SMART ENGINEERING SYSTEMS

CHAOS THEORY, AI, AND IOT IN MODERN ELECTRICAL APPLICATIONS

Editor
BİLAL TÜTÜNCÜ

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PREFACE

The convergence of emerging technologies such as artificial intelligence, metaheuristic optimization, advanced image processing, and the Internet of Things is fundamentally transforming the field of electrical and electronics engineering. This book presents a multidisciplinary perspective on intelligent system design and analysis, offering insights into how computational methods and smart technologies are shaping modern engineering solutions. The chapters reflect the integration of theory, simulation, and practical implementation, contributing to the development of more adaptive, efficient, and secure systems.

Addressing topics ranging from chaotic system synchronization to battery diagnostics and IoT-based monitoring platforms, the volume highlights innovative methodologies and real-world applications. By bringing together cutting-edge research in communication systems, energy storage technologies, and smart sensor networks, this book aims to serve as a valuable resource for researchers, engineers, and graduate students seeking to explore the frontiers of intelligent electrical engineering systems.

Assoc. Prof. Dr. Bilal TÜTÜNCÜ

Istanbul Technical University

İÇİNDEKİLER

CHAPTER 1

METAHEURISTIC ALGORITHMS BASED PID SYNCHRONIZATION OF CHAOTIC COMMUNICATION SYSTEM USING TIME DIVISION MULTIPLEXING

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MEHMET NURİ ALMALI[2]
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Introduction

Chaotic systems offer significant advantages to users of communication systems in terms of data confidentiality. These systems ensure that the original data can only be accessed by a receiver with an identical chaotic oscillator and synchronization. To increase the efficiency of the communication system, it is important to reduce the number of channels used. This is done through the use of time division multiplexing. Moreover, it is crucial to find the coefficients of the controller that will perform the synchronization.

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To find these coefficients, metaheuristic optimization algorithms based on animal and herd behavior were used instead of classical controller parameters finding methods. The Proportional Integral Derivative (PID) controller coefficients were found using genetic algorithm (GA), dragonfly algorithm, particle swarm optimization and world cup optimization algorithm. The performance analyses were conducted using spectral entropy and histogram analysis methods. This study found that synchronization between chaotic oscillators can be achieved digitally using the time division multiplexing method. In this study, GA algorithm outperformed PSO and Dragonfly algorithm in terms of synchronization. This performance difference provided better lossless transmission of the sound compared to other algorithms.

In today's world, communication systems face serious data security issues [1-4]. To prevent unauthorized access to transmitted data, cryptographic techniques have been used since the past. Chaotic oscillators, which are based on the chaotic nature of the universe, have been developed to address this issue. These oscillators enable the creation of systems that vary over time and provide different responses [5-11]. Initially, mathematical equations were developed based on this chaoticity, followed by the development of chaotic oscillator circuits. The process of data encryption and decryption can be securely achieved by using chaotic oscillators[12-16]. These oscillators are typically named after their creators, such as Chua, Lorenz, Sprott, and others [17-20]. Additionally, new types of chaotic oscillators are also utilized for this purpose. Studies have also been performed for the synchronization of these chaotic oscillators. Solving complex optimization problems is not possible with traditional and classical optimization methods. Advanced techniques are required, which include metaheuristic algorithms. These algorithms are computational intelligence paradigms designed to handle high-dimensional, nonlinear, and hybrid problems. There are different types of metaheuristic algorithms, such as swarm-based, evolutionary, physics-based, and human-based, based on their approach, whether nature-inspired or non-nature-inspired. They can also be classified as either population-based or single-solution-based [8]. Both classical methods and metaheuristic algorithms have been used to ensure synchronization between chaotic oscillators. In addition to chaotic oscillators, metaheuristic algorithms have been used to find the parameters of the PID controller in many multidisciplinary studies [21-22]. Time division multiplexing (TDM) is a technique used in various communication systems due to its numerous benefits. For instance, a MIMO radar system can employ TDM to achieve high spectral efficiency and wide bandwidth for both transmitters and receivers. The use of photonics based TDM in such systems results in high-resolution imaging [15-17]. Time Division Multiplexing (TDM), which is based on Passive Optical Networks (PON), is a method that provides flexible bandwidth and high bit rates. In this method, data can be transmitted in two ways: bit-by-bit (bit interleaving) or packet-by-packet (packet interleaving). Additionally, improved time division multiplexers are used in modular bridge converters, which are used in power electronics transformers to improve their efficiency.

A. Chaotic Oscillator Circuit

Chaotic oscillators are a type of electronic circuit that produce unique signals that do not repeat themselves over time. These circuits are created using different types of mathematical expressions such as Chua, Lorenz, Sprott, Arneodo, and Chen [17-20]. In our study, we focused on the Lorenz chaotic oscillator, which is characterized by its mathematical expressions given in Equation 1, Equation 2, and Equation 3. These expressions take advantage of the feedback principle of oscillators to create the chaotic signals.

$$\frac{dx}{dt} = \sigma(y - x)$$

(1)

$$\frac{dy}{dt} = -x.z + r.x - y$$

(2)

$$\frac{dz}{dt} = x.y - b.z$$

(3)

For equations 1, 2, and 3, σ=10, b=28, r=8/3, and initial conditions X_0=0, Y_0=-0.1, Z_0=9 are used. Figure 1 shows the X-Y chaotic attractor of the Lorenz system, and Figure 2 shows the plot of the Lorenz chaotic oscillator [8].

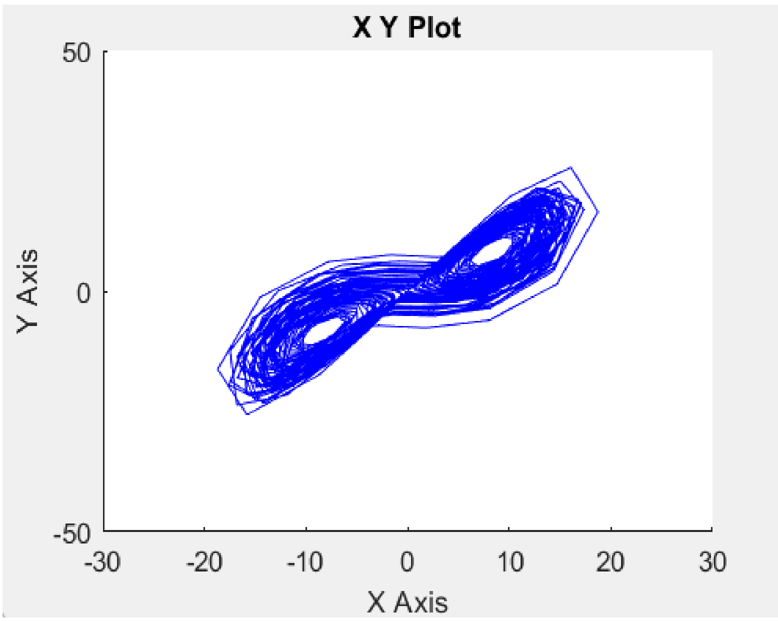


Figure 1 X-Y Lorenz chaotic attractor

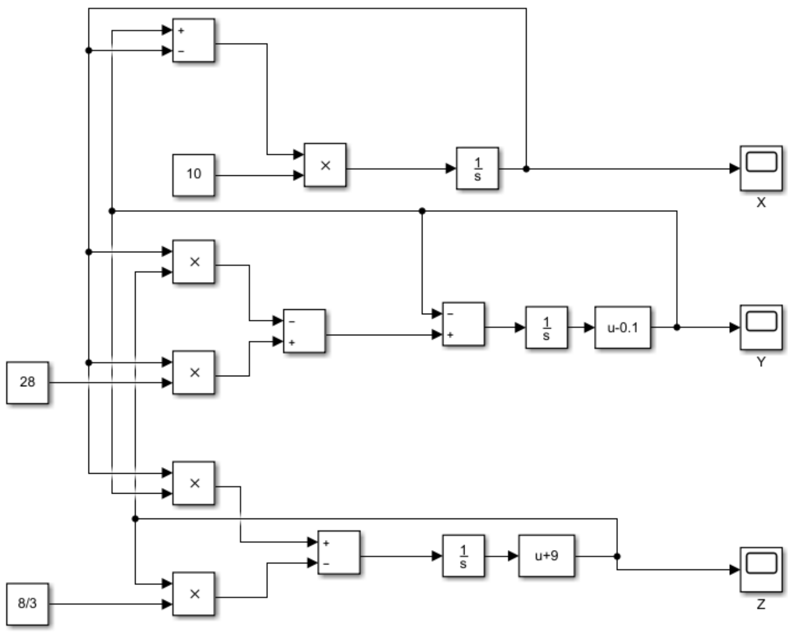


Figure 2 Lorenz chaotic oscillator

The chaotic oscillator shown in Figure 2 is used at both the transmitter and receiver sides of the communication system.

B. Metaheuristic Algorithms

Metaheuristic algorithms have been increasingly used to determine the parameters of various systems. These algorithms imitate the behavior of animals in their natural life cycles to find solutions. The feeding and sheltering behaviors of these creatures have inspired the creation of these algorithms. In order to apply these algorithms to a system, a cost function is used to determine the maximization or minimization of the desired answer. In our study, we use equation 4 as the cost function in our efforts to synchronize a chaotic communication system [9].

$$\text{cost} = \int_0^\infty e^2(t)t\,dt \tag{4}$$

The controller parameters is found by trying to minimize the cost function in Equation 4 for the desired synchronization. This minimization is based on the minimization of the error between chaotic oscillators.

C. Particle Swarm Optimization

Particle swarm optimization is a type of metaheuristic algorithm that searches globally and within a particle set to find the best controller parameters for a given number of particles. This search involves calculating the initial velocities and positions of particles in the swarm, followed by updates (iterations) where new positions and velocities are also calculated. Equations 5 and 6 are the mathematical equations used in these calculations [1, 2].

$$v_{k+1} = w * v_k + c_1 r_1 (pbest_k - x_k) + c_2 r_2 (gbest_k - x_k) \tag{5}$$

$$x_{(k+1)} = x_k + v_{k+1} \tag{6}$$

In Equation 5, Vk and Vk+1 are the current and next velocity, pbest is the best position of the particle and gbest is the global best position. Equation 6 shows the new position calculation with the help of the obtained velocity update.

D. Dragonfly Algorithm

The Dragonfly Algorithm is a type of swarm-based algorithm, similar to Particle Swarm Optimization. This algorithm takes inspiration from the behavior of dragonflies in nature, where they live in swarms and hunt smaller insects such as butterflies, bees, ants, and mosquitoes. During hunting, dragonflies move in static or dynamically shaped swarms, which have a specific search area. This search area can be virtually organized, and the position of the dragonflies within it is determined by the step vector ΔP, as shown in equation 7.

$$\Delta P_i^{t+1} = (s.S_i + \alpha.A_i + c.C_i + f.F_i + e.E_i) + w.\Delta P_i^t \qquad (7)$$

In equation 23, the variables represent the following weights and factors: s for separation weight, a for alignment weight, c for cohesion weight, f for food factor and e for enemy factor. The indented expressions Si, Ai, Ci, Fi and Ei refer to the individual separation, alignment, cohesion, food and enemy factors for the i-th iteration in computer simulations [3-5].

E. Genetic Algorithm

Animal herds have the remarkable ability to adapt their bodies to their environment, a process known as adaptation. This process involves a genetic algorithm that includes natural selection, crossover, and mutation, which lead to changes in the genotypes and phenotypes of animals. The survival of living organisms depends on their ability to adapt to changing environmental and climatic conditions. Animals that are unable to adapt to their surroundings cannot pass on their genes to the next generation through natural selection. In animal herds, only the strongest and most capable individuals are able to survive and flourish [9-11].

The genetic algorithm operates by creating a population of individuals that live within a certain habitat. In the cellular structure of each individual, there are chromosomes that contain genes. The genetic makeup of an organism, including both its physical and observable traits, is determined by the specific gene sequences found within its chromosomes. The genetic algorithm operates according to a flow diagram that is similar to other metaheuristic algorithms. In the process of creating a population, genes are formed using binary values of 0 and 1.

Firstly, genes are collected and arranged in chromosomes to form a group of individuals. These chromosomes undergo an evaluation process to ensure they meet specific predetermined conditions. After that, the crossover process takes place, where gene sequences from different chromosomes are combined to create new chromosomes without altering their biological properties.

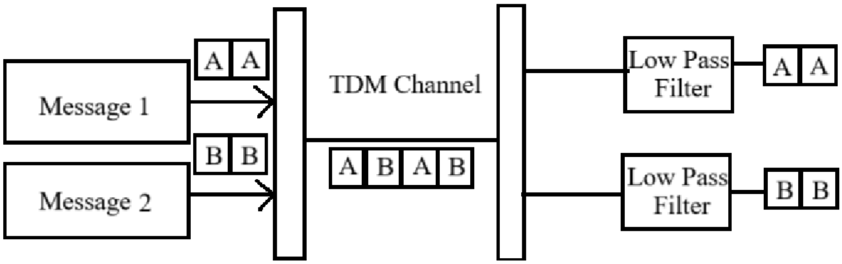
The crossover process in genetic algorithms can be either single-point or multi-point depending on the specific requirements. During the mutation stage, gene sequences in chromosomes undergo alteration.

The mutation process occurs at a specific rate, typically set between 0 and 1. Selection is performed in the final stage prior to reaching the maximum number of iterations and involves choosing individuals to be paired using methods like the roulette wheel and tournament method. The values for the PID controller were determined through the use of metaheuristic algorithms, and their codes were generated and used in time division multiplexing communication system [12-14].

F. Time Division Multiplexing

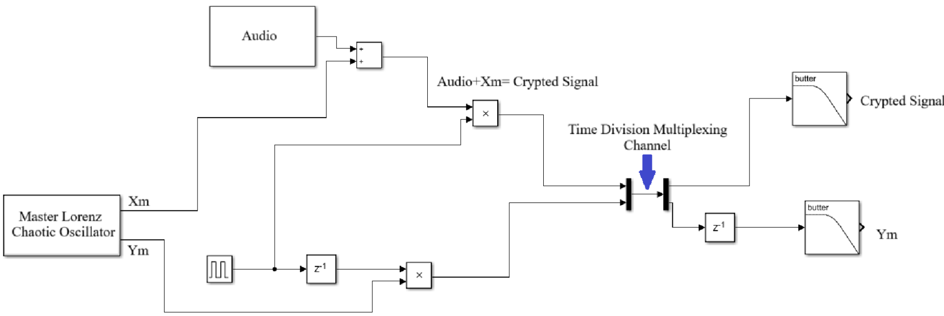
Time division multiplexing enables the transmission of data to the receiver over the same channel without the need for an external channel. In the created system, an encrypted audio signal and a second chaotic signal, which ensures synchronization between two chaotic oscillators, are sent over the same channel. The block diagram of TDM is presented in Figure 3 [15-17].

Figure 3 TDM block diagram [23, 24]



The given block diagram represents a TDM system, where both the encrypted audio signal and the chaotic signal are transmitted over a single channel to ensure synchronization between the chaotic oscillators. At the receiver end, butterworth low pass filters were used in the TDM system. Figure 4 illustrates the block diagram of the TDM system that we realized.

Figure 4 TDM system

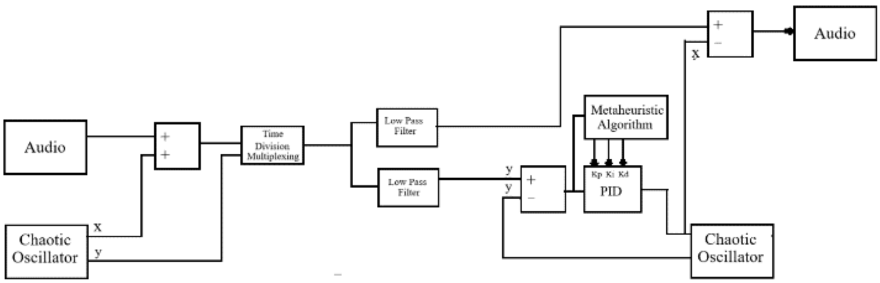


In the TDM system, the encrypted voice signal and Ym synchronization signal were transmitted on a single channel. This was achieved by triggering z and z^{-1} at a 99% duty cycle using a pulse generator. This created a time division which allowed both signals to be transmitted over the same channel.

G. Synchronization with Controller Parameters Obtained from Metaheuristic Algorithms

The time division multiplexing-based communication system, created using a chaotic oscillator, is synchronized with a PID controller. Figure 5 shows the block diagram of the chaotic communication system created with TDM system [21-24].

Figure 5. Chaotic communication system with TDM

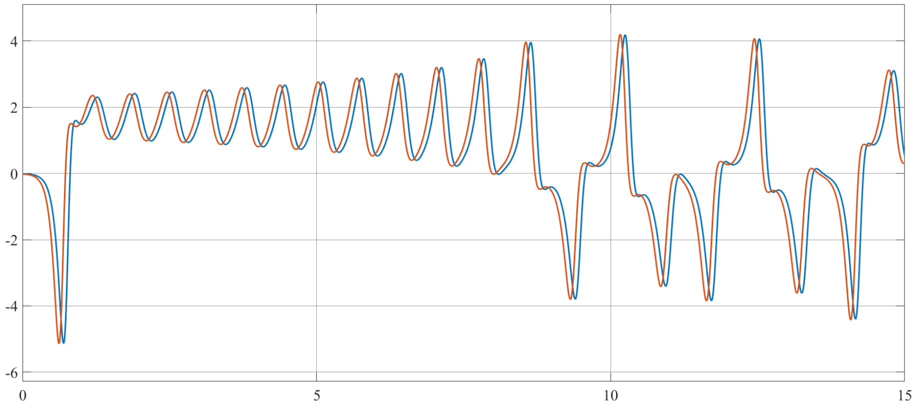


The parameters of the PID, which is the controller of the chaotic communication system created with TDM given in Figure a, were found using GA, PSO and Dragonfly algorithms. The parameters obtained are given in Table 1. In figure 6 and 7 synchronization of chaotic oscillator is shown. While the master system shows the blue line, the orange color shows the responses of the slave chaotic oscillator.

Table 1. PID controller parameters

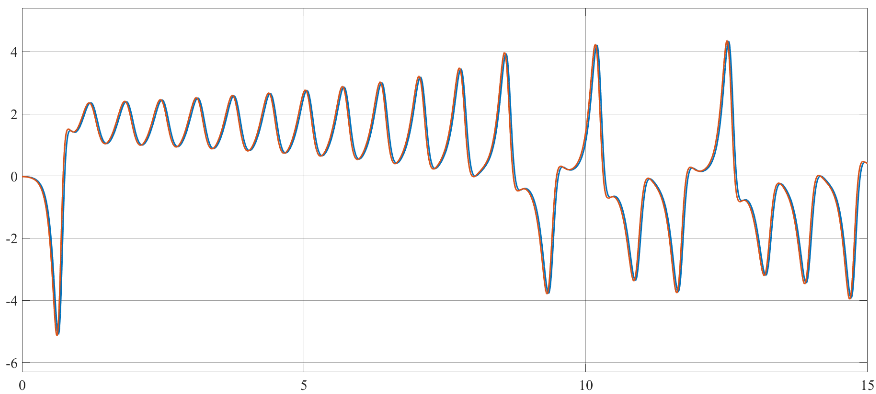
Algorithm	**Kp**	**Ki**	**Kd**
PSO	7.2039	2.6516	7.9010
DRAGONFLY	6.9795	1.9967	7.5521
GENETIC	6.4408	2.3369	8.7656

Fig. 6. Synchronization of Lorenz chaotic oscillator (PSO-Dragon)



The parameters obtained from PSO and Dragon gave the same results in terms of synchronization. The synchronization obtained with the genetic algorithm is given in Figure 7.

Figure 7. Synchronization of Lorenz chaotic oscillator (GA)



As can be seen in Figure 7, the synchronization with the genetic algorithm is better than the PID parameters obtained from PSO and Dragon algorithm.

H. Histogram Analysis

To determine whether the encryption of transmitted data is secure enough, an analysis of the data distribution is performed. This analysis involves the use of histogram techniques to determine the similarity between the original signal and the decrypted and encrypted data. Figures 8, 9 and 10 present the histogram analyses of the parameters obtained from GA, PSO and Dragonfly algorithm as an example to showcase the synchronization and encryption-decryption performances.

Figure 8 Original Audio signal histogram analysis (GA)

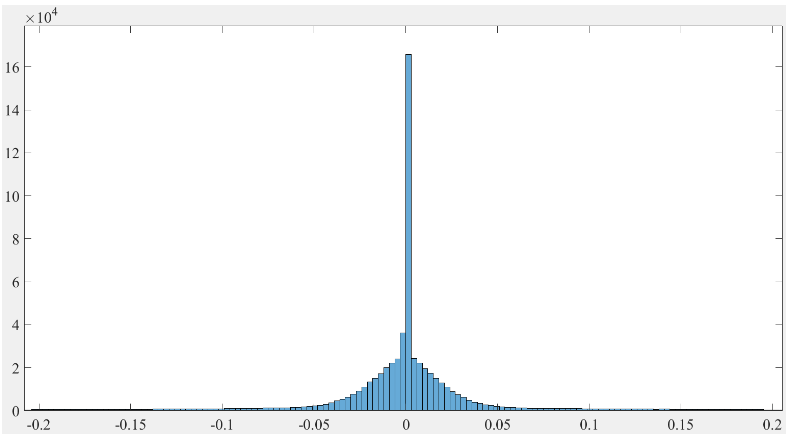


Figure 9 Histogram analysis of encrypted audio signal (GA)

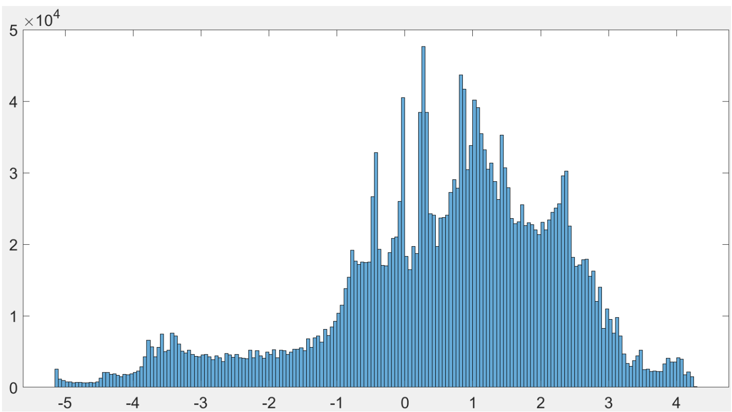


Figure 10. Decypted Audio signal histogram analysis (GA)

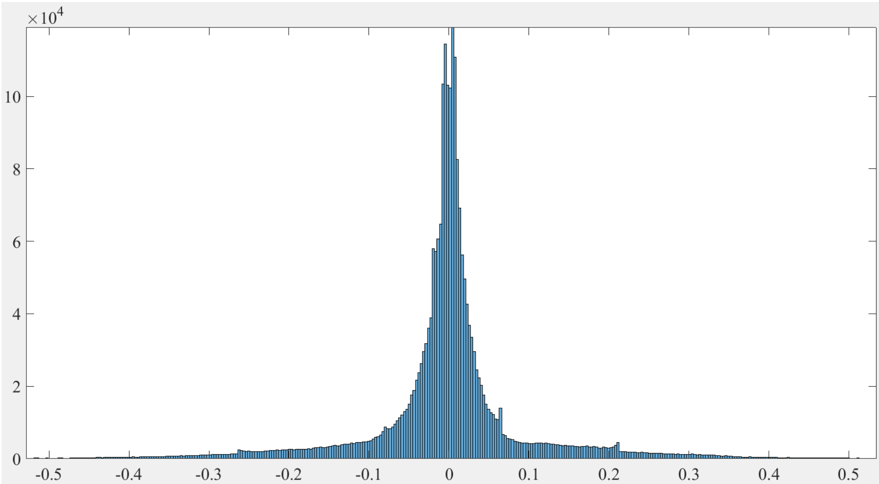
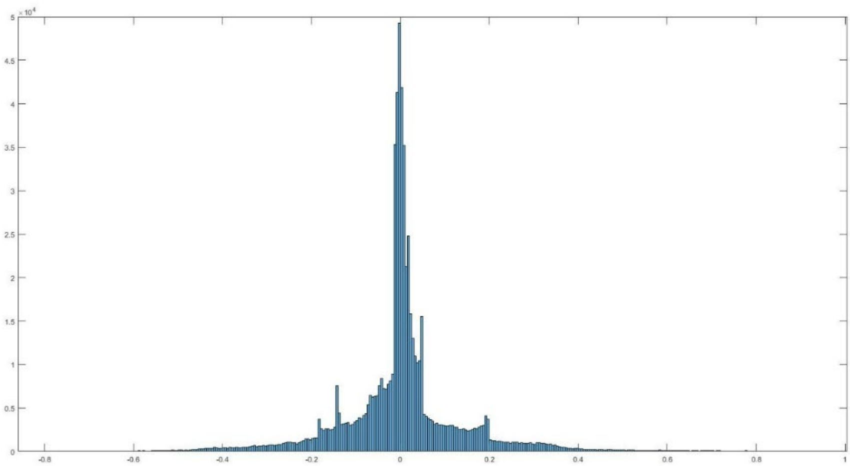


Figure 11 Decypted signal obtained with PSO and Dragon algorithm



When Figures 10 and 11 are compared, the decoded signal obtained from PSO and dragonfly has more distortion than the signal obtained from the genetic algorithm and is further away from the original signal. In this respect, the PID coefficients obtained from the genetic algorithm gave a better result

CONCLUSION

In this study, we have tried to find the PID parameters that will ensure the synchronization of the chaotic communication system created with time division multiplexing using particle swarm optimization, genetic algorithm and dragonfly algorithm, which are among the metaheuristic algorithm types. Although there is no difference in the decoding section between PSO and Dragon, less distortion was observed in the decoding of the audio signal since the coefficients found with the genetic algorithm performed the synchronization better. In the light of the data obtained, it is observed that the genetic algorithm performs a more robust synchronization than the dragonfly and particle swarm optimization algorithms. In this direction, the histogram analysis of the audio signal and the distributions obtained from the genetic algorithm are given.

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Towards High-Resolution Imaging With Photonics-Based Time Division Multiplexing MIMO Radar (TDM-1 ref)

Performance analysis of high speed bit-interleaving time-division multiplexing passive optical networks (TDM-PONs)

High-Efficiency Time-Division Multiplexing Modulation Technology for Modular Multiactive Bridge Converters

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CHAPTER 2

INTERNET of THINGS in ELECTRICAL ENGINEERING APPLICATONS: A CASE STUDY

ALİ SİNAN ÇABUK[1]

Introduction

The word electricity is derived from the Greek word "electron" and means amber. The ancient Greeks observed that amber attracted light objects as a result of friction and recorded this phenomenon. The historical development of electricity can be summarized as follows:

- Ancient Period: In 600 BC, Thales discovered that amber gained an electric charge through friction.
- Middle Ages: Although there were no systematic studies on electricity, some natural phenomena were observed.
- 17th and 18th Centuries: William Gilbert studied electricity scientifically, and Benjamin Franklin conducted experiments on electricity.

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- 19th Century: Michael Faraday and James Clerk Maxwell's studies on electromagnetism formed the basis of electrical engineering.
- 20th and 21st Centuries: Electricity began to be used in every area of life, from electronic circuits to communication systems. (Bugeja, 2025; Branstad, 2021).

Electrical engineering is an engineering discipline that deals with the fields of electricity, electronics and electromagnetics. It covers topics such as the production, transmission, distribution and use of electrical energy. It also operates in areas such as electrical machines, electric vehicles, lighting systems, renewable energy systems, electronic circuits, communication systems, power electronics, control systems and automation. Electrical engineers contribute to the advancement of technology by working in various fields from power plants to mobile devices. Electrical engineering is one of the fundamental building blocks of the modern world. Without electrical energy, critical areas such as industry, communication, transportation and health sectors cannot survive. Electrical engineers undertake critical tasks such as increasing energy efficiency, developing sustainable energy sources and designing next-generation electronic systems. Smart cities, renewable energy technologies and next-generation communication systems such as 5G can be realized with the contributions of electrical engineering. Electrical engineering emerged as a modern discipline in the 19th century with the increase in studies on electromagnetism. However, the use and science of electricity dates back to ancient times. In the ancient period, the ancient Greeks noticed that amber gained an electric charge through friction. In the 18th century, Benjamin Franklin's electrical experiments and Alessandro Volta's invention of the battery advanced the scientific study of electricity. In the 19th century, scientists such as Michael Faraday, James Clerk Maxwell and Nikola Tesla developed electromagnetic theory and laid the foundation for the widespread use of electricity. Thomas Edison's invention of the incandescent light bulb and the alternating current (AC) and direct current (DC) war between Tesla and Edison led to the birth of the electric age. In the 20th and 21st centuries, electrical engineering played a key role in the digital revolution with electronic circuits, semiconductors and computer technologies (Holmburg, 2021; Simoes, 2024).

Electrical engineering first emerged as an academic discipline in the late 19th century. The first Electrical Engineering Department was established in 1882 at the Massachusetts Institute of Technology (MIT) in the USA. This was the first program to provide formal academic education in electrical engineering. The first Electrical Engineering Faculties were Cornell University in the USA and Darmstadt Technical University in Germany, which were among the first universities to start electrical engineering education in 1883. 20th Century: Electrical engineering has spread worldwide and has formed sub-branches, especially electronics, communications and computer engineering. Today, electrical engineering is taught in an integrated manner with many advanced technologies such as artificial intelligence, robotics, renewable energy and smart systems. Today, electrical engineering covers many different areas. The basic topics covered by electrical engineering are as follows:

- Electrical Machines: Design and production of electrical devices such as motors, generators and transformers.
- Lighting Techniques: Design of lighting systems, energy efficiency and next-generation lighting technologies.

- Power and Energy Systems: Power plants, energy transmission, smart grids and renewable energy sources.
- Electronics: Integrated circuits, microcontrollers and semiconductor technologies.
- Communication: Telecommunication systems, wireless communication and internet infrastructure.
- Automation and Control Systems: Industrial automation, robotics and artificial intelligence-based control systems.
- Biomedical Electrical Engineering: Medical devices, magnetic resonance (MR) systems and biosensors.
- Renewable Energy: Sustainable energy sources such as solar, wind and biomas energy systems.

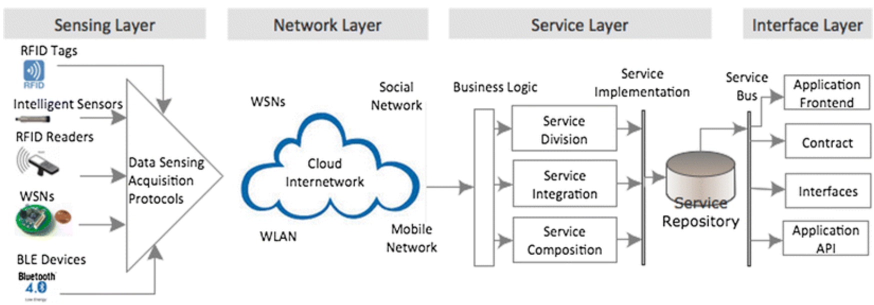
Electrical engineering is also closely related to other engineering disciplines. It has been effective in many areas from information technologies to mechanical engineering:

- Computer Engineering: Electrical engineering plays a critical role in the development of computer hardware and microprocessors.
- Mechanical Engineering: Robotics, mechatronic systems and automation technologies are at the intersection of electrical and mechanical engineering.
- Aerospace Engineering: Electrical systems, avionic systems and satellite technologies are of great importance in this field.
- Biomedical Engineering: Electrical engineers work in the design and development of medical devices.

- Civil Engineering: Intelligent building systems, energy efficient infrastructures and lighting systems are the interactions of electrical engineering with this field (Kline, 2019; Bazerman, 2021; Bazerman and Lander, 2001).

The Internet of Things (IoT) is a system that aims to connect all objects used in the world to the internet, communicate with each other, manage them remotely and provide decisive responses to management. It is a world where billions of objects can connect to each other via a special internet protocol, communicate with each other and share information. The data that these connected objects regularly collect and analyze to initiate action also provides strong intelligence for planning, management and decision making (Li et al., 2015). The structure of IoT is as in Figure 1.

Figure 1. The structure of IoT



Reference: Li et al., 2015

If we look at the historical development of the Internet of Things; in 1991, it was tested on a coffee machine at Cambridge University. The term IoT was first used in a presentation prepared by Kevin Ashton in 1999. However, the international acceptance and introduction of this concept was provided by the report 'The Internet of Things, ITU Internet Reports' published by the International Telecommunication Union in 2005. In this published report, according to the research of 2005, inferences such as element definition, embedded systems, nanotechnology for Internet of Things applications were made; ideas about the future of this system were put forward. After this first development phase, they found a place for themselves in many applications with smart sensor applications. In recent years, the importance of using the Internet of Things has been emphasized in various scientific conferences and studies. The first steps of creating stable systems and integrating IPv6 with this system date back to 2009. This integration process was carried out by the 'Internet Association' in 2012 (Altınpulluk, 2018; Oral and Çakır, 2017)

The Internet of Things (IoT) is a technology that enables devices to connect to the internet, collect data, share information, and be managed remotely. Today, the importance of IoT is increasing due to the following reasons:

- Increased Efficiency: It enables automation in industries such as manufacturing, energy management, and healthcare.
- Cost Reduction: IoT helps optimize energy consumption, reduce maintenance costs, and minimize unnecessary human intervention.
- Real-Time Data: Sensors and connected devices allow for instant data collection and analysis, leading to better decision-making.
- Smart Systems: Applications such as smart cities, smart factories, and smart homes become more efficient and sustainable with IoT.

Engineering involves designing, manufacturing, and managing complex systems. Today, engineering disciplines require the ability to analyze vast amounts of data, optimize processes, and utilize resources more efficiently. This is where IoT comes into play.

Through sensors and connected devices, IoT enhances engineering systems, making them smarter. It enables remote control of systems, real-time data analysis, and improved decision-making processes. Consequently, IoT helps reduce error rates and contributes to the development of more reliable and sustainable systems. Below are some detailed examples of IoT applications in engineering:

Smart grids are one of the most widely used IoT applications in engineering. In electrical engineering, IoT plays a crucial role in energy production and distribution. With smart meters, consumption data can be monitored in real-time, allowing for more efficient energy management. Additionally, IoT sensors help detect potential failures in power transmission lines before they occur, optimizing maintenance processes.

Industrial automation is another critical field where IoT is used in engineering. In IoT-enabled factories, predictive maintenance systems detect potential machine failures before they happen, ensuring uninterrupted production. IoT-connected robotic systems speed up production processes and reduce costs by minimizing human errors.

IoT in buildings is particularly important for energy efficiency. Smart lighting and heating-cooling systems use IoT sensors to adjust according to environmental changes, optimizing energy consumption. For example, IoT-based lighting systems can detect movement in a room and turn lights on or off accordingly, preventing unnecessary energy consumption.

IoT has brought a significant transformation to electrical engineering. It plays a crucial role in power generation, transmission, and distribution. The benefits of IoT in electrical engineering include:

- Smart Grids: IoT sensors enable real-time monitoring of power lines, allowing for quick fault detection and minimizing outages. Smart meters provide detailed electricity consumption data, optimizing energy management.

- Energy Management and Efficiency: IoT allows industries and households to monitor their energy consumption, reducing unnecessary expenses. Smart circuit breakers and automated load management systems help conserve electricity.
- Electric Machines: IoT enhances the efficiency of electrical machines such as motors, generators, and transformers. By continuously monitoring temperature, vibration, and load status, IoT-based sensors help predict failures and optimize maintenance schedules.
- Lighting Systems: IoT-enabled lighting systems can detect motion and natural light levels, automatically adjusting to reduce energy waste. Smart lighting solutions contribute to improved energy efficiency.
- High Voltage Systems: IoT is used in high-voltage networks to detect failures and monitor power quality. IoT-based monitoring devices in power transmission systems help prevent overloads, reducing the risk of power outages.
- Electric Vehicles: IoT improves battery management, optimizes charging stations, and enhances energy consumption in electric vehicles. Smart charging stations integrated with IoT provide recommendations for the best charging times and prevent excessive grid load.

- Renewable Energy Integration: IoT facilitates the effective management of renewable energy sources like solar panels and wind turbines. IoT-based systems analyze weather data to optimize energy production and improve energy storage processes (Hezron et al., 2021; Zahira et al., 2025)

INTERNET of THINGS PLATFORMS and CLOUD TECHNOLOGIES

Internet of Things (IoT) platforms are software and hardware infrastructures that enable IoT devices to be managed, data collected, analyzed, and communicated securely. IoT platforms are used in many areas such as smart cities, industrial automation, healthcare, and smart agriculture by enabling smart devices to connect with each other and large-scale data management.

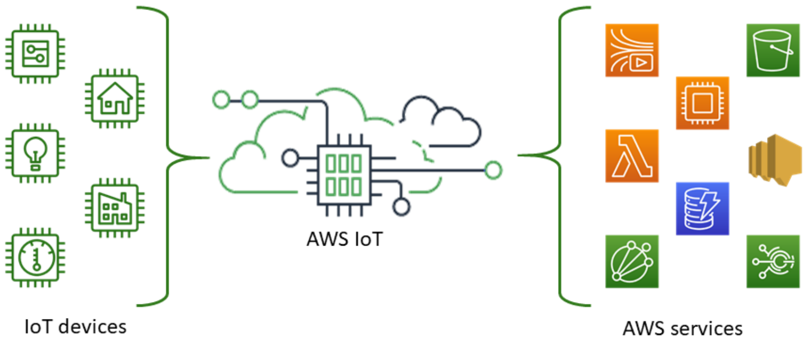
These platforms are generally systems that collect data from sensors, analyze this data, and provide meaningful information to the user. For example, machines on the production line in smart factories can be monitored through IoT platforms and maintenance requirements can be determined in advance. Similarly, smart home systems can be controlled remotely thanks to IoT platforms. From a technological perspective, IoT platforms generally include big data processing, machine learning, and artificial intelligence technologies. Protocols such as MQTT, CoAP, and HTTP are used to communicate between devices. The platforms also have encryption and authentication mechanisms to ensure security.

Popular IoT Platforms are as follows

1. AWS IoT Core: Developed by Amazon Web Services, AWS IoT Core stands out with its scalable cloud infrastructure. It is used in many areas such as industrial automation, healthcare and smart home systems. It offers high security with big data

processing and artificial intelligence support. This platform has a structure like in Figure 2.

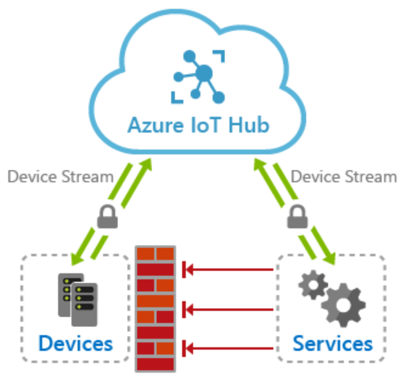
Figure 2. AWS IoT Core



Reference: AWS Developer Guide, 2025

2. Microsoft Azure IoT Hub: Azure IoT Hub offered by Microsoft offers a wide range of services for cloud-based IoT projects. It is suitable for large-scale enterprise projects as it works integrated with the Azure ecosystem. Microsoft Azure IoT Hub is as shown in Figure 3.

Figure 3. Microsoft Azure IoT Hub



Reference: Azure, 2025

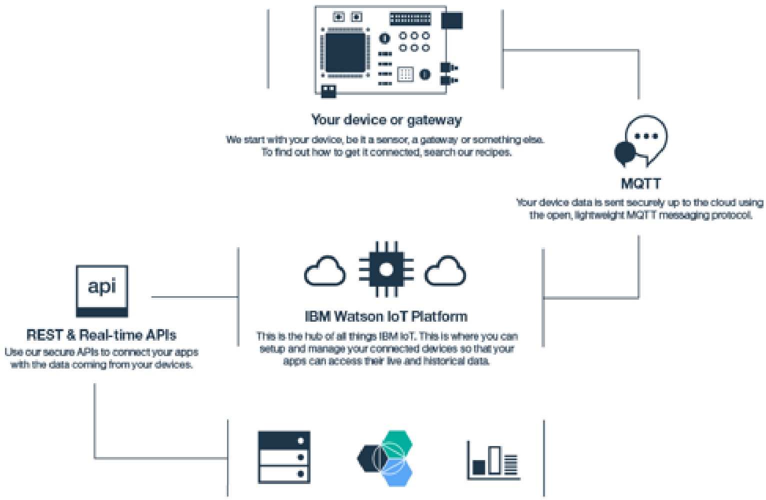
3. Google Cloud IoT: Google's IoT platform stands out with its strong analytical capabilities and artificial intelligence support. It is advantageous in terms of big data analytics and can be used with machine learning. Google Cloud IoT, which has a strong infrastructure, is as shown in Figure 4.

Figure 4. Google Cloud IoT

Reference: Google Cloud, 2025

4. IBM Watson IoT: This platform developed by IBM is especially strong for industrial automation and artificial intelligence-based analysis. It allows businesses to perform big data analysis more effectively. This platform is as given in Figure 5.

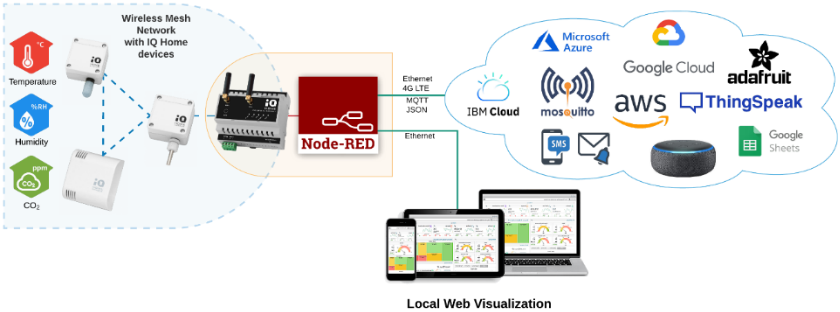
Figure 5. IBM Watson IoT



Reference: IBM IoT, 2025

5. Node-RED: Node-RED can be thought of as a flow-based and event-driven programming tool developed by IBM. Within this platform, information is represented by the behavior of the application, the graphic blocks communicating with each other and providing information flow (Sicari, 2019; Lekić, and Gardašević, 2018). Node-RED can interface with the API of all IoT platforms. This platform is as in Figure 6.

Figure 6. Node-RED (Node-RED, 2025)



Reference: Node-RED, 2025

The advantages of these platforms over each other vary depending on the sector and needs to be used. While AWS IoT Core offers a wider ecosystem, Azure IoT Hub is focused on enterprise solutions. Google Cloud IoT is strong in big data and AI integration, while IBM Watson IoT offers comprehensive tools for industrial solutions. Node-RED stands out with its open source code and free usage. Many IoT system users prefer Node-RED because of its open source code.

Cloud technologies are a system that provides data storage, processing and software services over the internet. It is a more flexible, scalable and cost-effective solution compared to traditional physical servers. Users can remotely access the computing resources they need without investing in physical hardware. Cloud technologies are generally offered in three basic models:

- Software as a Service (SaaS): Allows users to use a software over the internet instead of purchasing it (e.g. Google Drive, Microsoft 365).
- Platform as a Service (PaaS): Provides developers with an application development, testing and running environment (e.g. Google App Engine, Microsoft Azure).

- Infrastructure as a Service (IaaS): Allows companies to use cloud resources instead of physical servers by providing virtual servers and storage services (e.g. AWS EC2, Google Compute Engine).

These service models allow businesses and individuals to access more efficient computing systems with less hardware investment.

IoT devices constantly produce large amounts of data. Powerful infrastructures are needed to process, store and analyze this data. This is where cloud technologies come into play. Cloud systems collect and analyze data from IoT devices on a central server and, when necessary, process this data with machine learning or artificial intelligence to turn it into meaningful information. The following features are gained with the integration of IoT and cloud technology.

1. Real-Time Data Analysis: Data from IoT devices can be analyzed instantly and fast decision-making mechanisms can be created. For example, smart traffic systems can optimize traffic density with cloud-based analysis.

2. Scalability: The number of devices in IoT systems can increase rapidly. Thanks to cloud technologies, the management of these devices becomes easier and the need for infrastructure can be increased flexibly.

3. Cost Savings: Using cloud-based storage instead of physical servers reduces infrastructure and maintenance costs.

4. Security and Accessibility: Cloud-based IoT solutions provide advantages in terms of data security and backup. In addition, they provide remote access and enable IoT devices to be managed from anywhere (Park and Park, 2024; Sayed, 2024).

It has become an indispensable component for IoT systems. The data collected by IoT devices can be interpreted, stored securely, and accessed worldwide thanks to cloud computing. This increases efficiency in many areas, from smart cities to industrial automation, from healthcare to smart agriculture.

CASE STUDY with INTERNET of THINGS in ELECTRICAL ENGINEERING

Node-RED is an open-source, flow-based development tool created by IBM, specifically designed to simplify connections between IoT devices and services. It operates on a drag-and-drop interface, requiring minimal coding, making it a preferred choice for both experienced developers and beginners.

One of Node-RED's biggest advantages over other IoT platforms is its ease of integration and extensibility. It seamlessly works with popular IoT protocols such as MQTT, HTTP, and WebSocket, allowing effortless data transfer between devices. Users can quickly connect to REST APIs, databases, cloud services, and other IoT components, enabling the creation of complex workflows with minimal effort (Syahbana and Jata, 2025; McCarthy et al., 2025).

Another key benefit of Node-RED is its strong community support. Being open-source, it continuously receives new plugins and extensions, allowing users to develop customized solutions for their specific needs. While traditional IoT platforms may require dependency on certain programming languages or proprietary systems, Node-RED provides broad compatibility, supporting integration with Python, JavaScript, C++, and more. Node-RED offers flexibility by running on both cloud-based and local servers. Whether for small-scale projects or industrial automation, it provides an efficient and scalable solution for managing IoT systems. With its speed, flexibility, and easy integration, Node-RED has become one of the most preferred platforms for IoT applications.

Electrical engineering is a broad discipline encompassing various fields, including electrical machines, power systems, high voltage engineering, lighting technologies, automation systems, energy transmission and distribution networks, electric vehicles, and renewable energy systems. Today, each of these fields requires the integration of the Internet of Things (IoT) to enhance efficiency, safety, and intelligence in system operations.

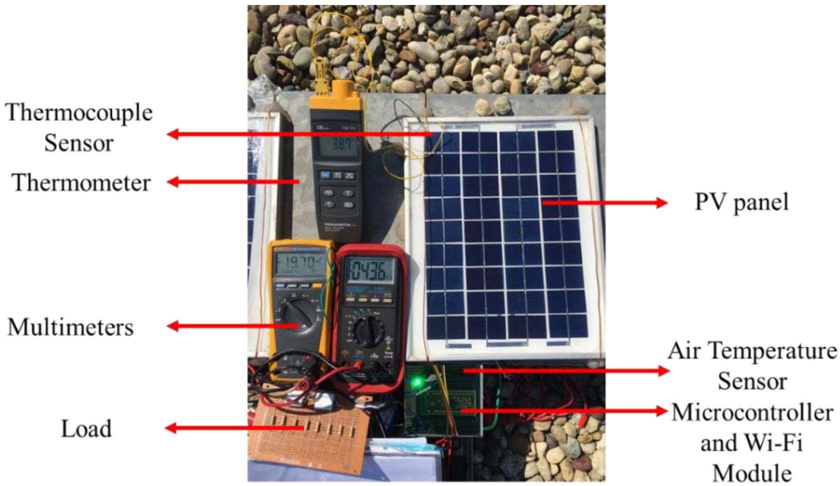
Renewable energy systems, in particular, are among the areas that most critically need IoT integration. Solar farms and wind turbine sites are typically located in remote areas where establishing wired communication infrastructure is challenging. This creates difficulties in monitoring energy production, managing maintenance processes, and optimizing system performance. With IoT systems, real-time data can be collected using wireless sensors and smart devices, enabling remote monitoring and control of these energy generation facilities. For example, the efficiency of solar panels can be continuously analyzed through IoT-based monitoring systems, allowing for early detection of issues such as dirt accumulation, shading, or malfunction. Similarly, sensors installed on wind turbines can measure blade vibration levels and weather conditions to predict maintenance needs in advance. This optimization not only improves energy production efficiency but also reduces operational and maintenance costs. Various fields within electrical engineering are increasingly integrating with IoT technologies to develop more efficient and intelligent systems. Renewable energy systems, especially those spread across vast and remote areas, benefit significantly from the wireless communication and remote management capabilities offered by IoT. This integration plays a crucial role in supporting sustainable energy production and shaping the future of smart energy systems.

In the scope of the case study, a thermal monitoring case study of a solar panel system is presented. Although this case study is only about solar panels, it shows a way to integrate other subjects related to electrical engineering with IoT with a similar setup.

Case Study System Design

The test bench includes a 10W, max. voltage 18V polycrystalline silicon solar panel, a thermocouple sensor, and an air temperature sensor. The experimental setup is shown in Figure 7.

Figure 7. PV Panel Setup



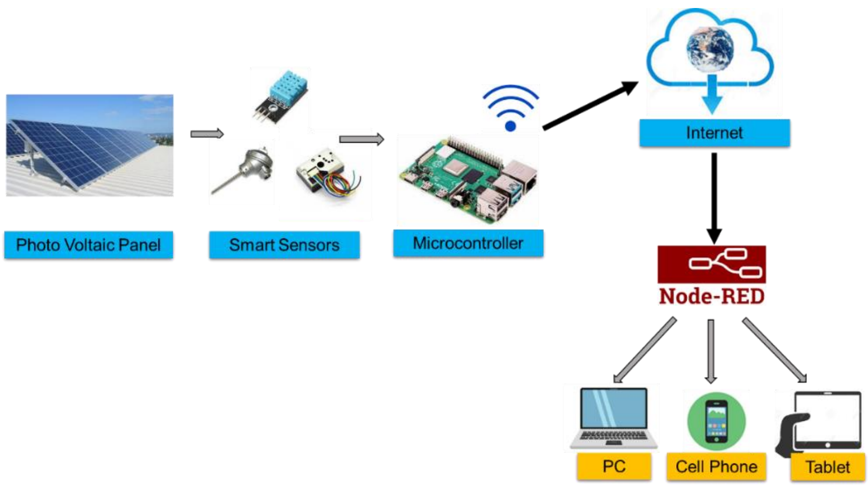
The temperature measurement system in the proposed setup utilizes two distinct measurement modules. The first module consists of a thermocouple sensor, while the second employs an air temperature sensor. The thermocouple sensor provides an analog output, offers high precision, and can measure temperatures up to 90°C. The sensor's signals are digitized using a microcontroller, which processes the input data through an Analog-to-Digital Converter (ADC) module.

For air temperature measurement, the system utilizes a DHT11 sensor, a combined temperature and humidity sensor with a digital signal output (Thinking Electronic Industrial Co. Ltd., 2023). By employing a specialized digital signal acquisition technique along with temperature and humidity detection technology, the DHT11 ensures high reliability and long-term stability. It consists of a resistive-type humidity measurement component and an XTC temperature measurement component, making it compatible with high-performance microcontrollers. The sensor provides a temperature measurement accuracy of ±2°C and a humidity accuracy of ±5% RH. Additionally, it features a fast response time, strong anti-interference capability, and supports temperature measurements up to 90°C.

The system is powered by high-performance STM32F205 microcontrollers, which operate at a frequency of 120 MHz and feature an ARM 32-bit CPU core for robust processing. These microcontrollers are capable of performing up to 1 million measurements per second. Moreover, they integrate three 12-bit ADCs and Wi-Fi modules, ensuring efficient data acquisition and seamless wireless transmission.

The principle diagram of the system considered for the case study is as in Figure 8.

Figure 8. Principle diagram of case study



There is a Wi-Fi signal in the application area of the case study. Therefore, the IoT system easily sends data to the cloud. This may not be possible in large-scale PV applications with solar fields. In rural areas, it is recommended to use GSM systems instead of Wi-Fi. For this case, there must be a GSM module on the development board where the microprocessor is located.

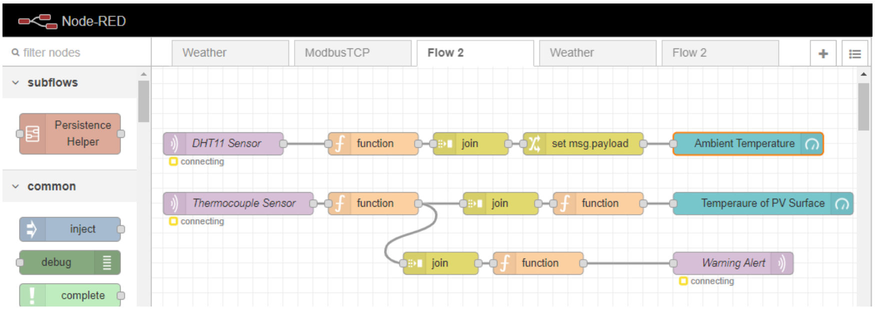
Case Study IoT Platform Design

Node-RED is an IoT platform that offers an open source and flow-based programming interface. It is frequently preferred by developers and engineers due to its easy use, drag-and-drop interface and extensible structure. Node-RED offers a more flexible structure compared to other platforms, especially because it can easily manage data flows and integrate with different systems. It is widely used in areas such as industrial automation, smart cities and energy management. It is also ideal for small-scale IoT projects with its low hardware requirements. Therefore, Node-RED is preferred as the IoT platform in this case study.

The temperature monitoring system of case study incorporates various functions, including sensor-based panel and air temperature measurement, data processing, cloud-based data transfer, and distribution to internet-enabled devices. The system is composed of two primary components: hardware and software. The hardware includes sensors and microcontrollers, while the software is based on open-source code running on the Node-RED platform.

Once the necessary connections were established to ensure seamless data flow between the sensors and the microcontroller, the sensor data was transmitted to the microcontroller. This data was then sent to the cloud platform via Wi-Fi and subsequently directed to the Node-RED interface. Figure 9 illustrates the design of the Node-RED interface, which enables real-time monitoring of temperature data.

Figure 9. Node-RED Interface

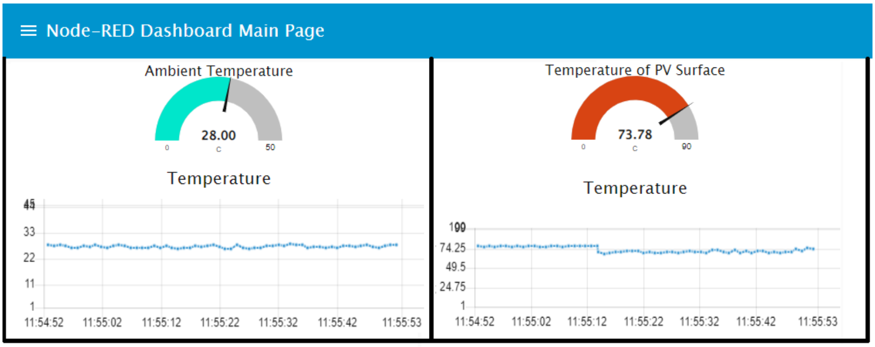


Monitoring System of Case Study

The Node-RED interface is composed of several sections. The first section handles data transfer from air data sensors. In the second section, temperature data is processed using function blocks. The third section consists of nodes responsible for processing the data before it is sent to the dashboard.

Real-time visualization of panel surface and air temperature data is achieved through the Node-RED control panel. This open-source web interface can be accessed from any web browser, eliminating the need for users to install additional applications on their devices. The control panel displays the processed data in multiple formats, including indicators, text, and graphical representations, as illustrated in Figure 10.

Figure 10. Monitoring System of Case Study



The solar panel temperature monitoring system presented as a case study can be easily adapted to many electrical engineering systems. Analog or digital sensors that make different measurements can be connected to the development board containing the microprocessor. These sensors can vary depending on the electrical engineering field to be used. Since the Node-RED platform is an open source and free platform, it can be easily integrated into all electrical engineering fields. At the same time, the data obtained from this platform can be monitored from all smart devices (PC, tablet, mobile phone, etc.) that have an internet browser. This monitoring does not require an application or similar software. In this context, this case study offers a simple, low-cost and easy IoT adaptation of electrical engineering subjects.

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CHAPTER 3

IMAGE PROCESSING IN BATTERY MONITORING: A METHODOLOGICAL REVIEW ON STATE OF CHARGE ESTIMATION

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SEÇİL GENÇ[2]
BARIŞ ÇAVUŞ[3]

Introduction

Battery energy storage systems (BESS) are widely utilized in various applications such as electric vehicles, enhancing grid flexibility, increasing system efficiency through integration with renewable energy sources, and enabling energy arbitrage. Batteries play a critical role in achieving national net-zero carbon emission targets and can be employed alongside renewable energy resources to enhance grid flexibility. Since renewable sources like wind and

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solar are climate-dependent, their generation is subject to fluctuations. These fluctuations may lead to frequency regulation issues when there is an imbalance between supply and demand. Therefore, BESS emerge as a key flexibility asset to mitigate such variabilities [1].

Battery management systems (BMS) are employed to monitor and control the performance of batteries used at both grid scale and in electric vehicles. One of the critical parameters of BMS is the state of charge (SOC), which indicates the remaining energy in the battery and informs the user accordingly. Accurate estimation of SOC is essential for the stable and efficient operation of the system [2].

Errors in SOC estimation may lead to adverse conditions such as overcharging or depth of discharge (DOD). Thus, developing accurate and reliable SOC estimation models plays a pivotal role in advanced control algorithm integration. In recent years, in addition to traditional methods based on electrical parameters, alternative approaches utilizing thermal, optical, and impedance-based data have also been developed [3].

For SOC estimation, methods such as Coulomb counting, Kalman Filter, Extended Kalman Filter, analysis of battery voltage-current curves through signal and image processing techniques, electrical equivalent circuit modeling, artificial intelligence, and machine learning techniques are employed.

The aim of this study is to methodologically examine the integration of various image processing techniques into battery systems for analyzing 2D or 3D representations of voltage-current graphs, thermal images, and ultrasonic visuals prior to SOC estimation. Drawing on examples from the literature, SOC estimation models based on deep learning are comparatively presented using visual representations such as current-voltage curves, thermal images, and electrochemical impedance spectroscopy (EIS) data, and the advantages and limitations of these methods are discussed.

Battery Lifespan

One of the most critical characteristics of batteries is ensuring not only their efficient operation during usage but also the optimal utilization of their lifespan. Therefore, monitoring and evaluating the battery lifespan is crucial. Although the objectives and constraints vary across different applications, it is essential to appropriately account for battery operating costs. The effects of repeated charging and discharging cycles constitute the primary source of these costs [4].

The term end-of-life (EoL) refers to the point at which a battery cell can no longer perform its intended function due to a decline in capacity—commonly defined as falling below 80% of its original capacity. The DOD, representing the absolute magnitude of each charge cycle, is a key stress factor contributing to cyclic aging. In addition, factors such as current, temperature, and terminal voltage also significantly influence degradation during cycling.

A widely used method for evaluating battery cycling behavior is the Rainflow Counting Technique, which is commonly employed to identify charge-discharge cycles and evaluate fatigue-related degradation.

SOC Estimation

The SOC refers to the remaining usable charge of a battery relative to its full capacity. In general, SOC cannot be directly measured but must be estimated from measurable variables. There are five primary methods for indirectly determining the SOC: chemical analysis, voltage-based estimation, current-based estimation, model-based methods and data-driven approaches.

In the literature, a wide range of artificial intelligence methods have been investigated for SOC estimation, including adaptive estimation strategies, extended Kalman filter (EKF), long short-term memory (LSTM) neural networks, and convolutional neural networks (CNN) [5–8].

The Coulomb counting method is one of the simplest and most widely used approaches for SOC estimation. According to this method, the change in the state of charge is calculated as shown in Equation (1). In this equation, I_{bat} represents the battery current, and $Q_{nominal}$ denotes the nominal capacity of the battery.

$$SOC(t) = SOC(to) + \frac{\int_{to}^{t0+\tau} I_{bat}.d\tau}{Q_{nominal}} \times 100\% \tag{1}$$

SOC and State of Health (SOH) estimation play a vital role in BMS, which are integral to most battery-powered applications, including BESS. Accurate state estimation helps prevent overcharging or undercharging, thereby enhancing battery safety and extending lifespan. In recent years, various techniques have been adopted for SOC and SOH estimation, among which data-driven methods have demonstrated significant effectiveness.

However, data-driven approaches face several critical challenges, such as data distribution inconsistency and insufficient data availability. To address these limitations, transfer learning-based methods have recently gained attention in research. These methods offer improved generalization under varying operational conditions and help mitigate the issue of domain mismatch in data distribution. Transfer learning techniques for battery state estimation are typically classified into three categories: fine-tuning methods, metric-based approaches, and adversarial adaptation techniques.

Unlike model-based methods that rely on domain expertise and predefined mathematical models, data-driven approaches are built upon extensive historical and operational datasets. Notable examples of data-driven algorithms include fuzzy logic, Gaussian Process Regression (GPR), and Support Vector Machines (SVM).

More recently, deep learning (DL) techniques have demonstrated remarkable success in SOC and SOH estimation. Among these, Recurrent Neural Networks (RNN), Multilayer Perceptrons (MLP), and CNN have shown promising results and have been widely applied across various domains, including battery condition monitoring and prognosis..

Battery Lifespan Estimation

Calendar life and cycle life are two commonly used terms to describe the lifespan of a battery. Calendar life refers to the duration a battery can remain in storage or undergo minimal use before reaching the end of its service life. The primary cause of calendar aging is the formation of a passivation layer on the negative electrode. The SOC at which the battery is stored has a significant impact on its calendar life. Additionally, storage temperature is a critical factor, as elevated temperatures accelerate chemical degradation. BMS monitor and control temperature to avoid hazardous side effects and prolong battery health.

Cycle life is defined as the total number of charge-discharge cycles a battery can undergo before its capacity falls below 80% of its initial value [3]. The operating temperature also influences cycle life; higher temperatures reduce both calendar and cycle life. Furthermore, charge/discharge rates impact battery degradation. Fast charging may cause damage to the battery's components and electrodes, thereby reducing its cycle life. Similarly, high discharge rates can accelerate aging. Other influential factors include DOD, charging regime, residence time at low or high SOC, and current fluctuations [9].

Interdisciplinary research on battery aging continues to evolve in the literature. As illustrated in Figure 1, various SOC and SOH estimation methods have been developed, including advanced data-driven techniques. Machine learning algorithms have been utilized to estimate the Remaining Useful Life (RUL) of lithium-ion batteries by considering battery health and operational conditions [10]. Using the first 100 data cycles, a CNN model was developed to predict the entire battery capacity degradation curve, using discharge voltage-capacity curves as input and employing convolutional layers to automate the feature extraction process [11]. A deep reinforcement learning-based approach was proposed to estimate remaining degradation trends by learning degradation patterns from partially observed cycle data. Unlike traditional methods, this technique can capture long-term trends under diverse formulations [12].

Moreover, a fusion neural network model combining the Broad Learning System (BLS) algorithm and LSTM networks was designed to predict battery capacity and RUL [13]. To further improve prediction accuracy while accounting for polarization recovery, a hybrid ensemble learning (HEL) model was applied, achieving high-performance estimations [14].

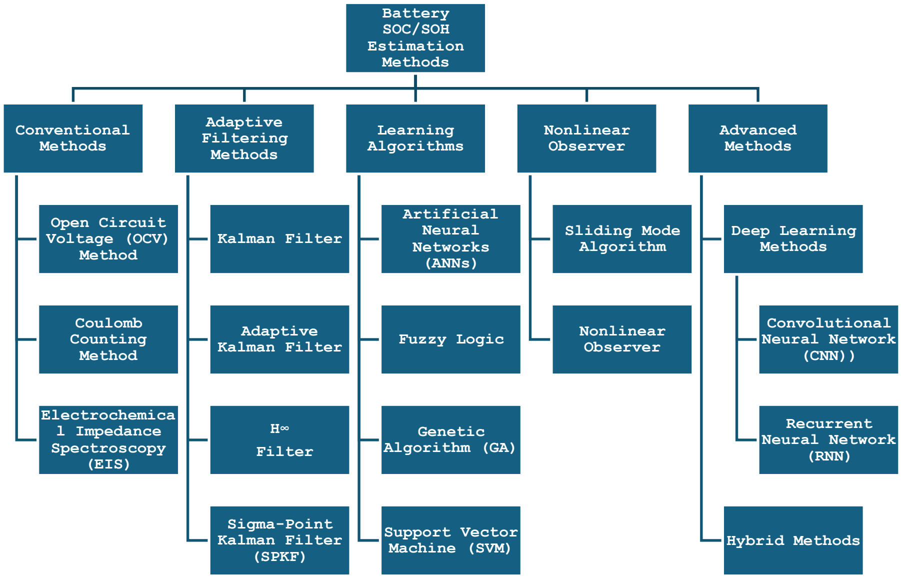

Figure 1. SOC and SOH Estimation Methods [15]

Image-Based Feature Extraction Techniques for SOC Estimation

Image processing techniques are methods used for enhancement and feature extraction on digital images. These techniques are particularly applied in areas such as image filtering, classification, fault detection, object recognition, and pattern recognition. Image processing techniques are powerful tools for extracting structural or statistical information from digital images. In recent years, they have been widely used in areas such as energy storage systems. These techniques, especially when integrated with thermal imaging systems to monitor surface temperature and behavioral changes of batteries, provide valuable data in terms of battery safety and performance tracking.

The image processing procedure typically begins with image acquisition and preprocessing; at this stage, raw images are made suitable for analysis through operations such as noise filtering, contrast enhancement, and normalization. In the following stage, edge detection algorithms are used to identify structural boundaries on the battery surface, which is a critical step in detecting temperature differences. Segmentation techniques allow the separation of meaningful regions on the image; thresholding and deep learning-based methods are frequently used for this purpose. Additionally, techniques such as histogram analysis, pattern analysis, and wavelet image analysis are used for feature extraction from the image, and these features are fed into machine learning models.

With the texture, color, and heat distribution information extracted from the images obtained through thermal cameras integrated into battery systems, it has become possible to estimate the SOC value. With the advancement of deep learning techniques, architectures such as CNNs can learn complex patterns in images and be directly integrated into classification or regression models.

The methods used for SOC estimation consist of current-voltage data, thermal images, impedance measurements, and image processing techniques integrated with them. In recent years, advanced image processing algorithms supported by machine learning and deep learning models have gained significant momentum in this field.

Estimation Using Voltage–Current Profile Characteristics

This approach is based on open-circuit voltage (OCV) and the voltage/current curves obtained during charging and discharging processes. Features are extracted from these curves and used for prediction through algorithms such as Kalman filters, SVM, and ANNs. Differential Voltage Analysis (DVA) and Incremental Capacity (IC) analysis are widely used image-based techniques in this context. It is suggested that these curves be transformed into 2D images and analyzed using CNNs.

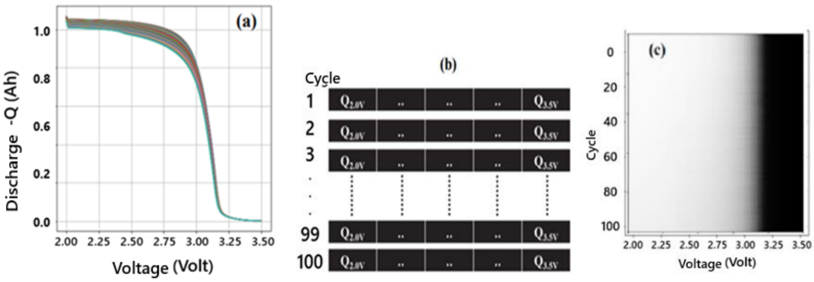

Figure 2. (a) Graphical representation of battery current-voltage variation values, (b) arrangement as a 100 × 100 matrix, and (c) visualization as a grayscale heatmap [16]

The study illustrated in Figure 2 presents an image processing-based CNN model developed to predict the battery capacity degradation curve and identify the onset point of sudden capacity loss (knee point) using visual representations generated from voltage–capacity curves [16].

State of Charge Estimation via Infrared (IR) Thermal Imaging

Internal temperature variations are directly related to the battery's internal resistance and SOC. Thermal images captured using infrared (IR) cameras detect both localized temperature differences and temporal thermal changes. These thermal images are then processed using widely adopted image processing techniques—such as histogram equalization, thermal mapping, and edge detection algorithms—for anomaly detection.

Figure 3 shows the actual image of the tested Li-Polymer battery on the left, while the thermal image captured by an IR camera is shown on the right. The thermal image represents the surface temperature distribution of the battery during the discharge process. It has been experimentally validated in the literature that SOC estimation can be performed by processing such thermal signatures [17].

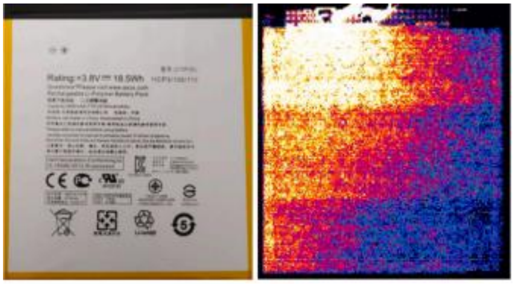

Figure 3. Visible and infrared (IR) images of the battery [17]

Visualization Using EIS

Impedance data are used to graphically represent the internal state of the battery. These curves can be visualized (e.g., in 2D or 3D) and interpreted using deep learning techniques.

Machine Learning and Image Processing

Charge curves (voltage–time) and temperature curves are preoceesed as 2D images, enabling SOC estimation through CNN-based models [18]. Figure 4 illustrates the end-to-end development process of SOC estimation algorithms based on machine learning and image processing techniques. The workflow begins with data acquisition, where voltage, current, temperature, thermal images, and ultrasonic visuals are collected. In the data processing stage, the acquired signals undergo normalization, filtering, and advanced signal processing (e.g., Wavelet or Stockwell transforms). The resulting data are then transformed to image representations suitable for machine learning. In the data classification phase, these processed images are fed into classification algorithms such as SVM or CNN to extract meaningful patterns associated with the battery's SOC. Finally, the SOC estimation step evaluates the model's performance using metrics such as RMSE, MSE, computational cost, and computation time [19, 20].

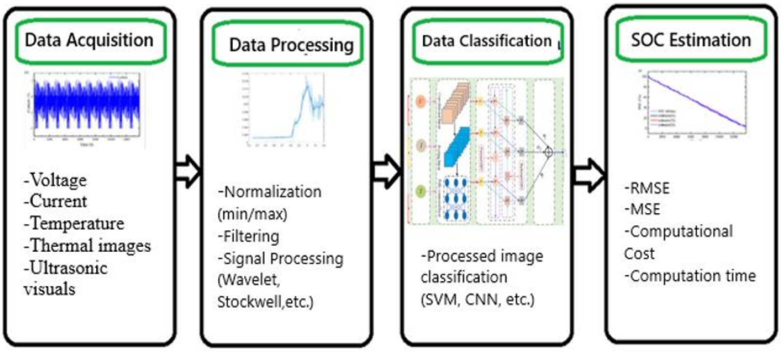

Figure 4. Development Processes of SOC Estimation Algorithms [19, 20]

Conclusion

In this study, the potential applications of image processing techniques for SOC estimation in battery energy storage systems have been systematically examined alongside traditional estimation methods. In the literature, widely used methods such as Coulomb counting, Kalman filtering, and artificial intelligence-based approaches have demonstrated notable accuracy and stability across various applications. However, most of these methods rely solely on electrical data and often fall short in capturing the physical or thermal state of the battery. Especially when external factors such as varying temperature, environmental conditions, and battery aging are considered, the limitations of purely electrical measurements become increasingly evident.

In this context, the integration of image processing techniques into battery systems emerges as a significant innovation. Thermal distribution data derived from infrared imaging provide indirect yet meaningful insights into internal resistance and aging behavior, making them a valuable complementary data source for SOC estimation. In particular, deep learning architectures such as CNNs have shown strong potential in analyzing 2D thermal maps and delivering high-accuracy classification and regression outputs. Moreover, visualizing and analyzing advanced diagnostic techniques like EIS offers a more interpretable alternative compared to conventional parameter-based models.

For the successful implementation of image-assisted SOC estimation models, several critical conditions must be met. First and foremost, a sensor infrastructure capable of high-resolution and synchronized data acquisition is essential. Additionally, sufficiently large and diverse datasets covering different battery chemistries and operating conditions are vital for enhancing the generalization capability of machine learning models. In this regard, techniques such as transfer learning can offer effective solutions to the problem of limited data availability.

In conclusion, this study highlights the need to move beyond traditional methods for SOC estimation in battery systems and suggests that image processing techniques can introduce a new paradigm in the field. Image-based modeling enables a more holistic analysis of battery behavior, and the integration of thermal condition variations into SOC estimation can significantly improve system reliability. Therefore, future studies are encouraged to develop more accurate, robust, and adaptive battery monitoring systems through hybrid approaches that combine image processing, deep learning, and physics-based modeling techniques.

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SMART ENGINEERING SYSTEMS

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