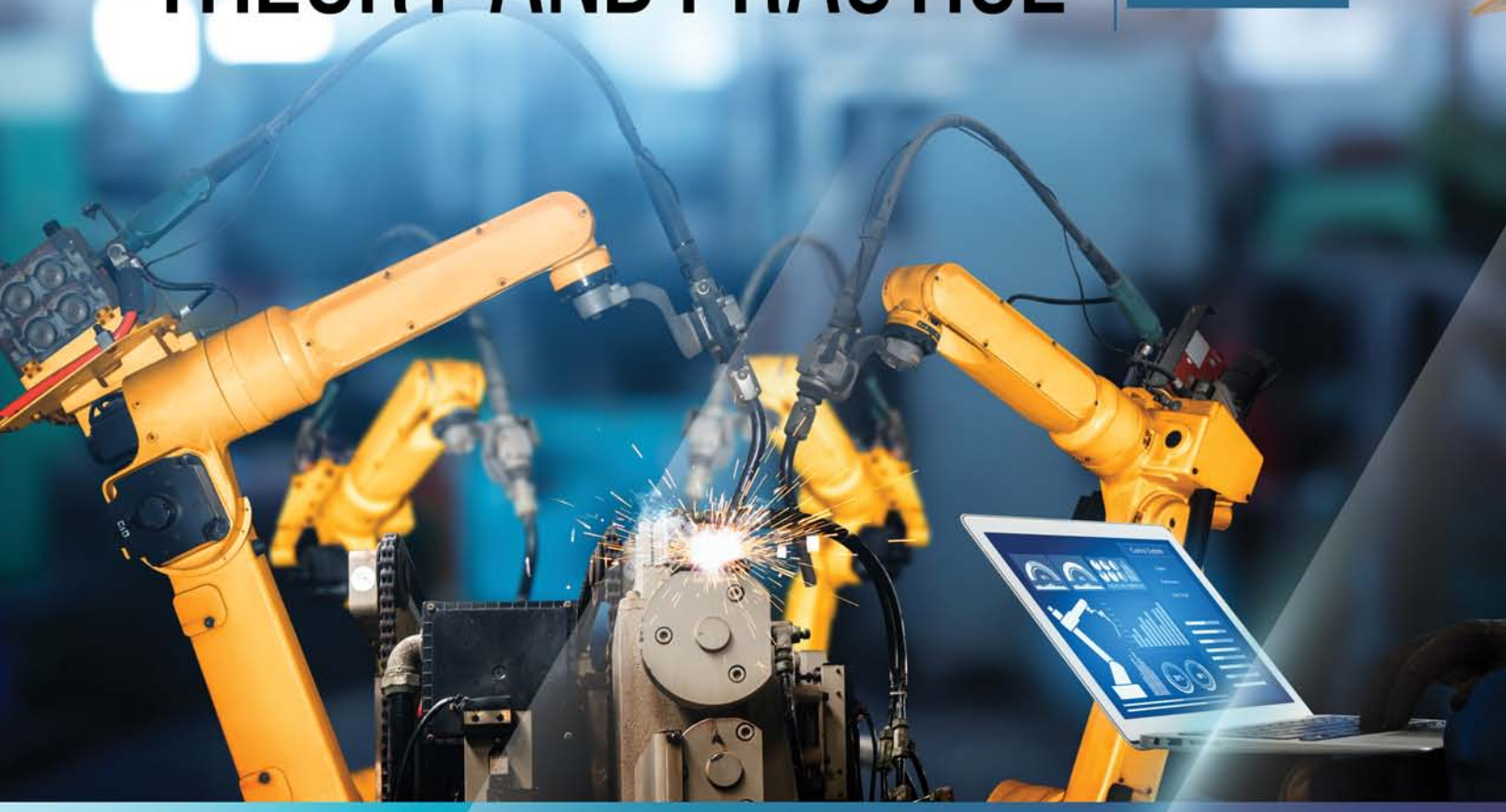
PRINCIPLES OF AUTOMATION AND CONTROL: THEORY AND PRACTICE

PART 2



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Ilesanmi Afolabi Daniyan

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Principles of Automation and Control: Theory and Practice

(Part 2)

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FOREWORD

Modern engineering systems are supported by automation and control systems enabled by emerging technologies such as smart sensors, Artificial Intelligence (AI), Internet of Things (IoT). This shapes how products and processes are designed, manufactured and managed especially complex processes. The principles of automation and control finds application in smart factories, autonomous vehicles energy systems and robotics which are central to technological advancement in the 21st century.

This book, Principles of Automation and Control II, provides useful insights into the fundamental concepts of automation and control and how the enabling technologies can be explored. It bridges the gap between theory and practical application, thus, offering readers a clear understanding of system modelling, control system, AI and IoT.

The balanced approach of this book makes it particularly valuable. It introduces core theoretical foundations and demonstrate the real-world applications, thus providing useful insights and procedural steps into how practical engineering challenges can be tackled. The integration of emerging topics such as intelligent control and data-driven approaches ensure that the book remains relevant in an era driven by data and digital transformation.

This book will serve as a valuable resource across multiple disciples. Furthermore, it will particularly be useful for students, educators, and practicing engineers as a guide to automation and control principles. It is my belief that readers will find both inspiration and practical knowledge in this book.

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PREFACE

The field of automation and control increasingly gaining increasing traction as industries move toward improved efficiency, precision, and autonomy. Thus, there is a need to understand the governing principles and the enabling technologies such as computing, communication technologies, Artificial Intelligence (AI), smart sensor and Internet of Things (IoT).

This book, Principles of Automation and Control II, discusses the foundational and fundamental concepts of automation and control. It combines both the theoretical background with practical applications to bridge the gap between theory and practice. This book is intended primarily for engineering students at all levels of study and related disciplines, as well as experts and professionals seeking to broaden their knowledge in this area. The book is organized to promote a seamless flow of thoughts and to progressively guide the readers from the basic concepts to more advanced topics. The Part 1 had laid the foundation on the basic and theoretical principles while this part 2 (chapter 14-25) details on the development of control systems, system modelling techniques and analysis methods, application of AI techniques in automation and control including practical examples. Practical examples include application of IoT and AI for sustainable energy management, in healthcare for prognostics and diagnostics operation, manufacturing system such as prediction of machine failure and for enabling manufacturing resilience, in the deployment of Unmanned Aerial Vehicle (UAV), in environment and agriculture for smart irrigation and in mechanical systems for switch gear and motor control. Wherever possible, theoretical discussions are complemented with examples and applications to enhance reader's understanding.

To promote clarity, mathematical rigour is maintained where necessary, and supported with conceptual understanding and empirical findings. The book also highlights emerging trends, such as AI and data-driven control approaches, to reflect the dynamics of modern engineering.

The journey written to support readers in their journey from theory to application. It will help readers gain useful insights necessary for the development monitoring, control and analysis of industrial systems in real-world settings.

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CHAPTER 1

Development of an Internet of Things Enabled Standing Fan with Passive Infrared Sensors for Sustainable Energy Management

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Abstract: This study explores the design, implementation, and social impact assessment of an intelligent standing fan system combining temperature-based speed control and Passive Infrared (PIR) sensors fortified with IoT devices for remote monitoring in an attempt to sustainably manage energy in homes with IoT capabilities. The system was developed using an Arduino Nano microcontroller, a PIR sensor, a thermistor, and a solar-powered standing fan. It detects when there is no motion and adjusts the fan's speed according to predefined temperature thresholds, while dynamically adjusting its operation based on occupancy and ambient temperature. The system's performance was evaluated in a controlled environment and compared to a traditional, non-intelligent standing fan. The results revealed that when turned off, the smart fan can save up to 100% more energy than the control fan, and when turned on at low speed, it can save 29.6% more energy than the control fan. Under temperatures below 25.0°C, the system keeps the fan running in energy-saving mode, but as the temperature increases, the speed is gradually increased. The system's responsive and efficient performance is confirmed by the observed fan speeds, which match the expected values. The system's potential for energy savings, ease of use, and autonomous functioning were all highly rated in user acceptance testing. This study highlights the potential of incorporating PIR sensors and intelligent control systems in domestic appliances to enhance energy efficiency and sustainable living in smart homes.

Keywords: Energy management, Home automation, Internet of Things (IoT), Motion detection, Smart home technology, Temperature-based speed control.

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INTRODUCTION

In recent times, the demand for smart homes and their associated technologies has witnessed a global astronomical rise, with an anticipated annual growth rate and projected market value of about 26% and $170 billion by the end of 2025, respectively [1]. It is not gainsaying that smart home technologies have the propensity to transform individuals' lifestyles through the smart interconnection of energy-efficient systems and smart devices [2 - 4]. Also, the advancement in the development of smart sensor technologies, and wireless communication devices such as the Internet of Things (IoT), Zigbee, and Wi-Fi, alongside cognitive algorithms, is paving the way for proper coordination of several home appliances in the realization of smart home automation, intending to facilitate improved energy management [5]. With the possibility of smart homes *via* smartphones, tablets, or voice assistants, users can operate several gadgets remotel,y such as smart water heaters, lighting systems, smart doors, smart televisions, and smart air conditioners, among others, with minimal effect of environmental barriers.

Also, these possibilities allow the users to flexibly automate their chores subject to user preferences or prevailing ambient environmental circumstances [6]. Furthermore, the core goal of leaning towards the adoption of home automation is to achieve appreciable energy savings in the face of a rising rate of energy billing by the utilities [7, 8], and in the search for efforts to reduce energy consumption by these devices has led to the adoption of Passive Infrared (PIR) sensors. Generally, PIR sensors can be used to configure or reconfigure the mode of operation of many home appliances based on detecting human motion and heat from warm objects such as people and animals within the home [9]. Fundamentally, PIR sensors are known as passive devices because they do not send out any energy; rather, they pick up the infrared light that things naturally emit, which makes them apt for automating lights, fans, and other devices based on movement [10].

In principle, when infrared light hits a pyroelectric material inside a PIR sensor through the Fresnel lens, it generates an electric charge that responds strongly to changes in temperature, and with this lens, movement within a certain area can be detected. Also, the levels of infrared radiation change when warm objects, such as a person, enter the sensor's field of view. Then, the change in radiation will be picked up by the pyroelectric sensor, which generates electrical signals that the microcontroller can easily handle. PIR sensors are very cost-effective and efficient because they do not need much power to get them activated. This makes them a suitable device for implementing energy savings in many home appliances such as electric heaters, cooling systems, and lighting systems, among others [11, 12]. Cooling systems such as air conditioners, electric fans, and extractor fans,

among others, are among the biggest energy consumers in the home. One of such factors contributing to this massive energy consumption can be traced to the fact that most of these traditional cooling systems, such as air conditioners and fans, often keep working even when no one is in the room, and the users do not switch them off, hence significant energy is being wasted in the process [13]. Research findings show that cooling homes accounts for almost 20% of the world's electricity, underscoring the need to adopt energy-efficient methods [14].

The advent of smart cooling devices with motion sensors and automation features is a good alternative approach to addressing concerns about energy conservation and environmental protection. Also, the combination of advancements in sensor technologies and wireless communication allows remote real-time monitoring of these devices with little or no location barriers. For instance, the incorporation of the Internet of Things (IoT) into smart devices not only enables seamless automation of electrical appliances but also enhances efficient remote monitoring and control. This remote monitoring and controlling is possible because of the capability of IoT systems to interconnect several devices to a central network so that data can be sent and received in real-time and smart decisions can be made [15]. When it comes to smart fans, IoT integration not only allows them to be flexibly controlled from afar but also enables usage tracking and enables them to work with virtual helpers like Amazon Alexa or Google Assistant [16, 17]. The IoT systems also help achieve energy-saving goals by tracking how users interact with devices and adjusting device behavior based on users' preferences. These aforementioned possibilities make IoT-enabled products integral parts of modern smart homes and are the popular choice of many users today [18].

To lay a good background for this research, a couple of relevant pieces of literature were reviewed. For instance, reference [19] proposed a system that uses PIR sensors, Arduino, and IoT to automatically turn on and off lights and fans when no one is nearby. Energy consumption was found to decrease significantly. Also, authors in reference [20] implemented a motion-activated smart fan that uses an infrared sensor to recognize people and an ultrasonic sensor to track their movements. This design emphasises directing airflow to occupied areas while deactivating the fan in unoccupied spaces, making this motion-responsive fan consume less energy than traditional fans [20]. Also, a research study [21] used a ceiling fan with integrated motion, temperature, and humidity sensors, and Artificial Intelligence of Things (AIoT) as part of the design. Based on sensor inputs, AIoT was utilised in this design to carry out the fan operation’s optimization in both controlled laboratory conditions and real-world situations, assessing the system's energy-saving capabilities. The findings demonstrated that energy usage was greatly reduced by the system's capacity to dynamically modify fan speed and to operate based on occupancy and environmental parameters.

CHAPTER 2

Bagging Approach for Clinical Diagnosis of Malaria Fever

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Abstract: Malaria fever is a life-threatening disease prevalent in Africa, exacerbated by inadequate medical facilities and practitioners. To address this, computer-aided diagnostic systems have been developed, but they suffer from limitations such as a lack of performance evaluation, small datasets, and single predictive models. This study aimed to improve malaria diagnosis by using the Bagging Approach to combine multiple models. The experiments were conducted in two steps. First, the JRip algorithm was used to generate a predictive model, employing 10-fold cross-validation. This model was then tested for performance on both the training and testing samples, achieving a detection rate of 99.02% on the training set and 94.12% on the testing set. In the second step, the JRip algorithm served as the base learner for Bagging, generating 10 models that voted to produce a single stronger Bagging model. The hybrid Bagging ensemble with JRip classifier improved classification accuracy, attaining 100% on the training set and 98.04% on the testing set. The result demonstrated the effectiveness of the hybrid Bagging ensemble with JRip classifier as the base learner in improving malaria diagnosis, providing a valuable tool for supporting healthcare professionals in making accurate diagnoses. The results showed significant improvement of the hybrid model in accuracy over individual models, making it a promising approach for addressing challenges in malaria diagnosis. Further studies are recommended to focus on implementing large image datasets and other approaches to train models for effective performance.

Keywords: Bagging algorithm, Data mining, Diagnosis, JRip, Malaria fever.

INTRODUCTION

Access to medical consultation service, as one of the most important components of any medical care delivery system, is not only scarce but also very expensive in Africa. The increasing world population necessitates a significant increase in the number of medical experts in the health sector to meet the health needs of people

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across the world. The ratio of the available health practitioners to the teeming population is grossly inadequate. Access to quality health services is easier within the urban areas compared to the rural areas, and this may put the rural dwellers at great risk. The development of e-health solutions (provision of health services through Information Technology) can help address the challenge of limited access to quality health services, especially in rural areas. This can be in the form of tele-health systems, which handle health-related services and medical information dissemination, as well as medical expert systems, which can perform the functions of medical experts in a particular domain of health care [1].

Medical diagnosis is a classification task that allows medical experts to investigate the root causes of a patient's health condition, while medical therapy falls under the prognostic task that proffers a probable solution to a diagnosed health problem [2]. Researchers worldwide are now focusing on the development of new computer applications to proffer solutions to medical problems [3], and this trend is rapidly increasing across the medical domains [4]. When a diagnosis is correct, the possibility of providing the matching treatment is high [5] and *vice versa*.

Data mining is one of the prominent tools being used today in medical diagnosis to predict the "unknown" value of a new sample from an observed data set. The training stage involves the use of a machine learning algorithm to learn from a sample of data and to generate a predictive model. However, the testing stage involves the use of samples not previously used during the training to test the predictive model to ascertain its performance. Various applications of data mining support the correctness of the "No Free-Lunch Theorem". The theorem states that "no single learning algorithm is best and most accurate in all applications" [6].

A lot of researchers have worked on different approaches to combining multiple models to produce a single stronger model called an ensemble. Research, both theoretical and empirical, has shown that a good ensemble is formed when the individual models that make up the ensemble are accurate and commit errors in different parts of the training space [7]. Popular ensemble learning techniques include Bagging, Boosting, and stacking, also known as stacked generalization [8].

Malaria is a mosquito-borne infectious disease and highly prevalent in tropical and sub-tropical regions of the world [2]. The Report of the year 2022 of the World Health Organization (WHO) on malaria fever revealed there were an estimated 247 million cases of malaria in 2021, in which 234 million (95%) of this total occurred in the African region, and 27% of the world's malaria cases occurred in Nigeria. The report further stated that malaria caused six hundred and

twenty-five thousand (625,000) deaths in the year 2021. It is quite worrisome that 599,000 of the total deaths occurred in the African region, while Nigeria alone accounted for 31% of the global malaria deaths for the year [9]. In accordance with WHO guidelines for the treatment of malaria, malaria fever can be suspected clinically on the basis of symptoms, but it is advisable to be confirmed with parasitological diagnosis. Where parasitological diagnosis is not available, treatment should commence immediately on clinical grounds [9]. This study aims to demonstrate the effectiveness of the Bagging Approach in improving malaria diagnosis by providing a valuable tool for supporting healthcare professionals in generating accurate diagnoses compared to existing methods and base learner approaches of malaria diagnosis.

REVIEW OF RELATED WORKS

Many scholars have developed some computer-based systems to diagnose malaria fever, where they placed much emphasis on the need for more research on the subject for further improvement. Some of these are presented in this section.

In the work presented [2], the scholars proposed the work because malaria has put half of the world's population at risk of death. The malaria fever diagnosis model was generated using Rough Set (Machine Learning technique). The developed system's performance was measured. This system used a small dataset and relied on a single machine learning technique; moreover, the accuracy of this study varied based on weather conditions in Nigeria, resulting in 95% during the rainy period and 86% during the dry period. A combination of two or more techniques may lead to a better system.

A malaria fever diagnosis system using Fuzzy Logic was presented [10]. The authors highlighted several reasons for the research, including the fact that malaria poses a threat to humans. A single technique was also used in this case. The authors [11] used the Reduced Error Pruning Tree technique to diagnose malaria fever because malaria kills more than AIDs (Acquired Immune Deficiency Syndrome). This system also employed a single predictive technique. A combination of two or more techniques could produce a promising diagnosis system for malaria fever.

Okebule *et al*. [12] developed an innovative hybrid machine learning approach for breast cancer prediction, demonstrating the potential of combined machine learning techniques in improving diagnostic accuracy. The Analytical Hierarchy Process (AHP) was used to diagnose malaria fever [13] with 90.5% accuracy rate. Partial Tree, also a Machine Learning Technique, was used to develop a malaria fever diagnosis model [14] with 93.4% of accuracy in diagnosing malaria fever. Similarly, an author [15] used Decision Tree algorithm to diagnose malaria fever

CHAPTER 3

Enhancing Industrial Automation through Machine Failure Classification using Machine Learning Techniques with Explainable Artificial Intelligence

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Abstract: In the modern manufacturing era (4.0), the ability to predict and classify machine failure modes is critical for ensuring operational efficiency, production, and reducing maintenance costs and downtime. Drilling and milling processes are an integral part of any manufacturing process and are prone to various failure modes that can lead to significant downtime if not detected early and accurately. Traditional methods of detecting failure are often time-consuming, not always accurate, and lack the interpretability needed for effective decision-making. This study addresses the challenge of accurately classifying machine failures using five Machine Learning (ML) classifiers: Random Forest (RF), K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Logistic Regression (LR), AdaBoost, and Explainable Artificial Intelligence (XAI) techniques. Two comprehensive datasets for drilling and milling machines were utilized. These datasets were preprocessed by filling missing values with the mean, normalizing with min-max, discretizing, and balancing using the Synthetic Minority Oversampling Technique (SMOTE). The Random Forest algorithm outperformed other models with 99.98% and 99.37% accuracy for the drilling and milling machine datasets, respectively. KNN also performed well, with 99.87% and 99.13% respectively, and AdaBoost performed the worst, suggesting that the bagging ensemble approach is better than boosting. To enhance the interpretability of the model's prediction, Shapley Additive Explanation (SHAP) and Local Interpretable Model-Agnostic Explanation (LIME) were employed, which show the positive interactions that exist between the features and their contribution to the prediction of the failure modes. The results demonstrate the effectiveness of combining ML and XAI for predictive maintenance in industrial settings, enabling operators to easily identify and proactively address failure modes.

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Keywords: Explainable artificial intelligence, Machine failure prediction, Machine learning, Mechanical drilling machine.

INTRODUCTION

Machine failure is a serious concern that should not be taken lightly, as it may result in significant losses for the company and the operator. The misclassification of failure might result in waste of funds, production delay, downtime, and failure recurrence. Predictive maintenance would help develop a preventive maintenance plan to prevent, to a large extent, damage that might result from delayed maintenance. In order to align with the current 4.0 industrial era, many industries are already integrating technological advancements like the Internet of Things (IoT) and sensors for plant and machine monitoring, and conducting a manual inspection of this equipment might be time-consuming and costly [1].

The advancement of technology and the availability of a vast amount of datasets that could be used to automatically classify and predict machine failures using machine learning techniques have really helped in simplifying industrial inspection. This faster, easier approach to predicting machine failure and correctly classifying its type would enable faster maintenance and reduced downtime, which may, in turn, result in increased production time and improved performance [2].

In most cases, mechanical machines show signs of deterioration through their physical variables like process temperature, rotation speed, cutting speed, and torque, among others. These variables could be captured across different data points to serve as a historical dataset for classifying machine failure modes. Exploring the potential of machine learning algorithms would help identify patterns in the dataset for real-world implementation. This will enable an accurate, faster, and more comprehensive classification. Moreover, accurate prediction and good performance of a machine learning model are not sufficient to demonstrate its effectiveness. Furthermore, the steps taken in making such a decision and arriving at results may not be sufficiently explained. To enable transparency, Explainable AI was introduced to ensure fairness and transparency in the decision-making process.

Post hoc explanation is provided after the model has made its decision (prediction or classification), to interpret the feature dependencies and interactions for a particular instance. Local explanation aims to provide clarity for a specific instance and explain what prompted the model to make a particular prediction. Local Interpretable Model-Agnostic Explanation (LIME) and Shapley Explanations (SHAP) are the most commonly used techniques for local explanation. LIME is a technique that manipulates input data to generate a series

of synthetic data. Some specific part of the artificially generated data is changed, and the impact of this change on the decision is studied. It essentially examines the attributes that significantly influence the model's decision-making process. SHAP is a game-theoretic approach that assigns a score to each attribute in the model, ranking their level of significance in the model's decision-making process. These frameworks would enable the interpretation and accountability of any output obtained from the implementation and evaluation of any ML model.

Many studies have used machine learning techniques for the development of predictive models. For instance, Yadav *et al.* [2] proposed various traditional and ensemble learning models for predicting machine failure, where XGBoost achieved the highest average predictive accuracy. Moreover, fault detection in a broken rotor bar was also analyzed by Quiroz *et al.* [3] using a random forest classifier. The study also included validation and reliability analyses of this fault detection, as a random forest achieved impressive performance and good prediction accuracy. The earlier good performance of XGBoost and the new performance of Random Forest show that ensemble learning models are effective across diverse engineering applications for fault or failure classification and detection. Similarly, Yan and Zhou [4] employed the Term Frequency - Inverse Document Frequency (TF-IDF) and Radio Frequency data from aircraft speed and torque sensors to develop predictive machine learning models for detecting aircraft defects and preventing air crashes caused by faulty speed and torque. TF-IDF was used to extract significant features from the raw RF data, and Random Forest (RF) performed the implemented machine learning algorithms. The wear and failures of a spindle motor and mechanical cutting machines were predicted by Lee *et al.* [5] using a historical dataset obtained from different data points. The study concluded that Support Vector Machine (SVM) and Artificial Neural Network (ANN) are good machine learning models for forecasting the longevity of the machines. Furthermore, the proven impact of machine learning techniques across diverse problem domains has enabled their application to mechanical machine failure mode classification and other mechanical machine-related tasks [6 - 12].

Pinciroli Vago *et al.* [1] also conducted a study to forecast the likelihood of failure in an industrial wrapping machine, a continuously operating blood refrigerator, and a nitrogen generator operating under the same principle as the blood refrigerator. The datasets used in this study were acquired from a company that handles the control of industrial and domestic appliances remotely. These datasets were normalized using min-max normalization and set to windows for forecasting; random over-sampling was applied to balance the dataset. SVM, RF, Logistic Regression (LR), transformers, Long Short-Term Memory (LSTM), and Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) were

CHAPTER 4

Development of Voice Controlled Robot for Optimal Performance

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Abstract: With the advent of the Internet of Things (IoT) for controlling appliances, and its extensive use in robotics for real-time control and management, there has been a significant opportunity to explore the limits of smart system control using IoT protocols. In this project, voice commands were used to control a rover using the ESP32 microcontroller because of its Wireless Fidelity (Wi-Fi) connectivity, which enables it to connect to mobile hotspots and Wi-Fi servers for internet access. The ESP32 was connected to a real-time database to access information and then signal the motors *via* a motor driver to execute the received commands. The real-time database used is Google's Firebase Realtime Database. During testing, the rover was controlled wirelessly through specific voice commands transmitted *via* Wi-Fi and the IoT protocol. The voice commands were processed by a desktop application developed using the Python programming language, which processed each voice command and stored it in an online real-time database. The robotic rover accessed this online real-time database to retrieve the required voice commands, which were continuously updated by the user. According to the data collected during operation, the speed improved from 0.617 cm/s to 61.667 cm/s, the charge time increased from 2 hours to 9.53 hours, and the retention time increased from 8 minutes to 110 minutes for a voltage range of 5 V to 32 V. Further advancements in voice recognition systems can lead to additional benefits in the coming years.

Keywords: Bluetooth, Commands, ESP32 microcontroller, Python code, Rover, Voice Control.

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INTRODUCTION

Despite advancements in technology and scientific advancements, human activities continue to pose risks, leading to daily deaths in hazardous environments. This issue is particularly concerning for those with mobility impairments, who find it challenging to adapt to these changes, even with the introduction of voice control devices [1]. This work aims to design and simulate a voice-controlled robot for optimal performance, including creating a structural compartment, developing a voice-controlled rover, and testing its performance.

Voice-controlled robots offer natural, effortless interactions between people and technology, benefiting those with mobility issues. They can increase productivity and efficiency in tasks like product organization in warehouses [2]. Additionally, voice-controlled robots can provide social and educational benefits, such as teaching new skills or keeping elderly individuals company [3]. They can perform tasks like cleaning, laundry, and meal preparation [4].

The history of robots began with humans creating self-operating machines called automatons. The term “robot” comes from the Czech word “robota,” meaning “forced labor.” Today's robots are sophisticated machines capable of various tasks. Early examples include a clay figure by Archytas, while inventors like Leonardo da Vinci and John Dee created basic automatons [5].

Voice-controlled robots like Alexa and KASPAR are increasingly ingrained in our daily lives. Research in this field has grown, with notable projects such as KASPAR, developed by the University of Hertfordshire, aimed at communicating with autistic children. These robots offer various benefits and technological advancements, contributing to the development of the Internet of Things. A study [6] developed a smartphone-controlled mobile robot using Microsoft's .NET Compact Framework and Bluetooth data communication, supporting various OS platforms from Windows to CE kernel-based Embedded OS, as shown in Fig. (**1**).

The study on Robot Control Using Mobile Phone [4] designed a robot with a DTMF decoder and an LPC2148 microcontroller, implemented in Embedded C and Flash Magic. The robot can move, halt, and execute commands from Android smartphones using wireless communication.

The paper “Voice Control Robot Using Android Application” [7] proposes a system that uses a human voice as a key to control a robot without a speech recognition module. The robot is controlled by processing text generated *via* voice recognition software for Android mobile phones. Voice-Controlled Robot with Human Interaction Ability [8] system is built on a microcontroller linked to an Android phone *via* Bluetooth, transforming the voice command into text. The

robot responds to commands by completing movements in the specified direction. The paper also discusses mobile control robots using Bluetooth control *via* an Android app and an Arduino microcontroller (Fig. **1**).

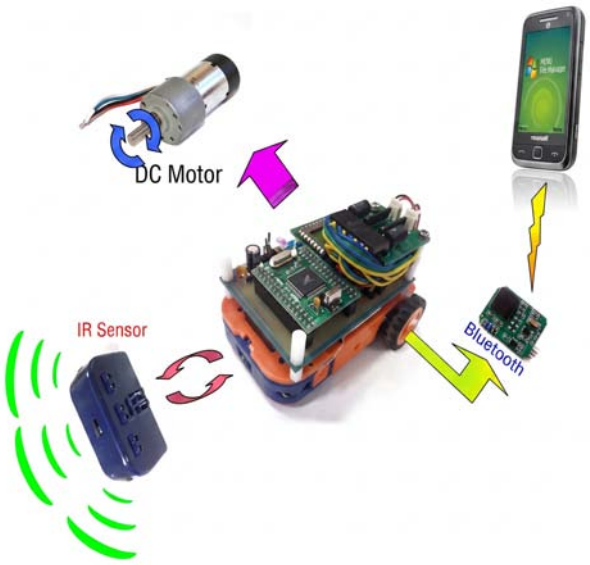

Fig. (1). Hardware configuration of smartphone-based mobile robot [6].

The SCOUT Robot uses a hidden Markov model to detect voice commands, which are then received *via* Bluetooth through a Bluetooth module, allowing it to control its movement as displayed in Fig. (**2**) [9].

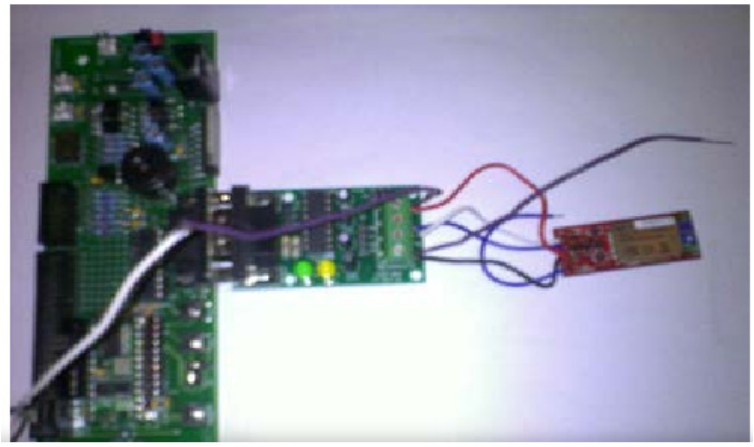

Fig. (2). Connections for the voice command detection system [9].

CHAPTER 5

Development and Control of Flapping Wing Unmanned Aerial Vehicle (UAV) Ornithopter

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Abstract: An Ornithopter flies differently from conventional drones by flapping its wings. Flapping wings are very efficient, enable astonishing agility, are much safer, and can make compliant contact with surfaces rather than shedding them as a rotor system does. This work focuses on developing a flapping-wing UAV Ornithopter model that mimics bird flight and can be adapted for reconnaissance missions. The Ornithopter is designed and constructed from a cost-effective, lightweight carbon fiber material. The Ornithopter development methodology involves selecting materials based on mission requirements, flexibility, lightweight design, precision, and affordability. The mechanical structure includes the fuselage, wing frame, gearbox design, flapping mechanism, linkages, joints, tail, and stability. The lift was designed to exceed the weight for sustained flight. Wing loading and mechanism design consider lift, drag, thrust, and weight. The choice of electric motor depends on torque requirements and flapping speed. The flight control system integrates tail angular orientation. The control design mitigates flexing problems by using hinges and bearings in the parts to meet the desired performance requirements. This flapping-wing UAV is built for remote surveillance, recreation-like contests, aerial robotics, and photography. A control system was developed and incorporated for flight control and monitoring data. Flight tests conducted show that the Ornithopter can sustain flight for excellent stability, carrying a minimum load of electronics. This study will assist the Ornithopter in maintaining stability for sustained flight of 5 minutes and achieving durability and agility.

Keywords: Aerodynamic simulation, Flight control, Gearbox design, Lifts computation, UAV Ornithopter, Weight estimation.

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INTRODUCTION

Biomimicry, imitating nature's flight patterns, has inspired the development of new technologies inspired by biological solutions. Despite modern aircraft's high airspeed, they lack stealth capacity. An alternative is an ornithopter, a drone disguised as a bird with less noise output, which can be used for intelligent surveillance and reconnaissance missions [1]. The goal is to replicate 6 degrees of freedom, create a robust, flexible structure, and use a small, lightweight mechanism. The monolithic structure is made using PolyJet 3D printers [2].

Chen *et al*. [3] utilised aerodynamic principles of insect flight to provide lift and quick manoeuvres. Bakhtiari *et al*. [4] numerical modelling offers an alternative approach. Abas *et al*. [5] found that birds' flapping wings are manoeuvrable and efficient. Geder *et al*. [6] developed a flight model for an artificial bird with flapping wings, demonstrating its ability to take off, fly, and land. A 2kg ornithopter simulation showed a lift force of 0.8N and a drag force of 0.2N, ensuring controlled flight with an upward thrust of 2.7 N at 5 m/s [7].

Aerodynamics and Flight Mechanism of an Ornithopter

Ornithopter design uses gravity to fly, similar to a bird flaps. Lift is crucial for flight, and good aerodynamics are needed to overcome drag and weight, producing adequate lift and thrust forces [8]. Wissa *et al*. [9] proposed a design to improve flight endurance, focusing on flight speed and range, addressing the viability of a hovering MAV in equation 1.

$$\text{Hove endurance, } t_f = \frac{S_b m_b}{P/\eta} \quad \textbf{(1)}$$

Where Sb is the battery energy density (J/m^3), mb is the battery mass (kg), η is the actuator and related power electronics' electrical-to-mechanical efficiency, and P is the mechanical power (kW) used to flap the wings.

The advance ratio, a non-dimensional quantity, J, which is equal to the ratio of the mean wingtip velocity to the forward flight speed V, is a straightforward method for predicting flight speeds.

$$J = \frac{V}{2\Phi f R} \quad \textbf{(2)}$$

Assuming an “acceptable” cruising value for J, we can estimate V from this expression.

Flight missions and flight modes are scheduled. Wissa *et al*. [10] and Nguyen *et al*. [11] used flight distance and duration calculations to create flight plans.

Ornithopter Weight Estimation

Weight estimation is crucial for sizing Flapping-Wing Micro-Air Vehicles (FWMAVs). Previous techniques included guesswork and statistical evidence. This study uses a method that separates structure and component weights independently [12]. The overall weight of the flapping MAV can be expressed as follows by adding the weight of the structure (WStr) and the weight of the electrical equipment (WEq) in equation 3 [12].

$$W_{TO} = W_{Eq} + W_{Str} \quad \textbf{(3)}$$

The weight of the structure, WStr, which is the other component of an FWMAV's weight, is as follows:

$$W_{Str} = W_{Wing} + W_{Tail} + W_{Fuselage} + W_{Mechanism} + W_{Other} \quad \textbf{(4)}$$

The electrical components' weight can be expressed as follows:

$$W_{Eq} = W_B + W_{PL} + W_{VA} + W_{PP} \quad \textbf{(5)}$$

WB stands for the weight of the battery, WPL stands for payload, which includes loads, sensors, cameras, and other similar weights, WVA stands for the weight of the avionic system, which includes servo motors, receivers, and navigation systems like the autopilot, and WPP stands for the weight of the power plant, which is made up of the motor and speed controller. The weight portions (WPP, WB, WPL, WVA, and WStr) of numerous flapping wings have been picked from [12].

Hassanalian and Abdelkefi [12] divide the mass of the entire vehicle, mt, into the assessment of the payload, battery, and actuators, we have equation 6.

$$m_t = m_p + m_b + m_a \quad \textbf{(6)}$$

Hassanalian *et al*. [13] presented a flow chart of the procedure for flapping wings' sizing depicted in Fig. (**1**).

CHAPTER 6

An Intelligence Framework for Enhancing Resilience and Cognitive Manufacturing

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Abstract: The dynamics of the manufacturing environments, as well as the various uncertainties and disruptive events, necessitate the development of resilient and cognitive manufacturing systems that can withstand adverse situations. This study explores the potential of Artificial Intelligence (AI) to develop a framework for resilient and cognitive manufacturing. The study employs a conceptual approach that involves identifying research questions and concepts related to AI, followed by the synthesis of existing literature to identify potential driving factors and research gaps. This leads to the development of a novel framework that establishes relationships among key factors and provides useful insights for the development of AI for resilient, cognitive manufacturing. The outcome of the study indicates that the success of AI in resilient and cognitive manufacturing depends on the availability of a large quality data set (both historical and real-time), the organization's needs and readiness, the skills and expertise of personnel, as well as investment in supporting infrastructure and enabling technologies such as Internet of Things, cloud computing, and data mining. Although the use of AI may result in certain job displacement or reassignment, it could also equip personnel with innovative skills while opening new possibilities, depending on the readiness and degree of acceptance with which organisations adopt and incorporate it. This study adds to the understanding of AI's roles in manufacturing and provides useful insights that can help manufacturing industries effectively deploy AI to achieve resilience and cognitive manufacturing.

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Keywords: Artificial intelligence, Cognitive manufacturing, Conceptual approach, Resilient manufacturing.

INTRODUCTION

In recent years, there have been many disruptions, such as COVID-19, wars, etc., that have disrupted the supply chains of manufacturing industries globally, thereby affecting their productivity and bottom line of profitability. In response to these disruptions, many manufacturers are embracing digital and emerging technologies such as Artificial Intelligence (AI) to promote resilience to disruptions, accelerate digital transformation, and enhance the development of systems to boost organizational performance [1].

Disruptions in manufacturing systems can be addressed by increasing the system's intelligence, and one way to do so is to embrace AI technology.

According to Rauch [2], the last decade of Industry 4.0 was driven by technological innovations, while the coming years will leverage the transformative power of data and AI. Hence, AI is seen as an enabler for the transition from smart to intelligent factories. While smart factories can apply the knowledge they have acquired, intelligent factories will be able to acquire new knowledge and apply it for self-optimisation.

AI can be deployed to achieve manufacturing resilience, efficiency, and scalability, which are important for withstanding inevitable disruptions resulting from wars, political conflicts, pandemics, etc [3 - 5]. Manufacturing resilience has been defined as the ability of a manufacturing system to withstand potentially high-impact disruptions by proactively mitigating or absorbing their impact and quickly recovering to normal conditions [5, 6]. On the other hand, cognitive manufacturing systems integrate technologies such as AI and learning approaches to create self-learning, self-optimizing system. Existing studies indicate that the interplay of Industry 4.0 and AI plays a significant role in achieving manufacturing resilience and stability of supply chains [6 - 8]. Techniques such as AI and Machine learning (ML) are suitable for supply chain risk management because of their attributes [3, 4].

Wong *et al.* [9] stated that AI has the potential to revolutionise the manufacturing landscape by promoting supply chain agility. It can also assist manufacturing industries to gain a competitive edge. Yu *et al.* [1] stated that AI can assist organisations in streamlining operational processes, thereby enabling more effective decision-making. With the rising need for automation of manufacturing systems, Zhu *et al.* [10] projected a significant growth in intelligent manufacturing, and one of the feasible technologies to achieve this is AI because

it has learning capabilities that can enhance the development of predictive models for forecasting potential disruptions. It can also be used for the prediction of operation dynamics *via* the acquisition and training of a relevant dataset. The prediction of operation dynamics can enable manufacturing industries to adapt effectively to the changing forces of demand and supply in order to meet production and performance targets [11]. Davenport and Ronanki [12], as well as Dubey *et al.* [13], classified the application of AI in manufacturing into three broad categories, namely: cognitive insights, process automation, and cognitive engagement.

The use of AI for cognitive insights involves the application of AI technology as a decision support tool in which specialised algorithms are used to train data and optimise process parameters in order to acquire useful trends necessary for decision-making. For instance, AI models can be used to analyse data to predict the time for maintenance. With optimised models, streamlined manufacturing processes, and predictive maintenance strategies enabled by AI, manufacturing organisations can develop systems that are resilient to disruptions [14]. For the second category, namely process automation, AI can be used to monitor manufacturing processes and for pattern recognition to detect anomaly trends. This will promote manufacturing efficiency, sustainability, and resilience [13]. Martínez-Peláez *et al.* [15] emphasised that digital transformation and intelligent decision-making are imperative for achieving sustainability.

The last category, which is cognitive engagement, relates to the use of AI for diagnostic and prescriptive operations. Other authors, such as Daniyan *et al.* [16], Martínez-Peláez *et al.* [15], as well as Magodi *et al.* [17], agree that AI-enabled solutions can promote manufacturing resilience and enhance the overall organisation's performance by offering diagnostic and prognostic capabilities and streamlined operations. Davenport and Ronanki [12] stated that organisational capability for AI technologies is central to effective applicability. Existing studies also indicate significant gaps in the application of AI techniques to achieve manufacturing resilience, underscoring the need for research in this area [18, 19]. For instance, some manufacturing industries that are limited in AI capability and expertise may be vulnerable to uncertainty or disruptive events [9]. Thus, there is a need to develop an AI framework that outlines practical, implementable steps for deploying AI technology to enhance manufacturing resilience and operational performance, which is the focus of this study. With manufacturing resilience, organisations will be able to withstand disruptive events without a significant adverse effect on the value chain. Existing studies stressed the need to promote resilience in the manufacturing supply chain, operational efficiency, and sustainability *via* the deployment of AI-enabled solutions [20 - 23].

CHAPTER 7

Responsible Application of Artificial Intelligence (AI) In Healthcare

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Abstract: This chapter aims to explore the principles of responsible Artificial Intelligence (AI) adoption within the healthcare sector, focusing on the ethical, social, and regulatory considerations associated with the development, deployment, and use of AI technologies. It employs "1100 medicine details" sourced openly from online pharmacies and healthcare portals. Using a machine learning approach, the medicines were grouped according to their similarities in composition, usage, dosage, and side effects, and a unique Natural Language Processing (NLP) model was developed to provide recommendations on usage. Testing of the computer program indicates that the recommendation system can take the name of the symptoms a user is experiencing, query them, and thereafter provide recommendations in terms of drugs and their usage. This research is significant because it addresses critical gaps and challenges that hinder the effective implementation of AI in the healthcare sector. By critically analysing the ethical, social, and regulatory considerations underlying the integration and implementation of AI in the health field, the study contributes to the development of guidelines, best practices, and recommendations for its adoption.

Keywords: Computer program, AI, Healthcare, Machine learning, NLP.

INTRODUCTION

The computational modeling of intricate mental processes connected to sentient human behavior, including as learning, decision-making, problem-solving, task execution, and self-correction, is the broad definition of Artificial Intelligence (AI). Technological breakthroughs have brought about a tremendous revolution in

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the healthcare business in recent years, with Artificial Intelligence (AI) emerging as a key driver of innovation. From early disease detection to personalized treatment plans, AI has demonstrated immense potential to revolutionize patient care, improve outcomes, and streamline healthcare operations. The introduction of AI in healthcare has primarily been aimed at diagnosis, treatment, precision medicine, and administrative tasks. The application of AI in healthcare offers numerous possibilities. AI-powered machines assist radiologists in promptly identifying malignant tumors, AI systems help administrative staff organize patient files and schedules, and AI chatbots provide instant answers regarding healthcare information, advice, and support. However, amid the excitement surrounding AI's capabilities, concerns about its ethical implications and responsible deployment have received increasing attention.

To perform tasks accurately, AI systems require access to massive amounts of data. In the context of healthcare, these datasets consist of patient health information obtained from various hospitals, sometimes including government institutions. This raises significant concerns about data privacy and security

Collaboration among healthcare providers, policymakers, researchers, and patient advocacy groups is essential for addressing ethical challenges, defining best practices, and promoting the equitable and beneficial use of AI in healthcare [1].

The rise of the use of Artificial Intelligence is rapidly taking over and being adopted in many fields (Sport, Medicine, Education, Mining). Responsibility is crucial since the healthcare industry handles sensitive data, and it becomes much more crucial when technology is used to support human decision-making [2]. Extensive philosophical literature delves into various understandings of responsibility [3]. Ethical and regulatory frameworks, such as those outlined by Bleher and Braun [4], the EU Commission [5], and the Government Accountability Office (GAO) [6], address issues concerning AI and responsibility. However, scant attention has been paid in management literature to how managers can effectively navigate the challenges of responsibility inherent in introducing AI in healthcare [7]. This disparity is troubling because, in an industry that is extremely important to many people, unresolved accountability concerns risk becoming everyone's problem but nobody's duty [8]. Given the high probability of AI becoming commonplace in healthcare, it is imperative to address these challenges proactively.

This chapter aims to explore the principles of responsible AI within the healthcare sector, focusing on ethical, social, and regulatory considerations associated with the development, deployment, and use of AI technologies.

This research is significant because it addresses the critical gaps and challenges to the effective implementation of AI in the healthcare sector. By critically analysing the ethical, social, and regulatory considerations underlying the integration and implementation of AI in the health field, the study contributes to the development of guidelines, best practices, and recommendations for its adoption.

REVIEW OF LITERATURE

Description of AI

AI is a branch of computer science that deals with the use of intelligent machines that mimic the human biological neurons for learning and problem solving. It involves the use of algorithms or sets of rules to replicate human cognitive processes for problem-solving [9]. Its use is pervasive and is changing daily life.

AI in Healthcare

The health sector has been a major forerunner in the adoption of the latest technology in performing tasks. The word "Artificial Intelligence" (AI) in healthcare refers to the broad use of various machine learning algorithms and software to support human cognition in the analysis, presentation, and synthesis of complex medical and healthcare-related data in any format, from structured to unstructured. A crucial application in the healthcare domain involves analyzing the relationships between clinical methodologies and patient outcomes [10]. With the availability of data, the application of Artificial Intelligence (AI) in the healthcare industry has expanded rapidly and has been shown to be financially advantageous [11]. Particularly in the European Union, where compliance and safety rules have recently been implemented, the integration of robots and AI is increasingly recognized as a vital technology in patient care [12].

The connection between the agent and the patient, which constitutes responsibility, can be established in both retrospective and prospective contexts [13]. Retrospectively, this refers to determining who is accountable for the action and its consequences, and who is rightfully subject to blame and punishment. This concept is often referred to as "accountability". Conversely, when discussing responsibility prospectively, it pertains to the duties and obligations that an individual holds.

This differentiation is significant as it highlights related yet distinct considerations for managerial practices. On the one hand, managers need to understand the responsibilities involved in implementing appropriate precautions through established routines and procedures, and to involve the relevant individuals in

CHAPTER 8

Adaptive Fuzzy Logic Controller for Optimizing Artificial Lighting Energy in the Presence of Daylight

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Abstract: — This research developed Fuzzy Logic-based Controllers (FLC) for the optimisation of artificial lighting systems in the presence of daylight. The controllers developed in this research addressed the limitation of traditional lighting control to adapt to the variation in daylight by dynamically regulating the artificial lighting output based on real-time conditions of daylight to ensure that the total lux level in the workspace meets the required standards and leads to user comfort. Since daylight at any point in a workspace varies from one point to another, and the artificial lighting in a workspace cannot be modeled by a mathematical function, a centralized Mamdani FLC was designed to regulate the output of artificial lighting by placing daylight sensors at different positions. The controller used average daylight values to regulate the amount of lighting to be imported or exported by the artificial lighting. The effectiveness of the proposed algorithm was tested on three different workspaces with different recommended lux levels based on the Illumination Engineering Society of North America (IESNA) standard. The results reveal that the developed FLC controller regulates the luminaries to import and export illuminance at high and low levels of daylight, respectively. In addition, the controllers allow energy savings ranging from 118% to 105% during the high level of daylight when the artificial lighting is importing luminance from the workspace, and the energy saved when the controller allows the artificial lighting to export lighting to the environment ranges from 80% to 18% in the workspace. The approach developed in this work enhances the use of centralized FLC for regulating artificial lighting in the presence of daylight, providing a solution for smart, sustainable building applications.

Keywords: Artificial Lighting, Daylight, Energy, Fuzzy logic controller.

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INTRODUCTION

Artificial lighting accounts for a large share of total electrical energy consumption in buildings [1 - 3]. The use of intelligent artificial lighting control can lead to energy reduction in buildings in the presence of daylight [4, 5]. This intelligent control system tends to achieve energy savings by adapting to dynamic environmental factors, such as fluctuations in daylight levels in the workspace, to regulate the luminance supplied by artificial lighting [6]. The superiority of intelligent artificial lighting controllers over traditional artificial lighting control systems, such as manual control using switches, timer controllers, photocells, and occupancy sensors, is the ability to dynamically adjust to the fluctuating levels of daylight throughout the day [7 - 9]. Lighting control in the presence of daylight poses a range of challenges that must be addressed to achieve optimal energy management and occupant comfort. These problems stem from the dynamic nature of daylight, varying building designs, sensor limitations, and the need for sophisticated control algorithms that will allow the dual operation of artificial lighting to import and export daylight [10].

Daylight cannot be a linear model because it is inherently variable and unpredictable and is affected by several factors, such as time of day, weather conditions, seasonal changes, building parameters, and the orientation of buildings, which significantly influence the amount and intensity of daylight entering a workspace [3, 4, 11]. Furthermore, there is variability in daylight from one point to another within the workspace, which affects the total illumination level. Traditional lighting control systems struggle to adapt to these rapid, frequent changes, resulting in either over- or under-illumination and human discomfort. Effective daylight harvesting requires precise placement and calibration of light sensors. Incorrect sensor positioning can result in inaccurate readings, causing improper adjustments to artificial lighting [12]. In addition, sensors need regular maintenance and calibration to ensure they function correctly over time, which can be labor-intensive and costly. Appropriate use of daylight in the workspace can save 30-70% of energy [4, 13]. It is therefore necessary to adopt daylight in buildings to reduce energy use. However, excess usage of light in a workspace can lead to glare, which can be uncomfortable for occupants and reduce productivity. Properly managing glare while maintaining adequate illumination levels is a complex task in the presence of daylight. The existing lighting control approach, such as switches, timers, and photocells, often lacks the sophistication to balance these competing requirements effectively. To address this challenge, advanced control strategies are being explored for their ability to handle the inherent uncertainties and variabilities in daylight availability.

Van De Meugheuvel *et al.* [14] developed a two PI controller for lighting adjustment in the presence of daylight. One of the limitations of a PI controller, the performance of a PI controller is highly dependent on its tuning parameters (proportional gain and integral time constant). Changes in system dynamics, such as daylight in the workspace, lighting fixtures, or environmental conditions, may require retuning the controller, which can be time-consuming and complex. The proposed approach by Borile *et al*. [15], uses a collocated control from a light sensor. The approach divides the workspace into zones based on the number of lighting fixtures, and a controller is attached to each zone. The controller's input is the minimum illuminance reading from the light sensor in the zone, to achieve a maximum output beyond the setpoint in the workspace. This approach will lead to over-illumination in the workspace, which can cause discomfort for users of the workspace since the objective is to achieve an illuminance above the setpoint. However, the approach can be improved by using an average illuminance of the controller input.

The techniques used by Seyedolhosseini *et al.* [16] to adjust the output of lighting fixtures in the workspace are based on a neural network that learns how the luminaries contribute to the required illuminance in the workspace. The Authors classified the workspace into different zones, assuming that each zone in the workspace required different lighting conditions. While neural networks are powerful, they require substantial data for training and can be sensitive to the quality and quantity of this data. The system continuously measures daylight illuminance and uses it as a bias value for the neural network. Variations in daylight, such as sudden changes due to weather conditions, might introduce errors or require rapid adaptation, which might not always be perfectly handled. In addition, the approach cannot be effective in maintaining illuminance in a workspace where equal conditions are required throughout the workspace

Papinutto *et al.* [17] explore the reintroduction of task lights as a solution and present a system that optimizes the use of daylight along with general and task lighting, using a machine learning model to predict key performance indicators like work plane illuminance and daylight glare probability. The approach was evaluated using experiments with 60 participants. The findings established that by prioritizing daylight and task lighting, an average energy saving of 35-watt-hour was achieved without compromising user comfort or productivity. The study also found that there is a relationship between system reliability and user acceptance. Therefore, the reliability of the lighting control approach is an important factor in lighting automation systems. Overall, the results highlight the potential for significant energy savings with user-centered lighting automation. However, the findings are based on a controlled experiment with 60 participants, which may not reflect broader real-world scenarios or large populations.

CHAPTER 9

Performance Evaluation of Artificial Intelligence Modules on *Cucurbita pepo* with the Measurements of Climatic and Hydro-Physical Parameter under Drip Irrigation System

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Abstract: A computerized drip sprinkling technique was deployed to reduce the high prices incurred using conventional irrigated techniques. This research work involved a design suited to third-world agricultural cultivation, using a charge detection technique to eliminate excessive water use, preserve soil, and ensure optimum yield. To realize this objective, a detection unit and control hub containing humidity detectors, turbidity detectors, and an atmospheric pressure sensor were developed. These parameters were relayed to a microcontroller, which then locked or unlocked the water discharge section depending on the sensor readings. The detected parameters were also transferred to a human monitor by employing a Global System for Mobile Communication (GSM) module. The collected parameters were displayed on a Liquid Crystal Display (LCD) and saved to a Secure Digital (SD) card every twenty-five minutes. When the automated drip irrigation technique was used on an actual farm site, it achieved high efficiency in nurturing plants in the nursery bed, thereby ensuring optimal year-round crop yield for cultivators. The results were accumulated over a period of time and showed variations in the parameters at different intervals due to climate variability. Therefore, the use of this computerized drip irrigation technique enables the designed system to operate optimally and remain profitable across all types and sizes of farmland, including for pumpkin cultivation.

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Keywords: Automated system, Control, Climatic and hydro-physical parameters, Drip irrigation, Pumpkin.

INTRODUCTION

This research focused on using pumpkin (*Cucurbita pepo L.*) as a case study. *Cucurbita pepo Linn* is a widely cultivated crop in Southwestern Nigeria, where it is locally referred to as "Elegede." It belongs to the family Cucurbitaceae, which contains a large number of edible crops. The tender leaves of pumpkin, known as "Gboro," are consumed in the preparation of local soups. When used for making soups, the leaves are not pre-treated or pre-processed before use, unlike some other edible vegetables that require processing before consumption [1].

In recent years, there has been a rapid improvement in the agricultural system of the country. Research has shown that cultivation activities are critical to humans across the globe [2]. The Nigerian populace is no exception, as it relies heavily on the output of cultivation for food. Conventional cultivation relies on irrigated schemes whose water demand and usage are often not quantified. This results in large-scale water wastage and, in some cases, crop damage.

However, technological advancements have greatly improved irrigation processes without direct farmer interference in daily farming activities. Irrigated cultivation is arduous, requiring significant man-hours and constant attention for successful outcomes. Although some farms employ mechanisms and equipment to reduce over-reliance on workforce and the time spent watering crops, such schemes are often not crop-demand controlled and therefore still result in water wastage [3].

Agricultural production also largely depends on thermal and precipitation conditions during the growing season, and faces ongoing challenges related to water and human resources. Only technological advancements such as Artificial Intelligence (AI) can effectively address these daily challenges [4]. This research was conducted to ensure proper data collection and to achieve the following benefits for future research: a rapid reduction in human resources input, which lowered the cost of hired labor; improved monitoring through a control system, which led to positive results; increased crop yield due to effective and efficient system operation; and improved water management through maximum system control.

Therefore, the automated drip sprinkling technique, also known as localized watering, is a system that applies water directly to crop roots or the topsoil near the crops using pressurized pipes, spouts (emitters), and controlled water flow. This allows slow and consistent trickling of water either to the root zone or the soil surface [5].

METHODOLOGY

A system for the measurement of climate and soil hydrophysical parameters for an automated drip sprinkling technique was introduced employing moisture detectors to sense soil moisture level, a turbidity sensor to measure the water turbidity, and a component named GY-BMP280-3.3 to quantify barometric pressures [6]. This research worked extensively with a program that was able to continually ascertain the moisture of the soil, together with measuring the applied water turbidity for the plants to thrive successfully, and also the air pressure [7]. The microcontroller deciphers were introduced to measure growth parameters and be programmed to respond appropriately. The microprocessor also transmits a signal to the relay, turning on the Direct Current water pumps, once the soil moisture drops below some predetermined threshold, which is 50%. Additionally, when the water pump has been turned on, the microcontroller sends a prompt to deactivate the relay, turning off the Direct Current water pumps if the soil moisture level rises to a certain threshold [8]. The values and the conditions of the Direct Current water pumps are continuously shown on a Liquid Crystal Display (LCD). The circuit, as shown in Fig. (**1**), was used to drive the Direct Current water pumps. This control unit contains mainly transistors and relays. The output signal from Arduino was transmitted to the transistor root, which causes the relays to switch on. This, in turn, activates the DC water pump. However, during the operation of switching of the relay, an electromagnetic field relay serves as the primary control switch for the Direct Current water pump [9]. A flywheel diode was connected across the relay coil to avoid spoiling the switching transistors, which could be caused by an overload charge across the relay coil. Table **1** presents the description and specification of the materials employed in this study, while the circuit diagrams for the entire research were presented as reflected in Fig. (**2**).

Table 1. Material description and specification of parts.

S/N	Material Used	Specification	Function
1.	Moisture sensor		Measuring moisture content
2.	Turbidity sensor		Measuring water turbidity
3.	Pressure sensor	GY-BMP280-3.3	Measuring atmospheric pressure
4.	Microcontroller deciphers		Measuring growth parameters
5.	Microprocessor		Turning on the DC water pump
6.	Liquid Crystal Display (LCD)		Read values of the DC water pump
7.	Control unit	*Arduino*	Turning on the DC water pump
8.	Flywheel diode		Prevent damage to the switching transistor

CHAPTER 10

Smart Motor Control Systems: Revolutionising Industrial Automation through Advanced Technologies- A Review

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Abstract: With rapid industrial automation developments, smart motor control systems incorporating allied technologies such as Artificial Intelligence (AI), Machine Learning (ML), digital twins, and fast sensor technologies have progressed. These systems provide accurate, adaptive, and trustworthy motion profiles for tremendous operational efficiency, energy savings, and sustainability. The latest advancements in energy-efficient drives, including Variable Frequency Drives (VFDs), high-resolution sensors, and extremely fast processing units enabled by Field Programmable Gate Arrays (FPGAs), are essential for delivering more responsive control mechanisms and greater accuracy in controlling the complex motion environment. AI and ML integration offers predictive maintenance, self-optimization, and autonomous decision-making, enabling the development of self-healing and self-adaptive systems. However, concerns about scaling, cybersecurity, and interoperability remain within the scope of increased interconnectedness of devices. Future directions focus on resilient security frameworks, scalable architectures, and intelligent algorithms that learn from operational data. The fusion of these technologies is anticipated to deeply transform industrial automation paradigms for Industry 4.0 that will lead to sustainability, reliability, and smart manufacturing. Ongoing R&D will be essential to overcoming challenges and realizing the full potential of smart motor control systems in many industrial applications.

Keywords: Artificial intelligence, Cybersecurity, Digital twins, Industry 4.0, Smart motor control.

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INTRODUCTION-FUNDAMENTALS OF MOTION CONTROL SYSTEMS

One must note how motion control technologies have been rudimentary, but in time, the wise evolution with changes such as fuzzy logic, adaptive algorithms, and various real-time feedback control strategies [1, 2] gained the attention of the industrial ones to endow flexibility, responsiveness, and adaptability to industrial systems. This situates motion control as a key driver to smart manufacturing and sustainable automation.

Motors, drives, sensors, and controllers would be synergistic components that comprise the core architecture of a motion control system. Motion control precision is determined through the roles of these components. In fact, one of the recent innovations, Variable Frequency Drives (VFDs), has been an enabler for the energy-efficient operation of electric motors. The VFDs provide motor speed control by varying the supply frequency and voltage, while also saving power. The efficiency gains are enhanced with the adoption of Pulse-Width Modulation (PWM) techniques [3]. Moreover, new safety features and intelligent feedback systems are integrated into modern VFDs to enable appropriate operating conditions that meet optimal performance standards [4].

Sensor technologies have also advanced significantly through the use of ultrasonic and sonomography feedback systems. These types of sensors provide very high-resolution, real-time data that are indispensable during operation stabilization and high-accuracy performance in complex motion environments [5]. On a parallel path in conjunction with these advances, high-capacity processing units such as Field Programmable Gate Arrays (FPGAs) have enabled faster response from actuators and a more accurate control mechanism, especially in systems featuring complex motion profiles [6].

Up ahead, AI and ML are almost definitely going to reshape motion control. They will provide capabilities such as predictive maintenance, adaptive decision-making, and real-time optimization for creating autonomous, self-optimizing systems [7]. AI-powered control systems could act as enhancers to the traditional methods, such as fuzzy logic or adaptive feedback; thus, significantly widening the multiple application prospects for motion control technologies [8].

The alteration of motion control systems is tethered to the improvements in technology and the industrial realm in a broader spectrum, namely, the quest for smart, sustainable, and interlinked manufacturing systems. As the proposed automation solutions become increasingly intelligent and responsive, the potential for robotics, aerospace, precision medicine, and next-generation manufacturing continues to grow immensely [5, 9]. This context has provided impetus to review

recent technological advances in smart motor control systems, their challenges, and future directions, questioning how they can shape present-day industrial automation.

RECENT ADVANCES AND TECHNOLOGIES IN SMART MOTOR CONTROL

Key Components of a Motion Control System

Motors

Industrial automation relies on motion control systems for accurate movement through the harmonisation of components such as motion controllers, actuators, sensors, and feedback mechanisms. The motion controller processes the input signals and controls the movement using multi-loop architectures; in this regard, several works highlight the need for torque and position loops for good tracking performance [10]. Actuators, including servo motors, convert control signals into motion, where their design significantly impacts system precision and speed [11]. Advanced technologies like Field-Programmable Gate Arrays (FPGAs) further enhance actuator responsiveness [12]. Sensors provide critical feedback for real-time adjustments, improving accuracy and stability, with innovations in ultrasonic and sonomyography sensors enhancing motion analysis [13]. These components, in union with advanced control strategies, provide the assurance of reliable and efficient motion control, and hence are inherent to industrial automation.

Drives

The primary task of the drives lies in interfacing power supply systems to motors and thereby controlling key operational parameters of voltage/current/frequency supplied to motors. This control is critical in obtaining the required speed and torque from the motor, features of interest to various applications ranging from industrial machinery to electric vehicles. Out of various drives, Variable Frequency Drives (VFDs) are used in the largest number since they can vary motor speed by changing the frequency of the power supplied to the motor, which in turn leads to higher energy efficiency and better performance [14].

VFDs act as speed controllers and also include protective features, such as overcurrent protection, that help keep the motor within a safe operating range. Such situations are vital for preventing severe damage to the motor and for proving the system's reliability [15]. Advanced control strategies applied within VFDs, such as Pulse-Width Modulation (PWM), have even increased the level of accuracy of the motor operational parameters, thereby increasing system efficiency [16]. The existence of feedforward and feedback systems in modern

CHAPTER 11

Smart Switch Gear Motor Control Systems: Revolutionising Industrial Automation through Advanced Technologies- A Review

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Abstract: The fast development of intelligent control systems has changed the way of industrial automation, while switchgear motor control systems are at the forefront in improving operational efficiency, safety, and sustainability. This manuscript presents a complete review of the recent trends in smart switchgear technology with a focus on integrating good solutions such as the Internet of Things, artificial intelligence, digital twins, and modular, scalable designs. The paper further deliberates on the `infusion' of the technologies in application areas like predictive maintenance, fault detection, remote diagnostics, and energy management. Furthermore, it will investigate advanced control strategies for dual-motor systems, the development of communication-enabled motor architectures, and novel materials and electromagnetic technologies. It also emphasizes the role of renewable energy integration and environmentally sustainable insulating gases in improving system performance. In conclusion, the article highlights the prospect of intelligent switchgear motor control systems in creating resilient, efficient, and eco-friendly industrial environments in the future. This synthesis will help bridge the gap between researchers and industry practitioners on current trends, challenges, and opportunities in industrial motor control systems.

Keywords: Artificial intelligence, Digital twin, Energy efficiency, Industrial automation, IoT, Motor control systems, Predictive maintenance.

INTRODUCTION

The reliable and efficient operation of electric motors in modern industrial settings is essential for productivity, safety, and sustainability. Advanced

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switchgear motor control systems have transformed industrial automation by providing intelligent solutions such as real-time monitoring, fault detection, and predictive maintenance. These modern state-of-the-art systems feature advanced components such as circuit breakers, contactors, overload relays, and top-notch technologies like IoT connectivity, artificial intelligence, thermal management, and more, all to optimize motor performance while providing equipment protection against electrical faults.

Switchgear power control technology embraces modular and scalable designs that make it easy to adapt the equipment quickly to changing operational demand while promoting energy efficiency as well as sustainability goals. The retrofit of renewable energy sources and hybrid energy storage in motor control systems optimizes grid behaviour while also improving industry environmental responsibility. Furthermore, closed-loop control and digital twin technology will enable accuracy, reliability, and remote diagnostic precision in reducing operational costs and downtime.

The present review is also comprehensive in scope, outlining the current critical roles and advancements in switchgear motor control systems within the broader domain of industrial automation, with a focus on power distribution, safety assurance, fault management, and intelligent technology integration. As industries strive towards greater efficiency, safety, and environmental sustainability, the development and operation of such innovative systems will remain vital for meeting the changing needs of modern manufacturing and energy management.

BACKGROUND OVERVIEW OF MOTOR CONTROL SYSTEMS

A common motor control scheme contains the key elements of motors, drives, controllers, and feedback devices that cooperate with each other to obtain accurate and efficient motion control in various applications. Motors like AC motors, DC motors, and stepper motors, provide mechanical motion. AC motors are favoured in industry for their robustness; DC motors usually control speed and generate torque; and stepper motors are known for their accuracy and repeatability [1 - 3]. The drives control electrical power parameters, such as voltage and frequency, by combining technologies such as Variable-Frequency Drives (VFDs) and Pulse-Width Modulation (PWM) to enhance performance and provide cost-saving avenues [4, 5]. The controllers, including PLCs and microcontrollers, treat the data coming from the sensors and implement advanced strategies such as PID control for stability and accuracy [6, 7]. These are encoders and resolvers that provide motor position, speed, and torque feedback, which are critical in real-time for ensuring precision and reliability in operations [8 - 11]. All these components,

when assembled, give rise to a coherent system that readily adapts to dynamic conditions with optimal performance.

Motor control systems are classified as depicted in Fig. (**1**) into open-loop and closed-loop systems, each depending on precision and adaptability needs, and are suitable for different applications. Open-loop systems are simple, with no feedback; they work well for predictable, repetitive tasks, but can produce large errors if the conditions change from controlled to dynamic. On the other hand, closed-loop systems use feedback from sensors that measure variables such as position, speed, and force to dynamically update their operations, thereby ensuring extreme precision and adaptability. These systems are crucial for applications needing accuracy, such as robotic surgery and CNC machining [12, 13]. During Human-Robot Interactions (HRI), closed-loop approaches enable the robot to imitate adaptive behaviours by adjusting compliance and stiffness, which increases safety and effectiveness in collaborative tasks, including rehabilitation. Open-loop systems may be easier to implement, but closed-loop systems are necessary for the roles that allow adaptation in dynamic and precision environments for each consideration.

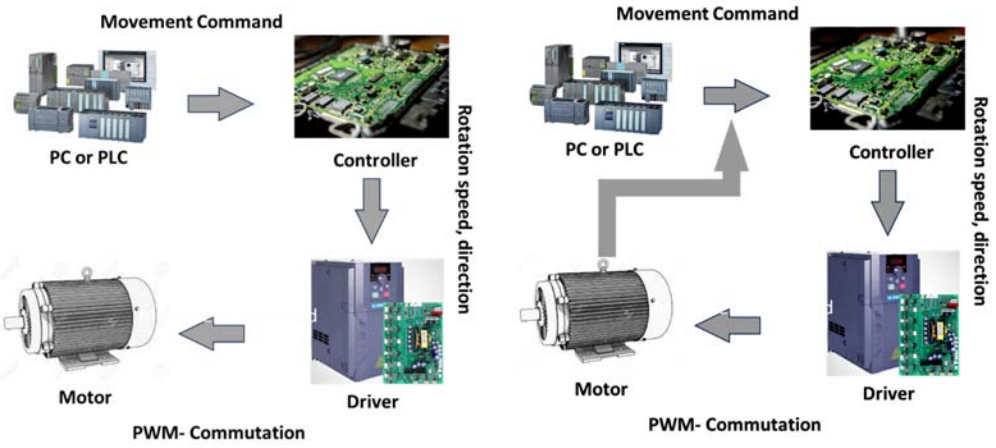

Fig. (1). (A) Open-loop System (B) Closed-loop System.

CLOSED-LOOP SYSTEMS AS INDUSTRY STANDARD

The adoption of closed-loop systems offers substantial advantages over traditional open-loop systems, as they rely on feedback mechanisms for real-time monitoring and adjustment to enhance precision, reliability, and adaptability. These are applied in highly demanding industries that require accuracy, such as aerospace, robotics, and manufacturing, where adaptive control techniques enhance robustness and enable real-time response to disturbances [14, 15]. By learning

CHAPTER 12

Practical Applications of Modern Motor Control Feedback Mechanisms- A Review

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Abstract: The review paper explains the importance of feedback mechanisms in current motor control systems, considering the significance of maintaining the accuracy, stability, and adaptability for myriad industrial situations. This chapter covers the journey from conventional control methodologies to modern techniques that include fuzzy logic, adaptive control, and real-time sensor feedback, all catalysed by recent advancements in AI, IoT, and sensor technologies. Conversely, the review details advanced control algorithms, integration of sensor data, and their applications to robotics, CNC machining, electric vehicles, and energy-efficient power grids. It also discusses challenges such as sensor reliability, computation delays, and security risks, while highlighting trends pointing toward fault-tolerant, autonomous learning, and energy-efficient designs. Therefore, these insights are expected to laser-focus future research on the creation of resilient, intelligent, and scalable motor control systems that meet the demands of new automation.

Keywords: Adaptive control, AI, Automation, Energy management, Fault tolerance, Feedback mechanisms, IoT, Motor control, Real-time control.

INTRODUCTION

The very basis of engineering lies in the functioning of motor control systems, which find applications in diverse fields, including industrial automation, robotics, electric vehicles, and renewable energy systems. For motor efficiency, speed, position, torque control, and so on, parameters must be closely and accurately controlled to ensure safer use and energy-efficient operation. The

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evolutionary trend in technology has shifted from conventional control designs, such as Proportional-Integral-Derivative controllers, to more adaptable advanced algorithms in the highly extendable and responsive serviceability areas of motor control systems, making the systems more efficient in several applications [1].

The feedback has been one of the most dominant forces behind this major change; it enables immediate corrections according to sensory inputs. A feedback control system can observe performance and environmental parameters continuously, ensuring that any disturbance or variability can be eliminated. And in doing so, the feedback control mechanism will enhance the robustness and stability of a system while finding applications in high-performance motors where the requirement for efficiency and safety is critical; this is like electric vehicles [2]. Control strategies using feedback mechanisms have increasingly become very sophisticated in handling nonlinearities and uncertainties, which pose serious challenges to motor operation [3, 4].

Recent technological advancements, especially in sensor integration, IoT, and AI, have further driven the development of feedback control and its strategies. Sensor technologies, for example, provide useful information for determining the current condition of a motor system and implementing predictive maintenance to reduce its potential failure [5]. This adaptation reduces energy waste and enables the system to make autonomous decisions, which is now highly valuable in modern industry, where adaptive and resilient operations are increasingly needed [6].

These advancements notwithstanding, numerous challenges lie ahead that stand in the way of widespread adoption of advanced feedback-based control techniques. The main concern is sensors: accurate and reliable measurement is pivotal for effective control, and any faults in data from sensor systems will severely degrade the performance of the larger system [7, 8]. Besides, computational difficulties in processing large amounts of data in real time may introduce delays or errors in the system's response and, consequently, negatively affect the gains achieved with advanced control algorithms [9]. These problems are further compounded by the security threats surrounding the interconnectivity of the systems. The more the control system relies on network structures, the more insecure it becomes, which calls for serious measures to protect sensitive operational data from being compromised [10].

The investigations in progress centre on refining these feedback control methods in terms of accuracy and utility for real-world applications. Novel methods, such as adaptive fuzzy tracking control, have emerged that address sensor faults and maintain system integrity even in uncertain situations [8]. Developing new control algorithms, in particular neural-based and adaptive ones, will add flexibility and

precision to control applications [5, 11]. These methods are applied to improve standard performance measures while simultaneously increasing the reliability of motor systems in fluctuating operating environments [12].

The feedback control dimension shall keep on shifting, while academics and practitioners work hand in hand to integrate novel technologies and tune existing feedback control models. Out of recent advancements in self-sensing materials and integrated sensor networks emerge smart systems that are capable of autonomous learning and adaptation [13, 14]. With this development, future motor control systems are expected to be much more energy-efficient, resilient against disturbances, and operate far beyond the real limits of the existing techniques [15]. On the other side, these systems will make feedback mechanisms become instrumental in the design of these systems, particularly now that smart technologies are scalable across all sectors from manufacturing to transportation and healthcare [16, 17].

EXAMPLES OF FEEDBACK MECHANISMS IN PRACTICAL APPLICATIONS

Feedback mechanisms are foundational to modern motor control systems, enabling precise operation in a wide range of applications. By continuously monitoring the system's performance and making real-time adjustments, feedback loops ensure that the desired outcomes—whether in position, speed, torque, or energy efficiency—are achieved. Here are several practical applications where feedback mechanisms play a crucial role in optimising performance:

Robotics

Feedback mechanisms are everywhere in robotic systems for motion control to achieve highly precise and stable movement. Applications in industrial robotics include repetitive creation tasks, assembly, welding, and many other tasks. For position and velocity feedback, all these systems operate using sensors in the form of encoders or resolvers, among others, which continuously give a report. This real-time data allows the controller to make adjustments if there is any deviation, hence enabling the robotic arm to reach the required position, apply the necessary force, and maintain the intended speed. Without feedback, there would be many inaccuracies, as robots cannot compensate for differences in load or changes in position, leading to significant errors in manufacturing processes [18].

Fig. (**1**) shows the robotic feedback mechanism.

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