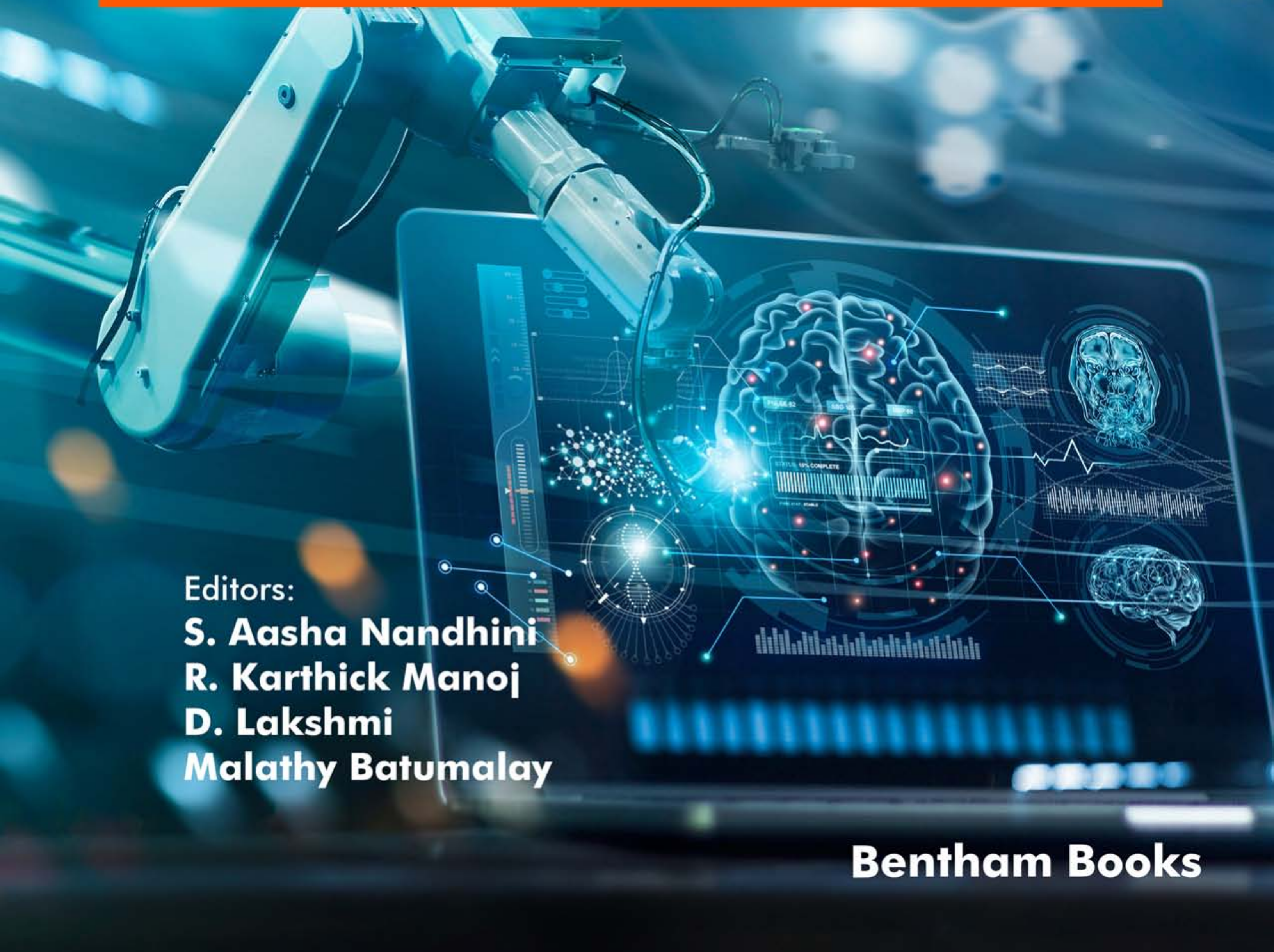
COGNITIVE COMPUTING WITH INTELLIGENT ENGINEERING PLATFORMS



Editors:
S. Aasha Nandhini
R. Karthick Manoj
D. Lakshmi
Malathy Batumalay

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Cognitive Computing with Intelligent Engineering Platforms

Edited by

S. Aasha Nandhini
Department of Electronics and Communication Engineering
Sri Sivasubramaniya Nadar College of Engineering, Chennai
Tamil Nadu, India

R. Karthick Manoj
Department of Electrical and Electronics Engineering
Academy of Maritime Education and Training (AMET)
Deemed to be University, Chennai
Tamil Nadu, India

D. Lakshmi
Department of Electrical and Electronics Engineering
Academy of Maritime Education and Training (AMET)
Deemed to be University, Chennai
Tamil Nadu, India

&

Malathy Batumalay
Faculty of Data Science and IT
Centre for Data Science and Sustainable Technologies
INTI International University, Nilai, Malaysia

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Editors: S. Aasha Nandhini, R. Karthick Manoj, D. Lakshmi & Malathy Batumalay

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FOREWORD

The 21st century stands as a defining moment in human history, one where intelligence is no longer confined to the human mind but embedded in the very fabric of our technologies, systems, and infrastructures. From the way we manufacture goods and deliver healthcare, to how we build cities and manage energy, the infusion of cognitive computing into engineering platforms is reshaping the foundation of modern civilization.

For decades, engineering systems have relied on deterministic processes and static models. While these systems laid the groundwork for industrial progress, they often fall short in meeting the dynamic, data-driven demands of our present and future. Today, the world is witnessing the rise of intelligent, adaptive, and self-learning platform systems that do not merely execute commands but understand, reason, and evolve with their environment.

This transformation is powered by cognitive computing: a convergence of machine learning, artificial intelligence, real-time data analytics, and human-centered design. When combined with intelligent engineering platforms, it enables breakthroughs that were once the domain of science fiction—smart factories that self-correct, power grids that adapt in real time, and healthcare diagnostics that rival human expertise.

My own journey as a researcher and technologist has illuminated how critical this integration has become. In industries across the globe, there is a growing need for solutions that are not only efficient but also autonomous, context-aware, and sustainable. The promise of cognitive engineering lies in its ability to create systems that learn from data, collaborate with humans, and respond to ever-changing conditions, making our world safer, more responsive, and more resilient.

Cognitive Computing with Intelligent Engineering Platforms is a testament to the strides being made in this field. This volume brings together leading voices from academia and industry to explore real-world applications of cognitive systems across diverse domains, including manufacturing, energy, transportation, cybersecurity, healthcare, and more. The contributors share case studies, frameworks, and innovations that bridge theory and practice, offering readers both inspiration and implementation strategies.

From edge computing architectures and AI-powered control systems to smart water management, battery diagnostics, and industrial IoT for healthcare, the chapters in this book illustrate how cognitive intelligence is being embedded across the engineering spectrum. Whether it's improving power system efficiency, enhancing cybersecurity, or advancing medical diagnostics, these chapters offer a panoramic view of intelligent innovation at work.

This book arrives at a critical time. As the world grapples with challenges like climate change, digital disruption, and the pursuit of global sustainability, the role of intelligent, data-driven engineering solutions becomes ever more vital. The shift is not just technological—it is cultural. It calls on us to rethink traditional engineering boundaries and embrace a mindset of continuous learning, cross-disciplinary collaboration, and human-machine synergy.

Whether you are a researcher, engineer, policymaker, or student, this book will deepen your understanding of how cognitive computing is transforming engineering. More importantly, it will equip you to be a part of this transformation.

I commend the editors for their vision and the contributors for their insights. This is more than a collection of chapters; it is a blueprint for the intelligent systems that will shape our collective future. Let this book inspire you to think differently, act boldly, and innovate responsibly. The era of cognitive engineering is here, and it is ours to shape.

V. Pramila
Department of Electrical and Electronics Engineering
B.S. Abdur Rahman Crescent Institute of Science and Technology
Chennai
Tamil Nadu, India

Preface

The evolution of engineering practices in the 21st century has been significantly shaped by the convergence of artificial intelligence, cognitive computing, and intelligent automation. The transition from traditional systems to intelligent platforms is not merely a technological shift; it is a fundamental transformation in how engineering problems are understood, analyzed, and solved.

Cognitive Computing with Intelligent Engineering Platforms is a timely response to this paradigm shift. The book aims to bridge the gap between theoretical advancements in cognitive technologies and their real-world applications in engineering. It explores how data-driven insights, machine learning algorithms, IoT integration, and cognitive systems are driving the next generation of adaptive, autonomous, and sustainable engineering solutions.

This edited volume comprises 8 contributed chapters and international institutions. Their work spans diverse areas such as healthcare, smart manufacturing, energy systems, cybersecurity, industrial IoT, and intelligent control. Each chapter offers in-depth research, case studies, or practical frameworks that demonstrate the transformative impact of cognitive computing on modern engineering environments.

We hope this book serves as a comprehensive resource for graduate students, academic researchers, engineers, and technologists seeking to understand and implement cognitive systems within contemporary engineering infrastructures. By bringing together a wide range of perspectives, we aspire to foster a collaborative and forward-thinking community committed to advancing intelligent engineering.

This book is intended for a broad audience, including:

Researchers and Academicians engaged in artificial intelligence, cognitive computing, data analytics, and intelligent engineering systems.

Postgraduate and Doctoral Students pursuing advanced studies in engineering, computer science, IT, and related disciplines.

Industry Professionals and Engineers working in smart manufacturing, energy systems, industrial automation, automotive engineering, and smart cities.

Technology Developers and System Architects designing intelligent platforms using IoT, cloud/edge computing, machine learning, and data fusion.

Today's world stands at a pivotal crossroads in the evolution of energy and engineering infrastructure. Environmental imperatives, escalating energy demands, and rapid technological innovation make the integration of cognitive and intelligent systems not just beneficial but essential. This shift toward smart, adaptive, and distributed platforms marks a vital step in building a resilient and sustainable future.

We hope the insights and innovations presented in this volume will not only inspire new solutions and interdisciplinary collaborations but also promote a shared commitment to building efficient, autonomous, and intelligent systems for generations to come. Progress toward cleaner, smarter, and more inclusive engineering practices demands bold ideas, sustained research, and a collective purpose. Let us move forward together in shaping that future.

We extend our sincere gratitude to all the contributors, reviewers, and institutions whose support has enriched this book and helped bring this vision to life.

S. Aasha Nandhini
Department of Electronics and Communication Engineering
Sri Sivasubramaniya Nadar College of Engineering, Chennai
Tamil Nadu, India

R. Karthick Manoj
Department of Electrical and Electronics Engineering
Academy of Maritime Education and Training (AMET)
Deemed to be University, Chennai
Tamil Nadu, India

D. Lakshmi
Department of Electrical and Electronics Engineering
Academy of Maritime Education and Training (AMET)
Deemed to be University, Chennai
Tamil Nadu, India

&

Malathy Batumalay
Faculty of Data Science and IT
Centre for Data Science and Sustainable Technologies
INTI International University, Nilai, Malaysia

List of Contributors

Ashish Kumar Dass	Department of Computer Science and Engineering, NIST University, Berhampur, Odisha, India
B. Kirubadurai	Department of Aeronautical Engineering, Vel Tech Dr. Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India
D. Lakshmi	Department of Electrical and Electronics Engineering, Academy of Maritime Education and Training (AMET) Deemed to be University, Chennai, Tamil Nadu, India
Emil Joseph	St. Joseph's College of Commerce (Autonomous), Bengaluru, Karnataka, India
G. Jegadeeswari	Department of Electrical and Electronics Engineering, Saveetha Engineering College, Chennai, Tamil Nadu, India
G. Sudhagar	Department of Electronics and Communication Engineering, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India
G. Abirami	Department of Computer Science and Engineering, B.S. Abdur Rahman Crescent Institute of Science and Technology, Chennai, Tamil Nadu, India
Ganesan Krishnan	Department of Physics, Faculty of Science, Universiti Teknologi Malaysia, Johor Bahru, Malaysia, Malaysia
Pandurang S. Londhe	Department of Instrumentation Engineering, Government College of Engineering, Chandrapur, Maharashtra, India
Poornima Vijay Kumar	St. Joseph's College of Commerce (Autonomous), Bengaluru, Karnataka, India
P. Vinothkumar	Department of Electrical and Electronics Engineering, Sri Krishna College of Engineering and Technology, Coimbatore, Tamil Nadu, India
R. Rajasaranyakumari	Department of Artificial Intelligence and Machine Learning, Saveetha Engineering College, Chennai, Tamil Nadu, India
R. Karthick Manoj	Department of Electrical and Electronics Engineering, Academy of Maritime Education and Training (AMET) Deemed to be University, Chennai, Tamil Nadu, India
Subratansu Panigrahi	Department of Computer Science and Engineering, NIST University, Berhampur, Odisha, India
Subhashree Sahu	Department of Computer Science and Engineering, NIST University, Berhampur, Odisha, India
S. Arunamary	Department of Electronics and Communication Engineering, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India
S. Priya	Department of Electrical and Electronics Engineering, Academy of Maritime Education and Training (AMET) Deemed to be University, Chennai, Tamil Nadu, India
S. Prakash	Department of Electrical and Electronics Engineering, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India
S. Aasha Nandhini	Department of Electronics and Communication Engineering, Sri Sivasubramaniya Nadar College of Engineering, Chennai, Tamil Nadu, India

T. Preethiya	Department of Networking and Communications, School of Computing, College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chengalpattu, Tamil Nadu, India
T. Pandiarajan	Department of Computer Science and Engineering, Rajalakshmi Institute of Technology, Chennai, Tamil Nadu, India

CHAPTER 1

Cloud-based AI Solutions for Smart Engineering Platforms

Ashish Kumar Dass[1], **Subratansu Panigrahi**[1,*] and **Subhashree Sahu**[1]

[1] *Department of Computer Science and Engineering, NIST University, Berhampur, Odisha, India*

Abstract: Incorporation of cloud-based Artificial Intelligence (AI) systems into innovative engineering platforms has revolutionized the engineering processes of design, management, and optimization. With AI, ML, and cloud computing, organizations can effectively analyze vast volumes of data, enabling intelligent decision-making, predictive maintenance, and optimized workflows. Cloud services provide the infrastructure needed to deploy AI at scale, enabling real-time data analysis to predict equipment failures, reduce downtime, and allocate resources in response to fluctuating project requirements. The fusion of the Internet of Things (IoT) and cloud-based AI makes clever engineering even smarter, enabling real-time decision-making and thereby optimizing energy use in smart buildings, regulating traffic in smart cities, and improving technological efficiency. Another significant benefit of security is that an AI-powered cloud platform analyzes the network traffic and seeks anomalies and cyber threats autonomously. In addition, the cloud enables engineering teams to collaborate smoothly from different locations using a shared dataset and tools. Cloud-based Artificial Intelligence is transforming modern engineering practices by enabling predictive analytics, dynamic asset management, IoT integration, improved security, and collective innovation. This research paper examines successful instances, citing case studies and best practices that demonstrate the impact of such technologies on Smart engineering.

Keywords: Cloud computing, Collaboration, Cybersecurity, Data analysis, Degradation modeling, Decision-making, Dynamic resource allocation, Engineering optimization, Industrial automation, Infrastructure scalability, Internet of Things (IoT), Machine Learning (ML), Operational efficiency, Predictive analytics, Real time processing, Reinforcement learning, Smart cities, Smart engineering platforms, Threat detection.

* **Corresponding Author Subratansu Panigrahi:** Department of Computer Science and Engineering, NIST University, Berhampur, Odisha, India; E-mail: subratansu25@gmail.com

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INTRODUCTION

The adoption of cloud-based Artificial Intelligence (AI) into innovative engineering platforms represents a milestone in the evolution of the engineering discipline. As organizations capitalize on large volumes of data collected from various sources, the integration of AI, Machine Learning (ML), and cloud technologies has also become a decisive enabler of improvement in engineering processes [1]. This revolutionary change is not just a trend; it also manifests a radical renewal of how engineering efforts are engineered, managed, and optimized. Cloud computing provides the requisite infrastructure, enabling the deployment of AI/ML algorithms at scale. In addition to its general effectiveness, this capability allows engineers to process and analyze real-time data, run more complex algorithms on large datasets, identify patterns, predict outcomes, and optimize workflows [2]. For example, Intelligent Maintenance is a prominent application of cloud-based AI solutions. By analyzing records from machinery and other devices, these systems can predict future growth before it occurs, substantially increasing efficiency and reducing maintenance costs. Additionally, the scalability embedded in cloud services enables organizations to flexibly adjust the distribution of their resources in response to anticipated changes in project demand. This degree of flexibility is beneficial in engineering projects where there are considerable variations in the amounts of work involved. Cloud-based AI solutions oversee dynamic resource management through automated scaling and other mechanisms, ensuring all engineering teams have access to computational power without overspending. The integration of the Internet of Things (IoT) and cloud-based AI provides innovative engineering platforms with integrated capabilities. IoT devices generate an ongoing stream of data that can be processed in real time using cloud infrastructure. That functionality enables on-the-spot decisions in the present situation, for instance, optimizing ECO usage in smart buildings or traffic management in smart cities [3].

The fact that it can analyze data from many connected devices simultaneously makes its decision-making more informed and its operations much more efficient. Security is also an essential part of this landscape. As cyber threats become increasingly sophisticated, there is an obligation to use AI for security monitoring and threat detection. Cloud platforms with advanced machine learning algorithms, such as reinforcement learning and decision trees, can analyze network traffic to detect anomalous behavior or potential breaches, enabling a proactive cybersecurity approach. Additionally, the collaborative nature of cloud computing promotes innovation within engineering teams. By leveraging common cloud resources, engineers can collaborate across borders, using the same tools and datasets. An efficient environment that supports collaborative work speeds up the development cycle, allowing teams to bring products to market faster without compromising high-quality requirements. In conclusion, integrating cloud-based AI solutions is altering engineering practices by making it easier to build predictive analytics, improve resource management, integrate IoT capabilities, implement stronger security measures, and foster greater collaboration. As organizations move to embrace further digital transformation, synergy among AI, machine learning, and cloud computing will play an integral role in shaping the future of engineering practices. This research aims to explore these themes further, bringing case studies and best practices into the light to showcase how accurately cloud-based AI solutions have been implemented in smart engineering settings.

THEORETICAL FRAMEWORK

The implementation of cloud-based Artificial Intelligence (AI) solutions within innovative engineering platforms represents a paradigm shift in modern engineering. The framework is based on three key pillars: cloud-to-computing, Artificial Intelligence and Machine Learning (AI/ML), and innovative engineering platforms. Every pillar plays a vital role in remodeling engineering processes, streamlining processes, and improving management practices. Cloud computing is the bedrock of such integration, providing an expansive, flexible environment for running AI and ML algorithms. The theoretical background is distributed systems and virtualization technologies that enable easy access to significant computational resources [4]. Cloud platforms can process real-time data in engineering settings, where decisions need to be made based on rapidly changing streams of data. This ability is critical in applications that require immediate response, such as Proactive Maintenance and operational analytics.

Artificial Intelligence (AI) and Machine Learning (ML) are critical for understanding complex data in engineering. The technologies underpinning these solutions are based on statistical modeling and computational learning theories to enable predictive analytics, anomaly detection, and workflow optimization. Such abilities are essential in cases such as Smart Maintenance, where analysis of traditional equipment data can avert operational failures. The incorporation of AI/ML into cloud environments increases resource allocation, reduces security measures, and enables sophisticated decision-making through predictive modeling.

Innovative engineering platforms serve as the foundation for cloud-based AI solutions [5]. Such platforms leverage a range of tools and technologies to optimize engineering workflows, foster collaboration, and improve decision-making. Theoretical frameworks of innovative engineering platforms underline their role as mediators between physical systems (*e.g.*, IoT devices) and

CHAPTER 2

AI-powered Control Systems: Bridging Cognitive Computing and Sustainable Engineering

Pandurang S. Londhe[1,*]

[1] *Department of Instrumentation Engineering, Government College of Engineering, Chandrapur, Maharashtra, India*

Abstract: Cognitive computing and Artificial Intelligence (AI) are together ushering in a new era of intelligent control systems, offering enhanced accuracy, adaptability, flexibility, and decision-making capabilities for solving complex engineering challenges. A cognitive AI-powered control system combines advanced AI techniques such as machine learning, deep learning, neural networks, and data analytics with cognitive computing principles like reasoning, perception, and contextual understanding. This integration enables real-time system optimization, intelligent fault diagnosis, and adaptive control, even under uncertain and dynamic operating conditions. This study analyzes AI applications in renewable energy, autonomous vehicles, and industrial automation to demonstrate the efficiency, safety, and cost-effectiveness of AI-driven control systems, with a focus on sustainability. A drone position control case study simulation shows the advantages of AI-based control over traditional approaches. Through the use of empirical data, simulations, and case studies, this study examines artificial intelligence-driven sustainable design solutions. Based on the findings of the research, artificial intelligence is able to improve the efficiency of industrial processes, foster environmental sustainability, and form intelligent control systems. In order to create sustainable engineering, this research offers direction for the design and implementation of control systems that are based on artificial intelligence.

Keywords: Artificial intelligence (AI), Control systems, Ccognitive computing, Sustainable engineering, Machine learning algorithms, Neural networks, Reinforcement learning, Fault detection, Autonomous systems, Renewable energy.

INTRODUCTION

Industry 4.0 is transforming the manufacturing landscape through the integration of smart cyber-physical systems, Internet of Things (IoT) devices, cloud-based

* **Corresponding author Pandurang S. Londhe:** Department of Instrumentation Engineering, Government College of Engineering, Chandrapur, Maharashtra, India; E-mail: pandurangl97@gmail.com

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computing, large-scale data analytics, and Artificial Intelligence (AI), all contributing to the development of intelligent, autonomous, and optimized industrial systems [1].

Artificial Intelligence (AI) that aims to emulate how people learn and reason is referred to as cognitive computing. Making control systems more intelligent is of the utmost importance. The combination of artificial intelligence and cognitive technology gives control systems the capacity to develop, enhance their performance, and make decisions in real time. By utilizing these newly developed technologies, it is now much easier to enhance dynamic processes, identify intelligent problems, and rapidly adjust to changes in the surrounding environment. The result of this is that industrial automation and smart infrastructure are more efficient, dependable, and long-lasting [2-4]. The combination of cognitive computing and machine learning has the potential to assist control systems in making decisions based on the conditions, improving performance on the fly, and precisely detecting and preventing issues before they occur. This represents a significant advancement in the field of engineering practices that are beneficial to the environment [5, 6].

LITERATURE REVIEW

AI and cognitive computing are working together to make substantial changes in engineering. Artificial intelligence makes control systems that endure longer, are more flexible, and work better. This literature study looks at the present state of control systems that incorporate artificial intelligence. It focuses on how adaptable they are, how much energy they require, and how they may be used in business.

Recent Developments in AI-Driven Control Systems

Artificial intelligence has completely altered the way control systems operate in every way. Because of this, things have become more exact, individuals have been granted greater flexibility to make judgments, and things have remained stable in regions that are undergoing fast change. Some recent studies have looked at how artificial intelligence can be employed in places that demand a lot of control. As part of Industry 4.0, they include closed-loop feedback control, autonomous energy transfer, industrial robots, microgrids, and predictive automation.

AI-powered control systems improve accuracy, flexibility, and efficiency across multiple domains ranging from closed-loop regulation [7] to adaptive energy transmission [8] and industrial automation within Industry 4.0 [9]. AI enhances automation in welding automation [10], refines quality control [11], and optimizes robotic vehicle navigation [12]. Its applications in microgrids and deep reinforcement learning for power systems highlight substantial efficiency and reliability advancements [13]. The detailed review of the summary of research work carried out in a similar study is demonstrated in Table **1** [14].

Table 1. Summary of literature review on recent developments in AI-driven control systems.

Authors	Year of Publication	Presented Work	AI Contributions	AI Technique	Domain-specific Challenges
[7]	2022	AI-driven improvements in closed-loop control systems for precision, adaptability, and optimization.	AI improves real-time adaptability and disturbance rejection.	Reinforcement Learning	Difficulty maintaining safety under high-frequency updates.
[8]	2023	An adaptive power beaming system utilizing a self-learning AI controller with a fiber-array laser transmitter.	Self-learning controller improves beam accuracy in real-time.	Model-Free RL (*e.g.*, SAC)	Environmental variability and convergence time.
[9]	2024	AI integration challenges in Industry 4.0, focusing on data interoperability and scalability.	AI improves data flow, automation, and interoperability.	ML + Rule-Based Logic	Data interoperability and integration with legacy systems.
[10]	2024	AI-driven welding robots for enhanced precision and automation.	Real-time welding precision using vision-based learning.	CNN + Decision Trees	High GPU dependency, lack of robustness in complex welds.
[11]	2024	AI-enhanced quality control systems for defect detection and efficiency.	Automated quality control using real-time classification.	Deep CNN + Transfer Learning	Domain-specific dataset needs and deployment cost.
[12]	2024	AI-powered hybrid control algorithm for robot vehicles.	Stability *via* AI-based hybrid control.	DRL (PPO/DDPG)	Hardware latency, safety certification issues.
[13]	2024	AI-based control strategy for Boost DC/DC converters to improve microgrid efficiency.	Optimized energy flow, real-time switching.	DRL (DQN) + PID Hybrid	Training instability, dynamic topology challenges.
[14]	2024	Deep reinforcement learning (DRL)-based control strategies for power systems without relying on explicit system models.	Model-free DRL for scalable control.	Deep Q-Learning	Offline training burden, real-world generalization.

CHAPTER 3

Transforming Industrial IOT with Cognitive Technologies: A Paradigm Shift

Emil Joseph[1,*] and **Poornima Vijay Kumar**[1]

[1] *St. Joseph's College of Commerce (Autonomous), Bengaluru, Karnataka, India*

Abstract: Industry 4.0 is the primary driver behind the penetration of the Industrial Internet of Things (IIoT) into manufacturing, supply chain management, and industrial operations, fundamentally changing how we approach productivity and efficiency gains. Cognitive technologies like AI, ML, and NLP have become ingrained in modern IoT applications. Hence, the profound transformations were observed. This transforms IoT from a reactive network into a predictive/configurable cognitive system that encompasses intelligent decision-making, automated processes, and improved human-machine collaboration. As we discuss in this chapter, cognitive technologies have the potential to change entire IoT ecosystems. They may address some of the challenges associated with current implementations, particularly issues related to scalability, interoperability, and real-time data analysis. Specifically, it details how IoT and cognitive computing are naturally complementary-working in harmony toward developing smart factories, predictive maintenance, and adaptive supply chain systems. Through case studies in manufacturing, healthcare, and energy, this chapter demonstrates how cognitive-enabled IoT has been put into practice. Edge computing has a prominent role in processing data near the device, performing faster and more secure operations. The chapter also addresses the hurdles-cybersecurity threats, ethical dilemmas, and skills gaps-that may stand in the way of embracing these advanced technologies. It also reviews potential future directions, such as the incorporation of quantum computing and blockchain to complement cognitive IoT bases.

Keywords: AI, Cognitive computing, Cybersecurity, Data analytics, Edge computing, Industrial IoT (IIoT), Interdisciplinary collaboration, Machine learning (ML), Natural language processing (NLP), Organizational readiness, Predictive maintenance, Smart factories, Workforce transformation.

INTRODUCTION

This new industrial landscape represents a seismic shift toward experiences and ecosystems, driven by new digital technologies and the convergence with the Internet of Things (IoT). One of the most transformational innovations in this area

* **Corresponding author Emil Joseph:** St. Joseph's College of Commerce (Autonomous), Bengaluru, Karnataka, India; E-mail: emiljoseph333@gmail.com

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is the incorporation of cognitive technologies-Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP). We are at the dawn of IQ (IIoT artificial intelligence powered with mechatronics), which is a transformation that will massively disrupt industries and drive efficiencies and growth. Intelligent systems, which can optimize the processing of enormous amounts of information, generate actionable insights, and take immediate action, are increasingly taking the place of conventional tools of process monitoring, regulation, and optimization [1]. It's not merely a buttressing of current systems; it's a whole new way of thinking about running an industrial business—that is, where machines and systems themselves can take place in the decisions. At the core of this revolution is the capacity to process and interpret data at a scale and velocity that was unimaginable even to the most far-sighted researchers. The hallmark of Cognitive Industrial IoT is the work performed in the cloud. While traditional industrial networks connected machines and systems to achieve efficient operation within the local network, these advanced, connected systems now also have the ability to "think" and process data in the cloud. For instance, predictive maintenance that predicts equipment failures before they occur can be enabled with AI algorithms, which reduce failure time and increase operational efficiency [2]. Similarly, NLP and advanced analytics can render human-human and human-machine interactions more natural, making way for collaboration and simplification of complex workflows. This results in a nimbleness and responsiveness that ensures industries are always on point and proactive in meeting dynamic needs. At first, it could well appear simple to throw away any suggestion that this paradigm shift relates to productivity/effectiveness gains. With cognitive-powered IIoT (Internet of Things), enterprises can drive fast-paced innovation to identify new business models, services, and revenue streams. And every industry, from manufacturing and energy to health care and logistics, is already gaining from intelligent systems that adjust and learn continuously. Moreover, the integration of these technologies ensured sustainability by maximizing the optimum usage of resources while minimizing waste [3]. For example, an AI-powered energy management system can optimize power use across an entire factory, which benefits not just the bottom line but also the environment. These developments are quintessentially cognitive technologies-and signal what the future of the industry could resemble.

However, these changes are not without their challenges. The industrial Internet of Things (IIoT) will require significant investment in infrastructure, skilled people, and cybersecurity plans to support the vast volumes of data being generated and exchanged. Additionally, organizations need to navigate the complexities of migration from legacy systems to next-generation tech [4]. Despite these headwinds, the impetus for this paradigm shift is unstoppable. As cognitive technologies are becoming more and more prominent in the industry, the future is going to be interesting as we are stepping into the age of harmony between humans and machines, with phenomenal inventions and propositions taking place in parallel with working towards a more efficient approach to everything industrial.

Using cognitive technologies is not just an IT advancement in IIOT; it is a qualitative revolution that redefines all parts of industries—not just how the industries function, but how they create value and maintain competitive advantage over time. This is a transformational change from traditional, reactive systems to AI, ML, and advanced data analytics-driven proactive and autonomous intelligent networks [5]. Cognitive Technologies are designed to work like humans. Therefore, they sense, learn, comprehend, based on their experience, make (which is also a quality of AI in itself), and take actions without the help of human beings. We are witnessing the overlap of the physical and digital worlds, creating smart sensors, connected devices, and intelligent algorithms that will change the entire industrial landscape. Central to this transformation is the recognition of data as a strategic asset. For decades, industries have used data as input to trim processes and enhance results. Yet the scale and complexity of current-day operations have outstripped the capabilities that conventional data-processing methods can provide. Cognitive technologies that offer the ability to use massive data sets for valuable information fill this gap [6]. For example, sophisticated machine learning algorithms are rummaging through terabytes of operational data in order to detect patterns and anomalies that would be beyond human perception. This is particularly beneficial for predictive maintenance as it prevents machinery and equipment from appearing when they are starting to fail or malfunction, thereby saving industries millions in repair and minimising the potential effects of unplanned hardware downtime. In addition to that, cognitive systems offer a significant data processing power with real-time functioning quality that enables industries to react instantly to alterations to the demand situation, raw material situation, or any such environmental situation, which ultimately increases agility and resiliency. Cognitive-powered IIoT also enables new frontiers for innovation, in addition to operational efficiency. AI systems can analyse market trends, consumer behaviour, and operational performance in a short period, which enables industries to deliver customised products and services faster than ever before [7]. In manufacturing, for instance, cognitive systems adjust production lines on the fly to produce highly customised products with no impact on overall operational performance. For example, AI technologies help optimise logistics delivery routes, minimising not only delivery time but also fuel consumption. At the same time, sector-wise connected devices and machine learning systems enable real-time monitoring and predictive diagnostics, giving healthcare providers improved outcomes for patients. Innovations have led the evolution of business models from product-oriented towards service-oriented: Economies built on services and experiences rather than products [8]. Moreover, cognitive technologies are the single most empowering technologies for sustainable initiatives and are the most relevant imperative in an eco-conscious world. These technologies are helping industries work towards reducing their ecological

CHAPTER 4

Intelligent Cognitive Support Systems for Operators in Industry 5.0

G. Jegadeeswari[1,*], **D. Lakshmi**[2], **R. Rajasaranyakumari**[3] and **B. Kirubadurai**[4]

[1] *Department of Electrical and Electronics Engineering, Saveetha Engineering College, Chennai, Tamil Nadu, India*

[2] *Department of Electrical and Electronics Engineering, Academy of Maritime Education and Training (AMET) Deemed to be University, Chennai, Tamil Nadu, India*

[3] *Department of Artificial Intelligence and Machine Learning, Saveetha Engineering College, Chennai, Tamil Nadu, India*

[4] *Department of Aeronautical Engineering, Vel Tech Dr. Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India*

Abstract: Industry 5.0 is driven by human cyber-physical systems, where human intelligence and advanced technologies converge to enhance innovation and efficiency. Unlike traditional automation systems, the systems discussed in this study function as interactive platforms that augment human flexibility, problem-solving, and decision-making. This study examines cognition in CPS through the lens of joint cognitive systems, which emphasize collaborative human-machine interactions. The integration of IoT, AI, and multi-agent systems enables real-time data processing, predictive analytics, and adaptive learning, facilitating seamless collaboration between intelligent systems and human op-erators. By optimizing cognitive workload and enhancing situational awareness, these systems em-power operators to focus on complex, high-level decision-making, fostering a resilient and adaptive industrial landscape in Industry 5.0. Joint Cognitive Systems (JCSs) improve situational awareness and free up operators to concentrate on higher-order cognitive processes by automating repetitive activities and lowering cognitive overload. This study emphasizes how CPS is influencing Industry 5.0, a field in which human knowledge and cognitive technology combine to build robust, flexible, and extremely effective industrial settings.

Keywords: Artificial intelligence (AI), Cognitive systems, Cyber-physical systems (CPS), Industry 5.0, Internet of things (IoT), Multi-agent systems (MAS).

* **Corresponding author G. Jegadeeswari:** Department of Electrical and Electronics Engineering, Saveetha Engineering College, Chennai, Tamil Nadu, India; E-mail: jegadeeswari.dharan@gmail.com

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INTRODUCTION

The constant advancement of technology is one of the primary drivers of shifts in commercial models, designs, and labor practices. Operators have a great chance to interact with contemporary industrial systems thanks to Industry 5.0. Operators receive invaluable support and work effectively with intelligent systems in addition to providing data and information to train machines and enhance operations. New and potent human-machine relationships are fostered by this reciprocal communication.

Therefore, a new generation of competent workers has to be taught to adapt to these changing technologies in order to drive genuine advancement in the business. The role of AI in promoting human lifetime learning has changed dramatically, starting with the early intelligent tutoring systems that used AI to track and assist user learning and continuing with the conception of human-computer combined learning systems [1]. Mixed learning environments are created by HCCL systems, which incorporate AI entities as cooperative partners alongside human learners. Through both simulated and real-world settings, these systems allow people to hone their problem-solving and decision-making abilities in certain domains, promoting a more dynamic and flexible learning environment [2].

In the context of Industry 5.0, AI entities can be used as embodied agents, voice assistants, or cognitive advisor agents to promote collaborative working behaviors between humans and machines. The development of industries that exhibit human-automation symbiosis, where people and machines work together harmoniously, is facilitated by these technologies [3]. Both parties can take the initiative in a variety of activities in this dynamic setting, which promotes a productive and well-balanced collaboration in industrial production.

In order to increase operators' effectiveness in Industry 5.0 automation systems, this study aims to offer a human-centered architecture for the design, deployment, and assessment of cognitive advisor agents within the framework of a human cyber-physical production system [4]. A proof of concept will be demonstrated using a multi-agent scheme where an intellectual robot and a collaborative robot cooperate to assist the operator in completing a cooperative task. This setup will be used to assess the proposed H-CPPS architecture. Fig. (**1**) depicts the configuration of the symbiotic operator cobot assistant robot structure.

This chapter is arranged as follows. The vital role of human operators in this sector is first discussed, together with the contemporary Industry 5.0 model. The human cyber-physical production system's proposed architecture is then shown. Additionally, this architecture's method for handling cognitive tasks is demonstrated. Finally, the cognitive adviser concept that was intended to be included in the earlier design is presented. The chapter is being closed with conclusions and directions for further investigation.

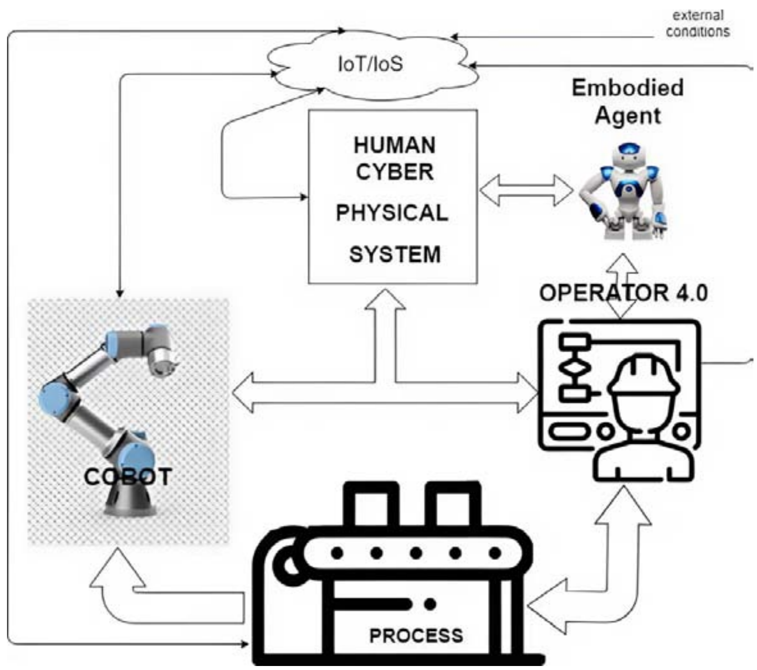

Fig. (1). Conceptual proof. The embodied agent helps the operator 5.0 work with the cobot.

Intellectual Robot: Refers to the physical robotic system (*e.g.*, a cobot) equipped with computational capabilities for performing tasks autonomously or semi-autonomously.

Embodied Agent: Refers to the robot as a whole, which physically exists and interacts with the environment.

Cognitive Advisor Agent: Refers to the virtual software agent that observes system states, analyzes human-robot interactions using models such as FRAM, and provides recommendations or interventions to support safe and efficient task execution.

THE WORKPLACE OF THE OPERATOR IN INDUSTRY 5.0

An operator in an industrial environment with the support of technology instruments is the broad definition of the operator 5.0 concept given in [5, 6]. Human operators remain essential components of production systems in the vision

CHAPTER 5

Innovations in AI for Smart Manufacturing and Automation

T. Preethiya[1,*], **T. Pandiarajan**[2] and **Priyanga Subbiah**[1]

[1] *Department of Networking and Communications, School of Computing, College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chengalpattu, Tamil Nadu, India*

[2] *Department of Computer Science and Engineering, Rajalakshmi Institute of Technology, Chennai, Tamil Nadu, India*

Abstract: Collaborations between Artificial Intelligence (AI) and the Internet of Things (IoT) have lately sparked interest in the business sphere. Conventional manufacturing techniques have changed significantly due to the numerous options for innovation, cost reduction, and efficiency increases provided by contemporary technology. From this chapter, the authors can understand the industrial sector's potential, where AI and IoT may be used, the combined consequences, and the obstacles. Today, many industrial companies are depending a lot on AI and the IoT to keep up with customers' constantly changing needs for high-quality products at reasonable rates. When in-dustrial businesses combine IoT sensors with AI algorithms, they may automate smarter jobs, make better decisions, analyze and use enormous amounts of data in real time, and speed up their operations. The emergence of extremely sophisticated, interconnected, and adaptable "smart fac-tories" is the result of integration. This chapter will cover the forecasts, case studies, and effects of AI and the Internet of Things on the industrial sector.

Keywords: AIoT, Automation, Artificial intelligence, Internet of things, Manufacturing, Smart factory.

INTRODUCTION

Businesses that sell goods and provide services-producing everything from vehicles and aircraft to computers and pharmaceuticals-are the backbone of every economy. The manufacturing sector, in particular, drives GDP growth, technological innovation, and employment creation. This sector's output relies on

* **Corresponding author T. Preethiya:** Department of Networking and Communications, SRM Institute of Science and Technology, College of Engineering and Technology, Kattankulathur, Chengalpattu, Tamil Nadu, India; E-mail: preethit3@srmist.edu.in

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three primary stages: design, manufacturing, and packaging. The modern manufacturing landscape is characterized by the following key features.

Advanced Technologies

The industrial sector has a rich history of capitalizing on economies of scale through process standardization and mass manufacturing. A shift towards customer-centric, agile, and adaptive strategies has occurred in the manufacturing industry throughout the past several years. Several factors, including globalisation, rapidly evolving technology, changing consumer preferences, and intense competition, are driving this change [1-3].

Global Supply Chains

Additive manufacturing, which uses terms like 3D printing, automation, digitisation, and machines, is the technology that powers many contemporary industrial operations. Due to these technological advancements, processing times and costs have decreased while efficiency, accuracy, and personalisation have been enhanced. As a consequence of globalisation, complex supply networks have developed to facilitate the procurement of goods, manpower, and resources. The best way to handle unpredictable market conditions is to have a supply chain that is stronger, more adaptable, efficient, and effective.

Quality and Compliance

Manufacturers must adhere rigidly to quality standards to guarantee their products are safe for customers and conform to all relevant rules and industry standards. Strict adherence to quality control protocols reduces product failures, recalls, and legal issues.

Sustainability and Environmental Responsibility

To deal with environmental concerns and the need to follow laws, many firms have put sustainability back on the agenda. Reducing carbon emissions, decreasing waste, and increasing knowledge of environmental concerns are the current motivators behind the push towards more environmentally friendly company operations.

Industry 4.0

Industry 4.0 initiatives employ cloud computing, big data analytics, the IoT, and AI to construct “smart factories” capable of autonomous operation, predictive maintenance, and real-time optimization. Digitalization and other technological developments have significantly impacted the manufacturing industry. Businesses that are able to take advantage of adopting AI and IoT will see that their future will depend on them [4, 5]. If the manufacturers use it promptly, they have the potential to compete higher, to play or do better. This chapter will examine how AI and the Internet of Things are used currently, what benefits and consequences they will have in the future for industry changes, and the replacement of outdated production techniques. The first pair of numbers is revolutionising the way several production processes occur with the help of the IoT and AI. In addition, the purpose is to provide a comprehensive introduction to the phenomenon, and in so doing, applies, supplies examples, and projects its future. The readers will have deep knowledge of how AI and IoT collaborate to provide different benefits and drawbacks, and how the two can be combined in a business setting.

REVIEW OF LITERATURE

There are recent developments in AI and IoT that allow the 'smart factories' to engage in database decisions, predictive maintenance, and collaborative machine learning [6]. It presents a comprehensive architecture for Cyber-Physical Systems (CPS) tailored for Industry 4.0-based manufacturing systems, emphasizing the synchronization of information between the physical and cyber spaces to enhance efficiency, collaboration, and resilience in manufacturing operations. In a study, the authors have used AI analytics and IoT sensors to track manufacturing operations in real time [7]. Finally, there would be far less downtime and much more efficiency. The framework proposed for Big Data-driven Product Lifecycle Management (PLM) emphasizes the integration of big data analytics with various phases of the product lifecycle, enhancing decision-making processes through real-time data collection and analysis. Predictive maintenance, which makes use of data gathered from IoT devices and AI models, can improve equipment cost-effectiveness and dependability [8]. The presented research introduces a novel framework for Smart Production-Logistics Systems (SPLS) based on Cyber-Physical Systems (CPS) and the Industrial Internet of Things (IIoT), primarily aiming to address challenges in job shop manufacturing and improve efficiency through intelligent modeling and self-organizing configurations. One of the key principles of Industry 4.0 is the development of AI and IoT-powered automated production systems tailored to individual customers [9]. Another study explained how AI and IoT affect industrial security, demonstrating that although these technologies are beneficial, they also pose new threats that need stringent cybersecurity policies to address [10]. Research shows IoT represents a key element in manufacturing operations and presents concrete benefits and information about implementation.

Smart manufacturing methods enabled by IoT using software-defined technology help manufacturers implement adaptive process control, mass customization, and

CHAPTER 6

AI-driven Collaborative Energy Management for Smart Cities Using Hybrid Optimization and IOT Data Fusion

S. Arunamary[1], **G. Sudhagar**[1], **S. Priya**[2,*] and **S. Prakash**[3]

[1] *Department of Electronics and Communication Engineering, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India*

[2] *Department of Electrical and Electronics Engineering, Academy of Maritime Education and Training (AMET) Deemed to be University, Chennai, Tamil Nadu, India*

[3] *Department of Electrical and Electronics Engineering, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India*

Abstract: Electric Vehicles (EVs), which are a cleaner and quieter alternative to conventional gasoline-fueled automobiles, are powered by electricity. An Electric Vehicle (EV) is one that is powered by electric motors and rechargeable batteries. This chapter describes a novel method for maximizing smart home appliance power consumption. It also introduces a new Secretary Bird Optimization ISBOA algorithm for more effective power consumption scheduling in time-of-use and critical peak pricing CPP schemes. To reduce energy costs and peak demand, two dynamic pricing methods, TOU-CPP, are used in this technique. This work addresses the major challenges in Smart home energy management, with a focus on enhancing user comfort while lowering electricity bills and peak demand. Through the incorporation of RES and ESD into the electrical grid, the proposed strategy creates a more efficient EMS. Because of this integration, CPP and TOU pricing schemes seek to reduce the Peak-to-Average Ratio (PAR) and redistribute the load to allow the best appliance sched-uling possible by categorizing household appliances, separated into three groups: hybrid, time-flexible, and power-flexible. The study creates a thorough load scheduling design that improves user comfort while maintaining energy efficiency. The benefits of the Tabu search method are combined with the pursuit and running habits of secretary birds in the ISBO algorithm, which improves on tra-ditional Secretary Bird Optimization (SBOA). This hybrid algorithm optimizes appliance scheduling based on power ratings and operational characteristics while dynamically adapting to current energy prices. The system allows users to schedule appliances more efficiently using Demand Response (DR) signals and real-time pricing data, resulting in cost savings and improved grid stability. The MATLAB simulation results show obvious decreases in energy use and electricity expenses in a range of situations.

* **Corresponding author S. Priya:** Department of Electrical and Electronics Engineering, Academy of Maritime Education and Training (AMET) Deemed to be University, Chennai, Tamil Nadu, India; E-mail: priyasakthikumar@gmail.com

S. Aasha Nandhini, R. Karthick Manoj, D. Lakshmi & Malathy Batumalay (Eds.)

Keywords: Demand response, Dynamic pricing, EMC, Improved secretary bird optimization, PAR.

INTRODUCTION

Due to continuous economic and technical developments, human energy consumption is continuously increasing, and the traditional power system is finding it difficult to meet this demand [1]. Meanwhile, rising worries about resource loss from energy consumption and ecological environment deterioration make it imperative to reduce energy consumption prices and boost energy efficiency [2]. The visualization of energy use and energy management using a HEMS as the main energy-saving remedy has been the progressive focus of residential energy optimization research in recent years [3]. One part of a Smart Grid (SG) is a Smart Meter (SM). Maintaining stability of supply and demand while respecting the SG's energy management goal. Furthermore, it seeks to reduce energy usage, improve Energy efficiency and consumer comfort, and attain optimal scheduling approaches [4]. To address these issues, home Demand-Side Management (DSM), a part of the smart grid concept, aims to regulate the electrical energy consumption that accounts for 269.9% of global final power consumption [5].

The demand for energy has significantly increased as a result of the economy's and population's continuous rise. At the same time, utility businesses and the environment are facing enormous strain. There are two realistic strategies to meet the rising demand for energy: DSM and GSM are two examples [6]. A framework for automating and optimizing domestic energy consumption scheduling that balances the number of hours required for each operating appliance to be in service with the requirement to reduce total power expenses. DSM is the name of this method [7]. One of the key components of the supply and demand sides to keep the SG in balance is DSM. In addition to assisting customers in lowering their electricity bills, DSM initiatives help utility operators maintain a reliable electric supply to assure user comfort. A key strategy within this investigation is to reduce load demand during peak times [8].

Dynamic pricing systems such as ToU, CPP, and real-time pricing are commonly utilized in DSM approaches. The pricing levels throughout operating hours are the main way that these plans differ from one another [9]. Throughout the day, the price varies under RTP. In addition to the shoulder, on-peak Prices are established under ToU, with a variable pricing scheme covering. With the exception of crucial peak periods, when it hits its maximum worth, the cost of power remains generally stable throughout the year under CPP [10]. Price changes have no influence on energy usage; they only affect the outcomes of energy expenses.

Smart home energy controllers receive a utility pricing indicator. The controller in energy management generates a timetable determined by the price signal and the user's load demand [11]. In the event that a dynamic pricing system is implemented in conjunction with DSM techniques, the price of power is based on the predicted energy consumption of the user. Generally speaking, prices can be raised when demand from customers outpaces supply. This increase in the cost of electricity affects all power system users [12]. By lowering peak demand, DSM regulates power prices in energy markets. As a result, there are two categories for all home loads: shiftable and non-shiftable groups [13]. Over the past few decades, a number of Demand Response DR answers have been developed to address the issue, especially throughout the busiest times of the day in residential areas. All of these advances have the same goals: reducing the PAR, consuming less power, and enhancing waiting time or User Comfort (UC) [14]. Different payment regimes are employed by utility companies; among the most popular ones include CPP, TOU, Day Ahead Price and RTP. Effective load demand reduction during the peak hours is achievable by this investigation [15].

The majority of this work's contributions are:

- A novel approach to scheduling appliance power consumption in a building based on the TOU and CPP pricing scheme is presented in this work. Peak demand and energy costs can both be decreased with this technique.
- An improved version of the Secretary Bird Optimization method is provided for scheduling appliances in smart homes. PAR, cost, and energy consumption are all optimized by ISBO by utilizing the secretary bird's hunting and fleeing habits in conjunction with the tabu search algorithm.
- Hybrid, power- and time-adaptable appliances are all combined in the proposed method’s hybrid design, and reduce overall investment in energy efficiency technologies on the grid by incorporating RES, such as solar panels. This makes energy management more effective.

LITERATURE REVIEW

There has been considerable research on the optimization of energy consumption in smart grids *via* Demand Side Management (DSM) aided by dynamic pricing mechanisms like TOU, CPP, RTP, and Day-AHead Pricing over the last few years. However, most techniques are either based on conventional metaheuristic methods or independent prediction models, which tend to fail to manage energy cost, PAR, and user comfort in actual operating constraints.

A number of studies have discussed metaheuristic-based DSM optimization. Particle Swarm Optimization (PSO) [16] and Grey Wolf Optimization (GWO)

CHAPTER 7

Deep Cognitive Computing with Swin-Bi-LSTM for Real-time SOC Estimation in Smart EV Battery Systems

S. Arunamary[1], **G. Sudhagar**[1], **S. Priya**[2,*], **S. Prakash**[3] and **P. Vinothkumar**[4]

[1] *Department of Electronics and Communication Engineering, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India*

[2] *Department of Electrical and Electronics Engineering, Academy of Maritime Education and Training (AMET) Deemed to be University, Chennai, Tamil Nadu, India*

[3] *Department of Electrical and Electronics Engineering, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India*

[4] *Department of Electrical and Electronics Engineering, Sri Krishna College of Engineering and Technology, Coimbatore, Tamil Nadu, India*

Abstract: State of charge (SoC) estimation is vital to the efficient and safe operation of Electric Vehicles (EVs). The exceptional properties of lithium-ion batteries, such as high-power density, long life, and wide operating temperature range, rapid charging, and low self-discharge, are making them more popular. To ensure that the EV batteries operate at their optimal level and safely, a Battery Management System (BMS) must be installed. By tracking the SoC, the BMS manages, preserves, and guarantees the longevity and operation of rechargeable batteries. The Li-ion battery dataset was first pre-processed through normalization and data cleaning. Inertial Weighted Principal Component Analysis (IW-PCA) derives features related to charge and discharge data from lithium-ion battery analysis. The derived features are then fed into the Swin-Bi-LSTM model, which is a combination of the Bi-LSTM model and the Swin transformer. The Transformer model has the ability to capture long-range dependencies accurately. The SA-AZOA method is then utilized to hyper-tune the proposed model. This optimization technique allows for efficient SoC estimation in order to acquire the optimal model configuration. Root Mean Square Error (RMSE), Normalized Mean Square Error (NMSE), Relative Error (RE), and Mean Absolute Error (MAE) are the evaluation indices that are employed. The proposed model, known as the Optimized Swin-Bi-LSTM (OSB) model, was tested on the NASA Li-ion battery dataset in MATLAB and showed higher performance, with the lowest RMSE of 0.76%. Reliable SoC assessment contributes to the increased confidence of consumers in their electric vehicles by accurately estimating battery status, reducing unscheduled vehicle downtime, and enhancing driving enjoyment.

* **Corresponding author S. Priya:** Department of Electrical and Electronics Engineering, Academy of Maritime Education and Training (AMET) Deemed to be University, Chennai, Tamil Nadu, India;
E-mail: priyasakthikumar@gmail.com

S. Aasha Nandhini, R. Karthick Manoj, D. Lakshmi & Malathy Batumalay (Eds.)

Keywords: American zebra optimization, Battery management system, EV, Li-ion battery, SOC, Swin-Bi-LSTM.

INTRODUCTION

The transportation sector is one of the greatest sources of greenhouse gas emissions due to its fossil fuel and internal combustion engine-based technology [1]. Electric Vehicles (EVs) are an option for cutting down on emissions and energy needs [2]. Emphasized by the interest in saving the environment and saving energy, EVs have evolved, particularly in the shape of Lithium-ion Batteries (LiBs) that have high energy density, long lifespan, and low self-discharge [3, 4]. LiBs are core to both the large (EVs) and small applications (mobile phones), and are central to renewable energy storage. The Electric Vehicle (EV) Battery Management System (BMS) monitors critical parameters such as voltage, current, and temperature for safe functioning [5, 6].

Enhanced charging optimizes Li-ion battery performance and lifespan, with overcharge protection managed by the BMS [7, 8]. SOC estimation is crucial for determining EV range and battery balance [9]. SOC estimation is, however, affected by factors like temperature variations and electromagnetic interference, making it a nonlinear instability issue [10]. Various methods, including circuit approaches, data-centric methods, AI, and traditional methods, have been proposed in order to cross this hurdle [11].

New artificial intelligence approaches have improved SOC estimation, surpassing traditional approaches by using extensive datasets to model SOC and battery parameter relations [12]. Data-driven techniques like SVM, deep learning, and neural networks correct the battery data nonlinearity and volatility [13]. RNN-based architectures like GRU and LSTM consider battery aging, but newer transformer models, which do sequence processing in parallel, have faster and more efficient alternatives [14].

The major contributions of this work are as follows

- Feature extraction with IW-PCA improves the accuracy and effectiveness of models through the reduction of dimensionality and the preservation of most data values, offering more flexibility than PCA in handling data variations.
- Integration of the Swin Transformer and Bi-LSTM models enhances performance by using the Swin Transformer to handle long-range dependencies and Bi-LSTM to handle past as well as future context in time series data.
- The paper also proposes a new approach known as the SA-AZOA algorithm. The optimization method that mimics the behavior of the American Zebras is

utilized to adjust the model parameters.

- The structure of the paper is as follows: Section 2 provides an overview of the literature. Section 3 describes the proposed method. Section 4 provides an overview of the findings. The conclusion of the paper is found in Section 5.

LITERATURE REVIEW

To rectify this, an Improved Adaptive EKF (IAEKF) was presented, using Sage-Husa EKF (SHEKF) with a forgetting factor to self-correct the error covariance matrix adaptively [15]. Although more robust, these techniques remain subject to constraints when implemented over diverse driving conditions and battery chemistries.

To surpass the shortcomings of conventional models, studies have turned towards Deep Learning (DL) paradigms increasingly. Feedforward Deep Neural Networks (FDNNs) have been used for multi-output prediction of SOC, modeling relationships among speed, mileage, voltage, and SOC [16]. More developments integrated Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks for extracting temporal features, allowing improved monitoring of dynamic system behaviors under different driving cycles [17, 18]. However, DL models are not immune to weaknesses such as overfitting, vanishing gradients, and poor generalization, which persist as problems. In response, hybrid models arose. For example, CNN-Bidirectional Weighted GRU (CNN-BWGRU) and NARX-LSTM models were created in an effort to improve feature learning and prevent gradient explosion [19, 20]. Nesterov Accelerated Gradient (NAG) utilization in Bi-GRU optimization provides better convergence with the use of momentum-based learning [21].

A number of works investigate hybridization to improve predictive accuracy. AdaBoost-BPNN approaches combine boosting with backpropagation networks, further enhancing estimation precision with weight adjustments of weak learners [22]. Similarly, the combination of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) with BPNNs improves resilience with noisy and unknown data conditions [23]. A Smooth Variable Structure Filter (SVSF) within the context of an Interactive Multiple Model (IMM) framework has been suggested to estimate SoC, internal resistance, and aging effects simultaneously [24]. Ensemble and hybrid methods were indicative of movement toward the development of adaptive noise-resistant systems. The depth in the architecture and regularization techniques has also been a point of emphasis. Research indicates that a 10-layer ANN with Dropouts and Batch Normalization layers provides the best performance for SOC estimation, avoiding overfitting and ensuring accuracy [25]. Furthermore, reconstruction networks have been proposed to recast voltage

CHAPTER 8

Cognitive Industrial IoT in Healthcare Revolutionizing Intelligent Care Delivery

R. Karthick Manoj[1,*], **S. Aasha Nandhini**[2], **G. Abirami**[3] and **Ganesan Krishnan**[4]

[1] *Department of Electrical and Electronics Engineering, Academy of Maritime Education and Training (AMET) Deemed to be University, Chennai, Tamil Nadu, India*

[2] *Department of Electronics and Communication Engineering, Sri Sivasubramaniya Nadar College of Engineering, Chennai, Tamil Nadu, India*

[3] *Department of Computer Science and Engineering, B.S. Abdur Rahman Crescent Institute of Science and Technology, Chennai, Tamil Nadu, India*

[4] *Department of Physics, Faculty of Science, Universiti Teknologi Malaysia, Johor Bahru, Malaysia*

Abstract: Industrial Internet of Things (IIoT) and cognitive technologies like AI, ML, and NLP are transforming healthcare. This adoption shifts marketplaces from reactive and compartmentalized to intelligent, networked, and patient-centered. The IIoT tracks real-time data for medical devices, wearables, and infrastructure, but cognitive technologies will help these systems learn, reason, and make decisions for predictive analytics, personalized treatment, and resource efficiency. The chapter then examines how cognitive IIoT changes the future of key health care domains like predictive maintenance, real-time patient monitoring, intelligent hospital operations, AI-assisted diagnosis, and cold drug logistics. Cognitive-enabled IIoT systems provide early diagnosis, optimize hospital opera-tions, and use data to make clinical choices, improving clinical outcomes, decreasing operational costs, and improving care. Although promising, large-scale cognitive IIoT adoption in healthcare has problems such as data privacy and security, integrating new technologies into legacy systems, ethical considerations in machine-led judgments, and high implementation costs. The chapter addresses how legislation, interoperability standards, and technology innovation might overcome these constraints. Thus, the cognitive IIoT represents a paradigm shift in healthcare delivery, not merely a tech im-provement. Healthcare providers may better meet patient requirements, streamline operations, and prepare for demand by using continuous, predictive, and intelligent technologies. This paradigm shift might change 21st-century and future healthcare delivery.

[*] **Corresponding Author R. Karthick Manoj:** Department of Electrical and Electronics Engineering, Academy of Maritime Education and Training (AMET) Deemed to be University, Chennai, Tamil Nadu, India; E-mail Karthickmanoj.r@gmail.com

S. Aasha Nandhini, R. Karthick Manoj, D. Lakshmi & Malathy Batumalay (Eds.)

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INTRODUCTION

The framework to be utilized in understanding the transformation by the cognitive IIoT in healthcare is to analyze its two main parts. Industrial Internet of Things (IIoT) and cognitive technologies, and inquiring about their synergistic combination. These elements combined give rise to a digital ecosystem built around the idea that data flows from devices into decision makers that are empowered by the machine intelligence that increases human capability.

INDUSTRIAL INTERNET OF THINGS (IIOT)

IIoT is the term used to describe the network of tangible objects, which, after integrating sensors, software, and connective capabilities, are capable of collecting, sharing, and reacting to data [1]. In healthcare, such devices include wearable fitness trackers to connected inhalers, and complex machines to hospital infrastructure systems [2]. Data captured from these devices includes physiological cues (*e.g.*, heart rate, blood oxygen levels), environmental cues (*e.g.*, temperature, humidity), as well as operational metrics (*e.g.*, equipment usage and power consumption). It is the real-time visibility into health and functionality of both patients and healthcare assets that makes IIoT valuable for real. Nevertheless, traditional IIoT systems can only process such data and need human intervention to decode the data into insights.

COGNITIVE TECHNOLOGIES

Cognitive technologies represent a set of AI-based approaches emulating human cognitive processes [3]. These technologies encompass machine learning for pattern recognition and prediction, natural language processing for unstructured text, and computer vision for images. In contrast, while rule-based automation needs to be updated manually with the introduction of new information about the work, cognitive systems learn from the data and can be adapted to take new information into account, and can generate outputs having a certain probability. In healthcare, cognitive technologies allow machines to analyze large amounts of data, establish subtle correlations, and help clinicians make decisions. They are especially good at dealing with complexity and uncertainty – two things that medical surroundings are bound to contain.

The Synergy: Cognitive IIoT

When combined, IIoT and cognitive technologies constitute a dynamic, intelligent ecosystem that can be capable of real-time sensing, contextual reasoning, and self-decision making [4]. This combined system works on a multi-layered architecture, transforming raw data to obtain actionable insights. At the Data Acquisition Layer, IIoT-enabled equipment like wearables, sensors, and smart medical equipment constantly stream real-time data from multiple sources such as patients, the hospital infrastructure, and environmental monitors. This new wave of data is then transmitted to the Data Processing layer, where it is cleansed, normalized, and structured to ensure that it meets the right quality and consistency to be analyzed further [5]. The next step is the Cognitive Analytics Layer, where artificial intelligence models are used for analysis of the processed data, including machine learning algorithms and pattern recognition tools. Such models recognize trends and detect anomalies, then make predictions or recommendations that are contextually appropriate to clinical and operational needs. The derived insights are then relayed to the healthcare provider *via* the Decision Support Layer, which could include intuitive dashboards, current alerts, or automated system responses, so that timely decisions are taken based on these insights. Finally, the Feedback Layer takes up a significant part in the system evolution; it tracks outcomes, tracks performance, and applies these insights to continuously improve and re-train the AI algorithm, making sure that it remains adaptable and improves over time. When combined, the multiple layers produce an architecture that not only collects data but also transforms it into useful insights. This fundamentally changes the dynamics of healthcare, allowing systems to shift from being merely data-rich to being insight-rich.

HEALTHCARE 5.0 PARADIGM

AI is bringing about a revolution in the medical field in the 21st century. Within the context of smart healthcare, this chapter investigates the shift in mentality that occurs when artificial intelligence is applied to healthcare organizations. Business 4.0 has been replaced by Industry 5.0 in the healthcare industry, which has resulted in the introduction of a new dimension and feeling. A new age of healthcare that is tailored, proactive, and efficient is about to begin with the introduction of smart healthcare [6]. The purpose of this chapter is to explain how artificial intelligence, as part of smart healthcare in Industry 5.0, has the potential to revolutionize healthcare delivery, improve patient outcomes, and address ethical and data privacy concerns.

A new level of ideology in the healthcare industry was reached as a result of the applications of Artificial Intelligence (AI), smart devices, and high-speed data

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S. Aasha Nandhini

Dr. S. Aasha Nandhini, Assistant Professor Grade II in the Department of Electronics and Communication Engineering, SSN College of Engineering (Autonomous), Chennai, has received her B.E. degree in Electronics and Communication Engineering from Anna University and M.E. degree in Communication Systems from Anna University. She obtained her Ph.D. degree from Anna University for her research work on Compressed Sensing based Secured Video Transmission in Wireless Multimedia Sensor Networks. Before joining SSN, she was an Assistant Professor at SRM Institute of Science and Technology. She has around 10 years of teaching and research experience. Her research interests include Wireless Multimedia Sensor Networks, Image and Video Processing, Internet of Things and Machine Learning. She has two books, six book chapters, ten publications in reputed international journals, eleven international conferences and a granted patent titled "A System, Device and Method for Plant Disease Detection and Alert" to her credit.

R. Karthick Manoj

Dr. R. Karthick Manoj is an Assistant Professor in the Department of Electrical and Electronics Engineering at AMET Deemed to be University, Chennai. He received his Ph.D. in Machine Learning from AMET Deemed to be University in 2024, with research focusing on artificial intelligence–based disease detection frameworks. His research interests include machine learning, computer vision, smart agriculture, IoT, and medical image analysis. He has published over 20 research articles in SCI/Scopus/Web of Science indexed journals and more than 25 papers in national and international conferences. He has authored three books and contributed over twelve book chapters with leading international publishers. Dr. Manoj holds four granted patents and two published patents in the areas of AI, IoT, and smart systems. He has served as Co-Principal Investigator for externally funded research projects and is an active member of several professional bodies.

D. Lakshmi

Dr. D. Lakshmi is a distinguished Professor in the Department of Electrical and Electronics Engineering at the Academy of Maritime Education and Training, Deemed to be University, Chennai, Tamil Nadu, India, with over 25 years of academic and research experience in power systems and intelligent energy technologies. She has successfully guided more than 40 undergraduate students, 15 postgraduate students, and 7 research scholars, with four scholars having completed their doctoral degrees. Her scholarly output includes 12 authored books, 21 book chapters, over 85 publications in SCI and Scopus-indexed journals, and numerous national and international conference papers. Her research interests span power system operation and control, renewable energy systems, microgrids, soft computing, electrical machines, and artificial intelligence applications in energy systems. Dr. Lakshmi has received several prestigious awards from organizations such as IEEE, the Institution of Green Engineers, and IEI. She is a Senior Member of IEEE and actively serves as an editor and reviewer for reputed international journals, contributing significantly to academic publishing and research advancement.

Malathy Batumalay

Dr. Malathy Batumalay earned her Master's degree in Engineering from the University of Malaya, Malaysia, and subsequently completed her PhD in Photonics Engineering at the same institution. Her research focuses on lasers, fiber optics, fiber sensors, and plasmonic sensing technologies. She has made notable contributions by developing fiber-optic sensors capable of detecting variations in relative humidity and chemical solutions. Dr. Batumalay actively collaborates with national and international researchers, resulting in numerous high-quality publications in reputed journals. She also serves as a reviewer for several scholarly journals and holds a committee position in the Optical Society of Malaysia, contributing to initiatives that support young researchers. She is a registered Professional Engineer with the Board of Engineers Malaysia and a Chartered Engineer with The Institution of Engineering and Technology, UK. Currently associated with a leading private university in Malaysia, she serves as Director of the Center for Data Science and Sustainable Technologies, Chair of the University Research Committee, Chief Internal Auditor for Malaysia Research Assessment, and Managing Editor of the Journal of Innovation and Technology.