable in visible light-based optical networks Danshi. (2021, March). In optical communication and networks, optical spatial modulation (OSM) and orthogonal frequency division multiplexing (OFDM) techniques contain low complexity with higher spectral efficiency. We first merge the OFDM and GOQSM schemes for spectral efficiency enhancement of optical networks. For OFDM and GOQSM systems, we need to prefer different detection techniques i.e., maximum likelihood and maximum ratio combining (ML-MRC) and deep neural network (DNN). For simulation results, we apply a deep neural networks detection technique and also suggest an OFDM-based GOQSM scheme and OFDM-based GOSM. Fig. 1. depicts the block diagram of the proposed OFDM-based GOQSM scheme Xin. (2021, August).

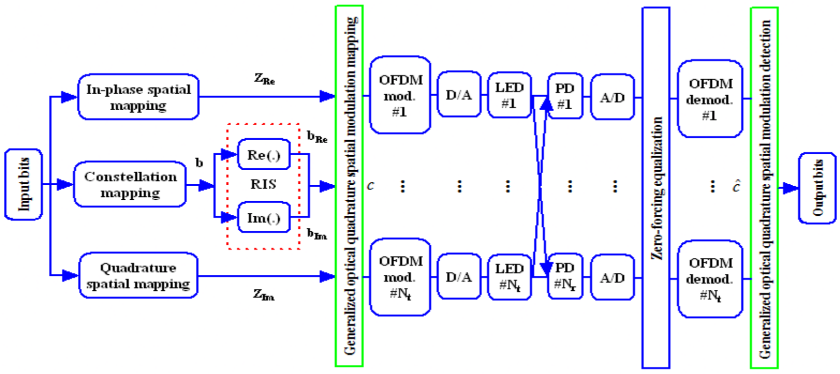

Fig. 1. Provides an overview of the block diagram of the OFDM-based GOQSM method.

After the introduction, Section II details the methodology, Section III presents the simulation results and their analysis, and Section IV provides the conclusion.

2. Methodology

We proposed a MIMO fiber system containing different light-emitting diodes N_t and photo-diodes N_r. If $s = [s_1, s_2, \dots, s_{N_t}]^T$ specify transmitted wave vector, H designate $N_r \times N_t$ multiple-input multiple-output channel matrix, $n = [n_1, n_2, \dots, n_{N_r}]^T$ indicates additive noise vector, and stipulate received wave vector $y = [y_1, y_2, \dots, y_{N_r}]^T$ can be demonstrated below,

$$y = Hs + n \tag{1}$$

The multiple-input multiple-output optical fiber communication system channel matrix of the $N_r \times N_t$ is defined as follows Hao. (2020, February)

$$H = \begin{pmatrix} h_{11} \dots h_{1N_t} \\ h_{N_r1} \dots h_{N_rN_t} \end{pmatrix} \tag{2}$$

where $h_{rt}(r = 1, 2, \dots, N_r;\ t = 1, 2, \dots, N_t)$ designate The DC channel gain linking t^{th} light-emitting diodes and r^{th} photo-diodes. In this paper, all the light-emitting diodes replace Lambertian beam pattern with LOS link. The h_{rt} is expressed as below,

$$h_{rt} = \frac{(l+1)\rho A}{2\pi d_{rt}^2} cos^l(\varphi_{rt}) T_s(\theta_{rt}) \mathrm{g}(\theta_{rt}) \cos(\theta_{rt}) \tag{3}$$

where $l = -ln2/\ln(\cos(\Psi))$ classify Lambertian optical emission parameter, Ψ define semi-angle (light-emitting diodes), ρ identify responsivity, A describes area (photo-diodes), d_{rt} depict distance, φ_{rt} characterize angle of emission, θ_{rt} categorize angle of incidence, $T_s(\theta_{rt})$ portray gain of optical filter, $g(\theta_{rt}) = \frac{n^2}{sin^2\Phi}$ represents gain of the optical lens, n determines refractive index, and $\boldsymbol{\Phi}$ expresses half-angle field-of-view. According to multiple-input multiple-output optical fiber communication systems, the additive white Gaussian noise (AWGN) is the combination of both shot and thermal noises Zhaocheng. (2020, April)

$$P_n = N_0\text{B} \tag{4}$$

where P_n indicates noise power, N_0 represents noise power spectral density and B determines signal bandwidth.

2.1. Principle of OFDM-Based GOQSM

This section describes the operating principles of an OFDM-based GOQSM system, with detection performed via maximum likelihood with ratio combining and DNNs.

2.1.1. OFDM-Based GOQSM

Fig. 1. illustrates the block diagram of the OFDM-based GOQSM system that contains N_t number of light-emitting diodes and N_r number of photo-diodes Tianyu. (2022, January) The bit stream is classified into 3 parts i.e., (1) a constellation symbol vector b (2) in-phase spatial mapping vector Z_{re} and (3) quadrature spatial mapping vector Z_{Im}. To represent the constellation symbol vector b below,

$$b = b_{re} + j \times b_{Im}$$

where b_{re} identify the real parts of b and b_{Im} describes the imaginary parts of b. The real and imaginary signals of $b$are obtained via RIS. The mapping function of the frequency domain concerning the I and Q components of optical components. It contains N_t number of light-emitting diodes with N(N≤ N_t) several activated LEDs. The N out of N_t I and Q parts of are b_{re}, b_{Im} with N_t-N is set to zero. To assume the real vectors c_{re}, imaginary vectors c_{Im}, and the symbol vector at the transmitter is denoted as $c = c_{re}$+ j × c_{Im}. Finally, the parallel orthogonal frequency division multiplexing scheme and D/A conversion are implemented. In the receiver section, the fiber-optic signals are found by N_r photo-diodes, and A/D conversion is employed to digitize the electrical signals. The ZF equalizer and parallel orthogonal frequency division multiplexing demodulation are discharged to calculate the transmitted symbol vector $\hat{c}$. After that, we need to predict symbol and spatial index vectors by using ML-RC and DNN-based detection techniques. A M-ary QAM technique to transmit the optical signals. The spectral efficiency is expressed as follows Devendra. (2023, September)

$$R_{GOQSM} \approx \frac{1}{2}log_2(M) + \lfloor log_2C(N_t, N) \rfloor \tag{5}$$

where ⌊. ⌋ identify floor operation, (.,.) describes binomial coefficient, 1^{st} term denotes constellation symbols, $\frac{1}{2}$ represents scaling factor, 2^{nd} term communicate in-phase and quadrature spatial index symbols. The new equation for spectral efficiency is defined below,

$$R_{GOSM} \approx \frac{1}{2}log_2(M) + \lfloor log_2C(N_t, N) \rfloor \tag{6}$$

2.2 Detection Techniques for OFDM-Based GOQSM

The generalized optical quadrature spatial modulation detection technique is identified to execute the bits after parallel OFDM demodulation. The OFDM-based GOQSM contains ML-MRC and DNN detection schemes.

2.2.1 ML-MRC Detection Technique

Fig. 2 represents the block diagram of the ML and MRC-based detection Kumar. (2021, March).

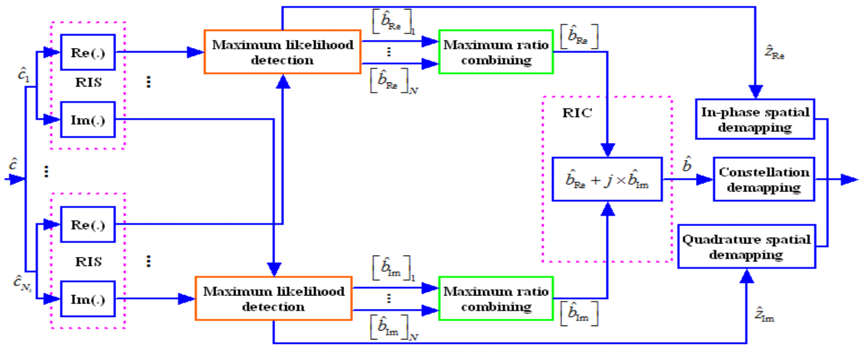

Fig. 2 Represents the block diagram ML and MRC-based detection.

The input transmitted symbol vector is predicted as $\hat{c} = \left[\hat{c}_1, \hat{c}_2, \dots, \hat{c}_{N_t}\right]^T$. From $\hat{c}_t(1, 2, \dots, N_t)$ RIS separates the I/Q parts. According to the ML-MRC detection for the real (in-phase) components execute $[\hat{b}_{Re}]m$, imaginary components perform $[\hat{b}_{Im}]m$, spatial index vectors denote $\hat{z}_{Re}$ and $\hat{Z}_{Im}$. To predict b_{Re} and b_{Im} through maximum ratio combining-based detection technique, constellation symbol vector $\hat{b}$ is combining with $\hat{b}_{Re}$, $\hat{b}_{Im}$via RIC. The I/Q spatial remapping and constellation are predicted for transmitted bits. Errors occur in step 1 of ML-MRC and in the 2^{nd} step, we will propagate the error. The propagation of errors lowers diversity gain, negatively impacting BER. If $\hat{c}$ is executed after zero-forcing equalizer and parallel orthogonal frequency division multiplexing demodulation, the optical networks suffer from noise amplification.

2.2.2 Deep Neural Network Detection Technique

In this section, we need to improve the development of the OFDM-based GOQSM technique.

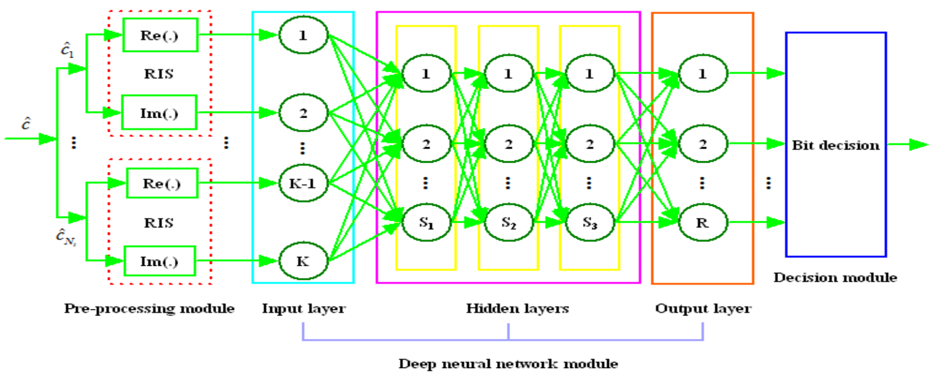

Fig. 3 Shows the DNN detection block diagram.

Fig. 3 provides the block diagram of the DNN-based detection method. Kumar. (2018, March). The deep neural network detection scheme contains a preprocessing stage, DNN stage, and decision stage. The pre-processing module classifies the I and Q components of $\hat{c}_t$ via real and imaginary separation (RIS). After that, it can produce the DNN input vector of size $K = 2N_t$. The feed-forward deep neural network has 1 input layer, 3 hidden layers, and 1 output layer. The input layer has K processing units and the hidden layers are identified as S_1, S_2 and S_3. The hidden layers learn the performance improvement of fiber-optic signals that contain a ReLU function Shakrajit. (2023, May).

$$f_{ReLU}(\alpha) = max(0, \alpha) \tag{7}$$

The output layer consists of R neurons and can contain a Sigmoid function with maps the output into the interval (0,1).

$$f_{Sigmoid}(\alpha) = \frac{1}{1+exp^{-\alpha}} \tag{8}$$

The total number of bits that the input vector can transmit with the value of R.

$$R = 2R_{GOQSM} \tag{9}$$

The relationship between input and output layer with feed-forward deep neural network module is dented below Shakrajit. (2025, January),

$$y_i = \alpha_i\left(W_{i-1\, y_{i-1}} + b_{i-1}\right), i = 2, \ldots, 5 \tag{10}$$

Where $\sigma_i(.)$ represents activation function, W_i describes weight matrix and b_i indicates bias vector. Decision unit can predict the final binary bits. If decision module input is expressed as $y_5 = [y_1, y_2 \ldots, y_R]^T$ and the predicted bits is $\hat{g}_q(q = 1, 2, \ldots, R)$ then the new equation is defined as follows,

$$\hat{g}_q = \begin{cases} 0, y_q < 0.5 \\ 1, y_q \geq 0.5 \end{cases} \tag{11}$$

MSE of g and $\hat{g}$ is denoted below Shakrajit. (2025, January),

$$e_{MSE} = \frac{1}{R}\|\hat{g} - g\|^2 \tag{12}$$

Table. 1 represents the system parameters. Table 2 denotes configuration of the deep neural network detection technique. Table 3 identifies the computing time of the different modulation and detection techniques Shakrajit. (2025, December).

Table 1. System parameters.

Parameters	Values
Dimension	4 m × 4 m × 4 m
Light emitting diode	3 m
Photodiode	12 cm
Semi-angle	65^0
Gain	1 dB
Refractive index	1.5
Half-angle	75^0
Responsivity	2 A/W
Height	0.9 m
Area	2 cm^2
Noise	$10^{-22}\ A^2/Hz$
Bandwidth	25 MHz
No. of light emitting diode	5

No. of activated light emitting diode	3
No. of photodiode	5
Receiver	3 m, 3 m, 0.9 m

Table 2. System parameters of the deep neural network detection technique.

Parameters	Values
Nodes	K=10
No. of hidden layer	3
Hidden layer AF	Leaky ReLU
Output layer AF	Sigmoid
Loss AF	Mean square error
Learning data rate	Stochastic gradient descent
Learning data rate	0.002
Training set	1525000
Validating set	634000
No. of neurons (1 bit's/s/Hz)	$S_1 = 25, S_1 = 35, S_1 = 15, R = 5$
No. of neurons (2 bit's/s/Hz)	$S_1 = 25, S_1 = 35, S_1 = 16, R = 7$
No. of neurons (3 bit's/s/Hz)	$S_1 = 25, S_1 = 35, S_1 = 17, R = 9$

Table 3. Computing time of the different modulation and detection techniques.

Efficiency	1 bit's/s/Hz	2 bit's/s/Hz	3 bit's/s/Hz
GOSM	11.21 s	11.33 s	11.75 s
ML-MRC	12.10 s	12.40 s	12.57 s
DNN	20.12 s	20.25 s	20.39 s
GOQSM	21.22 s	21.31 s	21.52 s

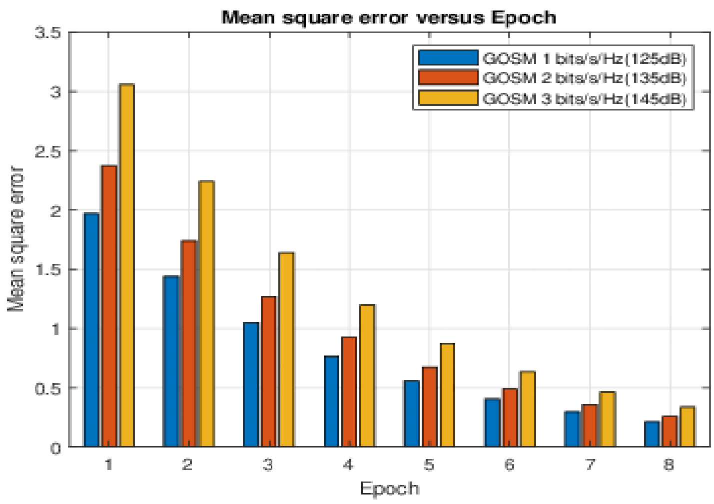

Fig. 4. GOSM MSE loss versus epoch for DNN detection.

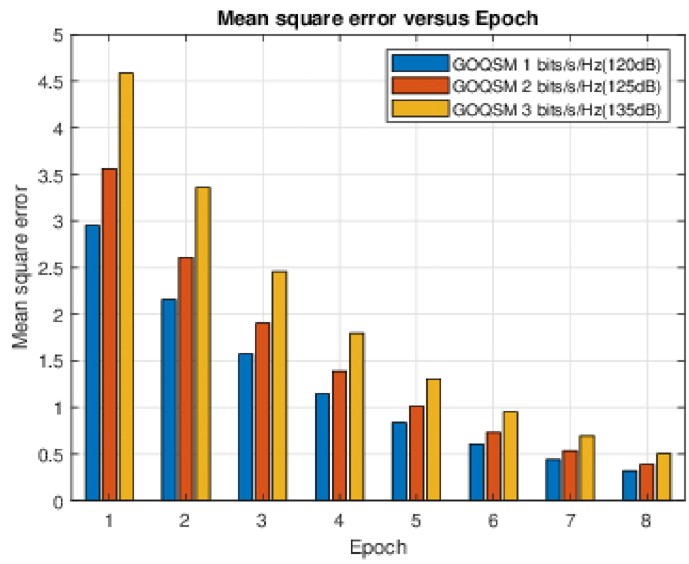

Fig. 5. Epoch-wise MSE loss for GOQSM using a DNN detector.

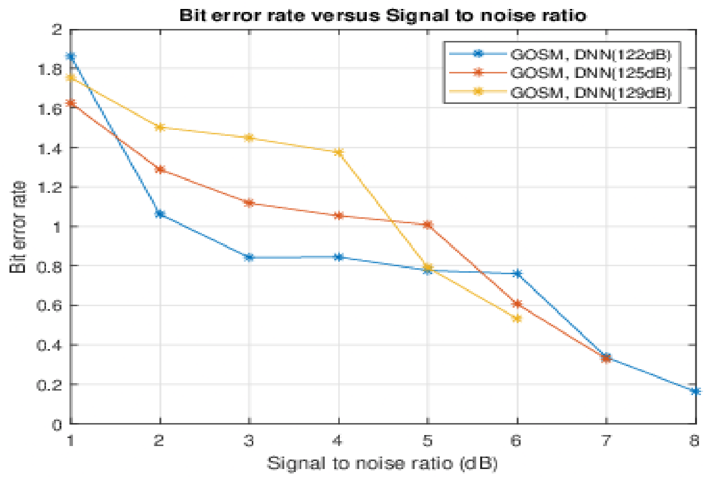

Fig. 6. DNN-assisted GOSM BER as a function of SNR (dB).

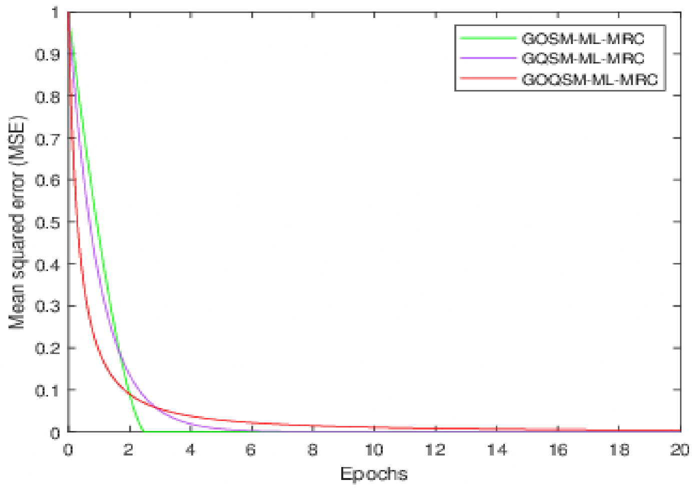

Fig. 7. MSE loss versus epochs for the DNN detector.

3. Results and Discussion

In this section, we must represent MIMO fiber networks with a 4 m × 4 m × 3 m dimension. The different types of light-emitting diodes climb up at the ceiling center at receiver height 0.9 m. OFDM-based GOSM versus GOQSM performance with ML-MRC and DNN detectors., we need to select four light-emitting diodes to transmit optical signals such as $N_t = 5$ and $N = 2$. In optical neural network training and testing, we need to add a mini-batch gradient technique that contains 105 symbol vectors. The training set is 1.5×10^6 and validation set is 6.3×10^5. The DNN performs sufficient showing with a small computational complexity. We need to measure the signal-to-noise ratios and bit error rates by using various light-emitting diodes and photo-detectors. The SNR expresses the ratio of the power of the desired signal to that of noise. and it occurs in a channel path loss. In the receiver section, we need to suggest multiple-input multiple-output-optical networks with a channel gain of 10^{-4} to 10^{-5} and an electrical path loss of 110 dB. Fig. 4. predicts GOSM MSE loss versus epoch using a DNN detector. Fig. 5. shows the performance for GOQSM mean square error loss versus the epoch using a DNN detector. For various bandwidth efficiency and training SNR levels the mean square error is minimized by maximizing the total epochs in GOSM and GOQSM training. To calculate the BER outstanding OFDM using GOSM and GOQSM under varying spectral efficiencies. Fig. 6. shows the GOSM BER versus SNR (dB) in a deep neural network (DNN). Fig. 7. shows the GOQSM BER versus SNR (dB) in a DNN.

For different spectral efficiencies of 1, 2, and 3 bits/s/Hz, the GOSM executes faster than the GOQSM. The SNR is greater than 150 dB for ML-MRC-based detection technique. To measure the SNR for GOSM and GOQSM to realize $BER = 10^{-2}$ are 16 and 161. The SNR gain is 1 dB. The DNN detection scheme can absorb the noise and the data symbols for both GOSM and GOQSM. The SNR for both GOSM and GOQSM is 122 dB and 124 dB. The GOQSM using a DNN detection technique for a signal-to-noise of 125 dB and BER of 10^{-2}. We need to compare the GOQSM by using ML-MRC-based detection technique for SNR of 25 dB. A DNN detection technique can eliminate noise amplification. To eliminate error propagation by using a DNN detection technique for a SNR gain of 1 dB, 2 dB, and 4 dB and BER 10^{-2}. From the simulation results, GOQSM carries out a better SNR gain than GOSM with greater spectral efficiency by using a DNN detection scheme. The computational overhead and execution duration of ML-MRC and DNN detection techniques were assessed for OFDM-based GOSM and GOQSM. For GOSM employing ML-MRC detection, the runtime is 11.50 s at spectral efficiencies of 1, 2, and 3 bits/s/Hz. Comparisons of DNN-based detection with ML-MRC indicate that GOQSM entails greater implementation complexity than GOSM.

4. Conclusion

We need to represent an OFDM based GOQSM technique for optical fiber communication systems. We should apply the GOQSM technique rather than the GOSM to improve different spectral efficiency of the optical fiber communication systems. Also, presents the error propagation and noise increase in OFDM GOQSM technique by using

ML-MRC-based detection technique and DNN detection scheme. Future work will explore AI, ML, and deep learning algorithms.

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LOAD SHEDDING USING 8085

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Abstract

This project presents the design and implementation of an automatic load shedding system using the 8085 microprocessor. The system aims to maintain power system stability by monitoring load conditions and disconnecting non-priority loads when the demand exceeds a predefined threshold. An 8255 Programmable Peripheral Interface is used to facilitate communication between input devices and the microprocessor, while relay circuits are employed to control electrical loads. The proposed system operates based on priority levels assigned to different loads, ensuring that essential loads remain active during overload conditions. The implementation demonstrates a simple, cost-effective, and reliable approach to power management. The results, obtained through simulated inputs, show that the system responds quickly to overload situations and performs load shedding efficiently.This project highlights the practical application of microprocessors in real-time power distribution and control systems.

Keywords

Load Shedding, 8085 Microprocessor, 8255 Interface, Power Management, Priority Control, Relay Switching, Automation, Embedded Systems

1. Introduction

1.1. Background

With the increasing demand for electrical energy, power systems often face overload conditions that can lead to instability and equipment damage. Load shedding is a commonly used technique to balance supply and demand by disconnecting non-essential loads during peak demand periods. Traditionally, load shedding is performed manually or through basic automatic systems, which may lack efficiency and flexibility. The use of microprocessors, such as the 8085, provides a smarter and more reliable approach to load management. By integrating programmable devices and control logic, automated load shedding systems can respond quickly to changing load conditions, ensuring efficient power distribution and system protection.

1.2. Literature Review

Recent studies have focused on improving load shedding techniques using embedded systems and automation. A 2025 study on priority-based load shedding systems highlights the importance of disconnecting non-critical loads to maintain system stability and efficiency. Ogidan et al. (2026) developed a microcontroller-based automatic load shedding module aimed at educational and practical applications, demonstrating real-time monitoring and control of loads. Their work emphasizes system reliability and adaptability in dynamic environments.

Similarly, a 2022 study on load shedding time management systems introduced programmable control strategies that allow load shedding based on both time schedules and demand conditions. These approaches show significant improvement over traditional methods in terms of accuracy and automation. These works collectively demonstrate that automated load shedding systems are effective in managing power demand, and they inspire the implementation of such systems using microprocessors like the 8085.

1.3. Objectives

- To design an automatic load shedding system using the 8085 microprocessor
- To monitor load conditions and compare them with a predefined threshold
- To implement priority-based control of electrical loads
- To automatically disconnect non-essential loads during overload conditions
- To ensure efficient and reliable power management
- To demonstrate the practical application of microprocessors in power systems

2. Methodology

The proposed load shedding system is implemented using the 8085 microprocessor along with the 8255 Programmable Peripheral Interface (PPI) for efficient input and output control. The methodology is divided into the following sub-sections:

2.1 System Setup

The system consists of an 8085 microprocessor kit interfaced with the 8255 PPI. Input devices such as switches or current sensors are connected to the input ports of the 8255, while output ports are connected to relay driver circuits that control electrical loads.

2.2 Load Simulation / Sensing

Load conditions are simulated using toggle switches for demonstration purposes. Each switch represents an individual load, and different combinations of switches indicate varying load conditions. Alternatively, current sensors can be used for real-time load measurement.

2.3 Data Acquisition

The input signals corresponding to load conditions are fed into the 8255 interface. The 8085 microprocessor reads this data using input instructions and temporarily stores it in the accumulator for processing.

2.4 Decision Making

A predefined assembly language program is used to compare the input load value with a preset threshold. Based on the comparison:

- If the load is within permissible limits, all loads remain active
- If the load exceeds the threshold, load

2.5 Priority-Based Load Control

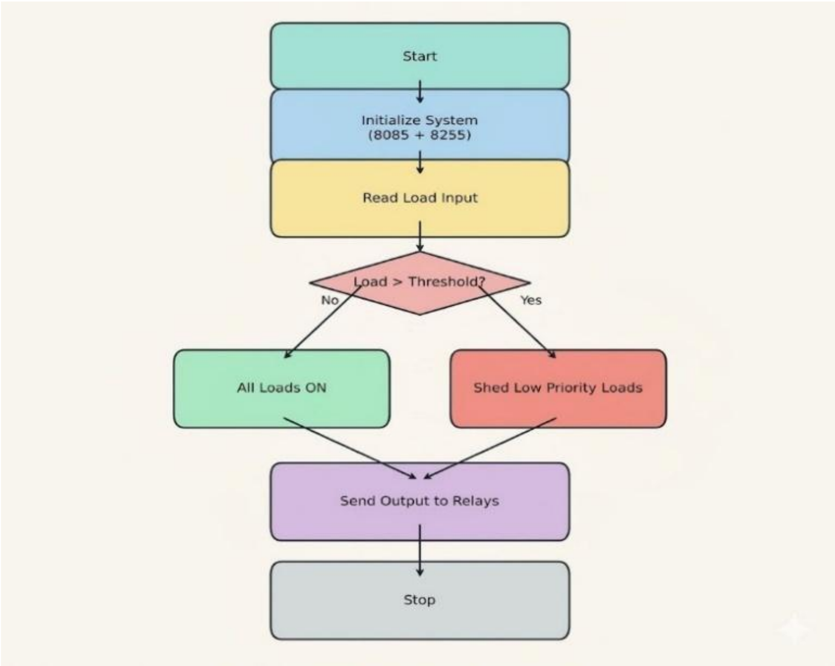
- Ad shedding is initiated Loads are categorized based on priority:
- High-priority loads: Essential loads that remain ON at all times
- Low-priority loads: Non-essential loads that are disconnected during overload

The system ensures that lower-priority loads are shed first to maintain system stability.

2.6 Output Control

The processed output is sent from the 8085 through the 8255 to relay driver circuits. These relays act as switches to connect or disconnect loads based on the control signals received.

2.8 Flowchart



3. Results and Discussion

To evaluate the performance of the proposed load shedding system, three different load conditions were simulated using priority and non-priority loads. The system response was observed based on predefined threshold conditions.

3.1 Experimental Scenarios

Case	Priority Load (Units)	Non-Priority Load (Units)	Total Load (Units)	Threshold (Units)	System Condition	Action Taken
1	2	2	4	6	Normal	All loads remain ON
2	3	4	7	6	Overload	1 Non-priority load disconnected
3	4	5	9	6	Severe Overload	All non-priority loads disconnected

3.2 Observations

- The system correctly identified load conditions in all scenarios.
- During normal conditions, no load shedding was performed.
- When the total load exceeded the threshold, non-priority loads were automatically disconnected.
- In severe overload conditions, all non-essential loads were shed while priority loads remained active.
- The system maintained stability and prevented overload effectively.

3.3 Discussion

The experimental results demonstrate that the 8085-based load shedding system operates efficiently under varying load conditions. The priority-based control ensures that essential loads are always supplied with power, while non-essential loads are managed dynamically. The system shows reliable and fast response, making it suitable for basic power management applications.

4. Conclusion

The proposed load shedding system using the 8085 microprocessor successfully demonstrates an effective method for managing electrical load under varying demand conditions. The system continuously monitors the load and compares it with a predefined threshold, ensuring that overload conditions are detected in real time.

By implementing priority-based control, the system ensures that essential loads remain operational while non-priority loads are automatically disconnected during overload situations. This improves the reliability and stability of the power system.

The experimental results confirm that the system performs accurately and responds quickly to changes in load conditions. The use of the 8255 interface and relay-based switching provides a simple and cost-effective solution for load management.

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STUDENTS

Achievments 2025-26

4th from the right

DEBASIS PATRO

Final Year Undergrad

- VSSUT Cricket Team secured 1st position in Utsahan 2026 at IGIT Sarang, on March 10, 2026, competing against top state institutions.
- Showcased athleticism, strategic gameplay, teamwork, and determination, winning the championship.
- Competed in Prarambh 2026 at VSSUT, Burla (January 22–24), facing strong teams from various institutions, and secured the champions trophy.

5th from left (Standing)

Rabi Narayan Deep

RABI NARAYAN DEEP

Final Year Undergrad

- Winners of the VSS Cup at Prarambh 2025, showcasing strong performance, teamwork, and strategic gameplay in football throughout the tournament.
- Runners-up in the Utsahan 2026 at IGIT Sarang, demonstrating consistency, resilience, and the ability to compete against strong opponents, while leading the football team as Captain.

- Winners of the football tournament at Vriddhi, NIT Rourkela 2026, showcasing strong performance, teamwork, and strategic gameplay throughout the tournament.
- Showcased athleticism, strategic gameplay, teamwork and winning the championship.

AMAN RAJ MINZ

Final Year Undergrad

- Abhita Anwesha Biling secured 1st position in 21km half Marathon, organized by VSSUT on 11/01/26.

ABHITA ANWESHA BILUNG

Final Year Undergrad

STUDENTS

Achievements 2025-26


From left, 1st : Charan; 2nd: Rahul


Rahul Ray

CHARAN RAJKUMAR & RAHUL RAY

Pre-final Year Undergrads

- Winners of the VSS Cup at Prarambh 2025, showcasing strong performance, teamwork, and strategic gameplay throughout the tournament.
- Runners-up in the VSS Cup at Prarambh 2026, demonstrating consistency, resilience, and the ability to compete against strong opponents.


2nd from left: Aryan; 2nd from right: Rahul


1st from left: Aryan; 3rd from left: Rahul


1st from left: Aryan; 2nd from left: Rahul

D. ARYAN DORA & RAHUL RAY

Pre-final Year Undergrads

- Winners in badminton at Vriddhi 2025, the annual sports fest hosted by NIT Rourkela, showcasing outstanding skill and teamwork.
- Runners-up in badminton at Spardha 2025, IIT BHU's national sports fest, demonstrating consistent performance against top competition.
- Winners in badminton at Shaurya 2025, IIT Kharagpur, highlighting competitive excellence and sporting dedication.
- Winners in badminton at Utsahan 2026, IGIT Sarang, highlighting competitive excellence and sporting dedication.

- Samangya Dash secured 1st position in Carrom (Girls) and a consolation prize in the BIS Quiz.
- Showcased strong competitive spirit and consistency across diverse events.
- Her achievements reflect dedication, all-round excellence, and active participation.

SAMANGYA DASH

2nd Year Undergrad

STUDENTS

Achievements 2025-26

OM PRAKASH SAHU, SHRABAN KUMAR PRUSTY, SWASTIK SENAPATI

2nd Year Undergrads

- Start-up Idea, CookieVerse secured 2nd position at FTBI, NIT Rourkela, conducted by E-Cell VSSUT, competing against strong entrepreneurial teams.
- Achieved finalist status at I-Summit, IIT Madras, a prestigious national innovation platform.

RIYA MISHRA, YASH PRATIK, BISWAJIT SAHU, ABHINAV DAS, RISHIKA KUMARI BEHERA, PRADYUMNA KUMAR ACHARYA & KUNAAL SAHOO

2nd Year Undergrads

- Startup Idea, Chitrasyaa secured 1st position in Pitch Verse, conducted by E-Cell VSSUT.
- Achievement highlights innovation, strategic thinking, and leadership skills in a competitive platform.

- Chinimya Rout with the Aerotech Club of VSSUT Burla participated in the SAE DDC Workshop 2025 at Prathyusha Engineering College, Tamil Nadu.
- Represented VSSUT Burla in a dynamic learning environment.

1st from left

CHINIMYA ROUT

2nd Year Undergrad

- Dibya Ahwan Mishra secured 2nd position in 50m swimming race, at Prarambh 2026, VSSUT Burla.
- Competed in Illumina 2025, secured 2nd position in 25m swimming race and 3rd position in 50m swimming race.

DIBYA AHWAN MISHRA

2nd Year Undergrad

DR. RABINDRA KUMAR SAHU

- Ranked among the Top 2% of Most Cited Scientists in the World by Stanford University and Elsevier for three consecutive years 2021, 2022 and 2023.
- Recipient of the IEEE Best Paper Award in 2013 for his research contribution in power system engineering.
- Awarded the MHRD Government of India Scholarship during both his M.E and Ph.D studies in recognition of his academic excellence.
- Served as Session Chair at the International Conference on Computational Intelligence in Data Mining in 2017.
- Successfully guided 7 Ph.D scholars and supervised 25 M.Tech research scholars, contributing significantly to research mentorship in electrical engineering.
- Published 29 research papers in reputed international journals and 19 papers in national and international conferences.
- His research publications focus on automatic generation control power system stability, facts devices optimization techniques, deregulated power systems and soft computing applications in electrical engineering.
- His work widely explores intelligent optimization algorithms such as differential evolution firefly algorithm gravitational search algorithm and fuzzy based controllers for improving stability and control of modern power systems.
- Currently serving as Dean of Post Graduate Studies and Research at VSSUT Burla, contributing to academic leadership and research development at the university.
- Fellow of the Institution of Engineers India and Life Member of ISTE, reflecting his active engagement with the professional engineering community.

DR. GYAN RANJAN BISWAL

- Extensive experience in cyber-physical systems, control, and automation across VSSUT Burla, Thapar University, Shiv Nadar University, and BIT Durg.
- Published in top journals including IEEE TIM, IEEE TIE, IEEE Systems Journal, IEEE Sensors Journal, IET GTD, and IJEPES (Elsevier).
- Research focuses on Smart Sensors, Li-Fi, Power System Automation, Hydrogen Storage/Processing, Cooling Systems, and Fuel Cell-based energy.
- Developed generator cooling systems, process C&I, and gas/moisture sensors; notable works include a capacitive humidity sensor (IEEE Sensors Journal) and SF6-GIS monitoring system (IEEE TIM).
- Holds multiple patents in hydrogen cooling and ultrasonic gas density monitoring technologies.
- Authored books and chapters on smart sensors, smart grids, microgrids, renewable integration, GIS, and control.
- Editorial board member of Complex Engineering Systems.
- Awards: Best Faculty (VSSUT 2021–22), INSA CICS (USA), and nominee for Shanti Swarup Bhatnagar Award (CSIR 2022–23).
- Received sponsored research grants of USD 320,000 and consultant of industrial field projects of INR 70 crores.
- Established Automation and Sensors Lab funded by CPRI, DST Odisha, and ANRF.
- Supervised 2 PhDs, 9 Master’s, and 3 ongoing PhD theses.

DR. SANTI BEHERA

- Set up three sessional laboratories for B.Tech Electrical and Electrical Engineering (EEE) under her headship.
- Recipient of Institution Prize (2019) for research on Power Quality Analysis of Hybrid SPV-Wind Integrated Systems.
- Awarded Institution Award (2020) for research on Fault Detection in Distributed Generation Systems using Neuro-Fuzzy Techniques.
- Received Institution Award (2005) at the 46th Annual Technical Session of the Institution of Engineers (India), Odisha, for technical contributions in Electrical Engineering research.
- Honored with Banabihari Memorial Award (2025), Odisha State Centre, for research on Scour Evaluation of Barrages under Clear Water Scour Conditions.
- Best Paper Award (2021), IRIA, for voltage control optimization of grid-connected three-phase PV inverter using equilibrium optimizer.
- Received Best Paper Award (2023) in Advances in Machine Learning and Big Data Analytics for research on Integration of Renewable Energy Systems into Utility Grid: Power Quality Issues, Mitigating Devices and Control Algorithms.
- Published several research papers (total 29) in reputed international journals and national/international conferences.
- Research areas include power system stability, voltage stability, power quality, and optimization techniques.
- Member of professional organizations including Institution of Engineers (India) and ISTE (Indian Society for Technical Education), supporting engineering education and research activities.
- Ongoing AI-based dam health monitoring project (Feb 2024 – Feb 2026), funded by IIT Guwahati Technology Innovation and Development Foundation.
- Guided 13 M.Tech students in research projects, contributing to academic and research development.

DR. SASMITA BEHERA

- Best Faculty Award (2022–23) under the Assistant Professor category at VSSUT. Best Paper Award (2021) at the IEEE International Symposium of Asian Control Association for research on voltage control optimization of grid-connected photovoltaic inverters. Best Paper Award (2023) at IEEE ICESS for research on a wideband antenna for 5G NR FR2 bands and on-body performance analysis.
- Ph.D. research guidance: Guided 2 Ph.D. scholars successfully and supervising additional research scholars. Guided 13 M.Tech students in research projects.
- Research publications: 24 international journal publications. 48 conference publications in national and international conferences.
- Research projects: Project on reactive power control of wind–diesel hybrid systems funded under TEQIP-II (World Bank) (Principal Investigator). Project on energy management and PV generation dispatchability in microgrids funded under TEQIP-III (Principal Investigator). Photovoltaic power forecasting and islanding detection using intelligent techniques funded by OSHEC (Odisha) (Principal Investigator). Sustainable Mitigation of Air Pollution Challenges in India Employing Membrane Technology funded by ANRF-PAIR, Govt. of India in collaboration with NIT, Rourkela (Principal Investigator).
- Professional memberships: Member of The Institution of Engineers (India). Life Member, Indian Society for Technical Education, Odisha Bigyan Academy and Bharatiya Paramparik Gyan Vigyan Samaj.
- Academic and community contributions: Organized national conference RAREC'15, TEQIP sponsored seminars and AICTE sponsored short-term training programs in power systems and soft computing. Initiated Alumni ConEEEct, a monthly alumni interaction program for student career guidance.

DR. SARMILA GARNAIK

- Published 7 international research papers in reputed journals and conferences in the areas of speech signal processing and biomedical signal processing.
- Contributed to research on speech signal analysis including vowel detection keyword detection in children's speech and noise reduction techniques using advanced signal processing methods.
- Published research in journals such as International Journal of Speech Technology and Multimedia Tools and Applications, and in IEEE conferences including TENCON and NCC..
- Authored a Springer book chapter on ECG noise reduction using hybrid signal processing in computational intelligence and data mining.
- Supervised M.Tech research students in signal processing related topics contributing to postgraduate research in the department.
- Received seed grant support under TEQIP at VSSUT for research activities related to signal processing.
- Actively involved in organizing academic workshops and technical activities including faculty interaction programs and academic events at VSSUT.
- Serves in several academic and administrative responsibilities such as Faculty Advisor of the department UGC coordinator resource administration coordinator and laboratory development activities supporting departmental growth.
- Felicitated with a certificate of " SCART NABARATNA AWARD" in the field of education From State Council For Artistic Research & Training, Govt Of Odisha
- Felicitated with " Niladri Bije Samman" from Sri Jagannath Niladri Bije Trust, Puri, Odisha.
- Certified Yoga Teacher & Evaluator from Yoga Certification Board, Ministry of Ayush, Govt. Of India.
- Resource Person in various National Level ATAL Program.

DR. LINGRAJ DORA

- Dr. Lingraj Dora has contributed significantly to research in medical image processing pattern recognition and communication systems, developing intelligent computational techniques for analyzing medical images and solving complex engineering problems.
- He has published several research papers in reputed international journals and conferences, including works on brain image classification MRI image segmentation face recognition and multimodal image fusion using advanced artificial intelligence techniques.
- His research publications appear in well-known journals such as Expert Systems with Applications Engineering Applications of Artificial Intelligence IEEE Reviews in Biomedical Engineering and Applied Soft Computing, demonstrating his contribution to interdisciplinary research in artificial intelligence and biomedical engineering.
- Dr. Dora has also contributed to scholarly books and book chapters related to artificial intelligence and biomedical engineering including the book AI Techniques for Biomedical Engineering Applications published by LAMBERT Academic Publishing.
- He has guided postgraduate research students, supervising 6 M.Tech scholars and one Ph.D scholar, supporting research in areas such as image processing, face recognition and data-driven medical analysis.
- He has been involved in sponsored research activities and collaborative research projects under TEQIP and TEQIP-III, contributing to the development of innovative research in signal processing and intelligent systems.

DR. BIBHUTI PRASAD SAHOO

- Dr. Bibhuti Prasad Sahoo has over 13 years of teaching and research experience in Electrical Engineering and focuses on developing analytical and problem-solving skills among students
- Research interests include soft computing, power system control, and power electronics for improving stability and performance of modern and renewable-based microgrids
- Guided 9 M.Tech research scholars in power system optimization and intelligent control techniques
- Published research in national and international conferences, including IEEE, on topics such as intelligent controllers for load frequency control in microgrids using optimization algorithms
- Research also covers signal processing and computational techniques, including medical ultrasound image diagnosis
- Member of Instrumentation and Signal Processing Research Group at VSSUT, contributing to measurement systems, power system optimization, and intelligent control
- Received Best Paper Award at National Conference on Recent Advances in Electrical, Electronics and Information Technologies (NCRATEEIT-2018), Keonjhar, Odisha
- Professional memberships: Member, Artificial Intelligence and Machine Learning Innovative Entrepreneurs and Engineers Association; Life Member, Odisha Bigyan Academy; Life Member, Bharatiya Paramparik Gyan Vigyan Samaj
- Research project: "Renewable Energy Integrated Secure Network Control and Protection Strategies" funded by ANRF-PAIR, Govt. of India in collaboration with NIT Rourkela (Co-Principal Investigator), 5-year project starting from 16-10-2025

ER. PRASANTA KUMAR PARIDA

- Has experience in teaching and academic mentoring in Electrical and Electronics Engineering, contributing to undergraduate education in core subjects such as Digital Circuits Electromagnetics Control Systems Digital Signal Processing and Communication Systems.
- Served as Lecturer in the Department of Electronics and Telecommunication Engineering at IGIT Sarang Odisha from January 2013 to May 2014, gaining valuable academic experience before joining VSSUT.
- Actively involved in research in the area of Medical Image Processing, contributing to interdisciplinary applications of signal processing and communication engineering.
- Guided M.Tech research students in their postgraduate research work and supported academic research activities in the department.
- Pursuing doctoral research (Ph.D.) at VSSUT Burla, demonstrating continued engagement in advanced research and academic development.

Society Activities

Noumis Rana
EEE Society Secretary

Debasis Patro
Spectrum Secretary

Hitesh Palo
Class Representative
& E-Cell Coordinator

Tanmay Ranjan Nayak
Class Representative

Sanjana Supriya
Class Representative

Shruti Rekha Swain
Alumni ConnEEEct
Coordinator

Manisha Panigrahi
Alumni ConnEEEct
Coordinator

Pratikhya Samal
Training & Placement
Coordinator

Sandip Kumar Swain
Training & Placement
Coordinator &
IQAC Coordinator

Adityansu Pati
IQAC Coordinator

Sanjay Kumar Nag
Maitri House Captain

Society Activities

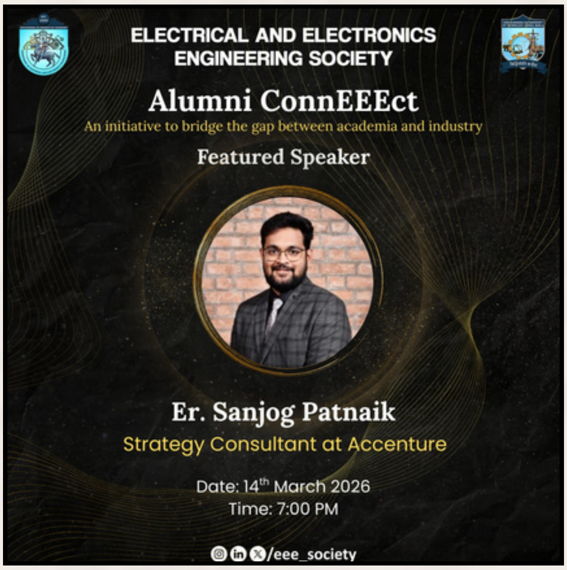
Alumni ConnEEEct

Alumni ConnEEEect: From Classroom to Career

Alumni ConnEEEct is a flagship initiative of the Department of Electrical and Electronics Engineering that strengthens alumni–student connections. It provides a platform for alumni to share their journeys, industry insights, and guidance, helping students relate academics to real-world applications.

In 2025–26, a total of 7 sessions were held, the programme featured sessions by distinguished alumni from diverse fields, offering insights into core and emerging domains while emphasizing strong fundamentals, adaptability, and continuous learning.

It continues to foster mentorship, inspiration, and a well-connected EEE community.



Society Activities

“Clean Campus, Green Campus”
A cleanliness drive was successfully organized by Dr. Sarmila Garnaik, Department of Electrical and Electronics Engineering, VSSUT, on 4th September, 2025.

Teacher’s Day was celebrated on 5th September 2025 at the EEE Seminar Hall to honour the valuable contributions of teachers in shaping students’ academic and personal growth.

Society Activities

A plantation drive was successfully organized by Electrical and Electronics Engineering Society of VSSUT on 5th September 2025, to promote environmental awareness and sustainability.

The Electrical and Electronics Engineering Society organized the Viswakarma Puja celebration on 17 September 2025 at the EEE Department, VSSUT, Burla.

Society Activities

The Bharat Maha EV Rally 2025, organized by IFEVA, is a significant 100-day initiative promoting sustainable mobility in India. Running from September 9 to December 18, 2025.

Er. Sovan Das, Senior Systems Engineer, SLD Lasers (Kyocera Group) delivered a talk on Li-Fi technology, in the Department of Electrical and Electronics Engineering at Veer Surendra Sai University of Technology Burla, on 13th March 2026.

First Year 2025-2026

DISTINGUISHED ALUMNI

Manas Ranjan Mishra
Senior Power System Engineer

Akshaya D.
Finance,
Ernst & Young

Vivek Pradhan
Management Consultant,
Deloitte

Chinmaya Patnaik
Senior Hardware Engineer

Sanjog Parnaik
Accenture S&C

Vartika Agarwalla
Security Engineer

EST. 2010

VEER SURENDRA SAI UNIVERSITY OF TECHNOLOGY

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

The only way of discovering the limits of the possible is to venture a little way past them into the impossible.

Aurthur C. Clarke

SPECTRUM

SCAN TO VISIT

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

/eee_society