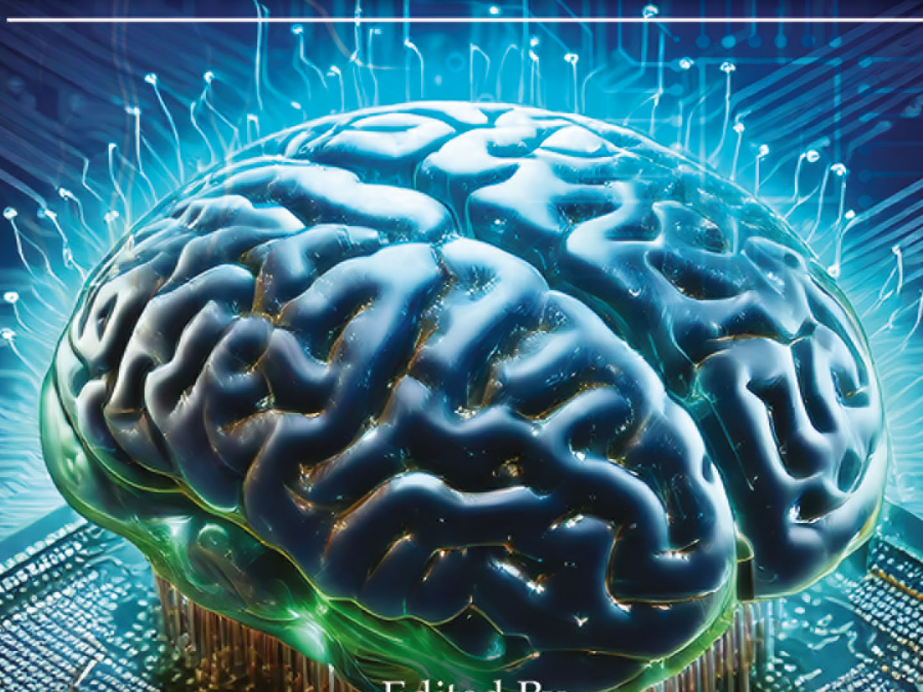

INTEGRATING NEUROCOMPUTING WITH ARTIFICIAL INTELLIGENCE



Edited By
**Abhishek Kumar, Pramod Singh Rathore,
Sachin Ahuja, Umesh Kumar Lilhore**

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Foreword

The convergence of neurocomputing and artificial intelligence (AI) marks a transformative era in computational sciences. As AI continues to evolve, its intersection with neurocomputing has paved the way for brain-inspired models, cognitive computing, and adaptive intelligence, leading to groundbreaking applications across various industries. This book, *Integrating Neurocomputing with Artificial Intelligence*, provides a timely and comprehensive exploration of this emerging domain, offering insights into both foundational theories and cutting-edge advancements.

In the current technological landscape, AI has made significant strides in machine learning, deep learning, reinforcement learning, and natural language processing. However, despite these advancements, conventional AI systems often struggle with energy efficiency, real-time adaptability, and cognitive reasoning, areas where neurocomputing plays a crucial role. Neurocomputing, inspired by the structure and function of biological neural networks, provides novel computational paradigms that aim to mimic the brain's learning, perception, and decision-making abilities. This book delves into the integration of these fields, showcasing how neuromorphic computing, brain-inspired AI, and hybrid models can create more efficient, intelligent, and sustainable systems.

The chapters in this volume bring together leading researchers, engineers, and industry experts, presenting a multidisciplinary perspective on topics ranging from neuromorphic architectures, spiking neural networks (SNNs), bio-inspired computing, and hybrid AI models to their applications in healthcare, robotics, autonomous systems, cybersecurity, and smart environments. This compilation not only highlights state-of-the-art research but also underscores the challenges and opportunities that lie ahead in building more adaptive, interpretable, and scalable AI systems.

As industries increasingly adopt AI-driven solutions, the need for brain-like intelligence, real-time decision-making, and computational efficiency has never been more critical. This book serves as an essential resource for

academicians, professionals, and students seeking to understand and contribute to the rapidly evolving field of AI-integrated neurocomputing.

I commend the editors and contributors for their remarkable effort in compiling this insightful volume. I am confident that *Integrating Neurocomputing with Artificial Intelligence* will inspire researchers, innovators, and practitioners to explore new frontiers in intelligent computing, ultimately shaping the future of AI-driven technologies.

Dr. Rashmi Agrawal

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Preface

This book is organized into seventeen chapters. In Chapter 1, energy management in modern smart grids requires intelligent decision-making systems that optimize energy distribution and consumption. This chapter explores the synergy between fog computing and AI-driven energy models, presenting an architecture that enhances energy distribution efficiency. Using machine learning and neural networks, the authors demonstrate an advanced cloud-fog-based decision-making framework that ensures seamless energy optimization while addressing latency issues.

In Chapter 2, neural networks have revolutionized language processing and text analytics, yet challenges remain in integrating temporal dependencies efficiently. This chapter introduces a hybrid approach that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for superior performance in natural language processing (NLP) tasks. Through detailed simulations, the authors provide insights into architecture design, training techniques, and performance benchmarking.

In Chapter 3, this chapter explores the use of Industry 4.0 is driven by autonomous mobile robots, which require secure, real-time decision-making systems to navigate industrial environments safely. This chapter presents a cyber-physical security framework that leverages Software-Defined Networking (SDN) and Internet of Robotic Things (IoRT) to enhance robotic safety. The proposed system enables secure communication, real-time threat mitigation, and automated attack detection.

In Chapter 4, in this research chapter, Medical diagnostics have greatly benefited from AI-powered feature extraction and pattern recognition techniques. This chapter explores a hybrid neuro-fuzzy computing framework designed for disease classification and medical image analysis. The authors present a linguistic fuzzification model that enhances disease detection accuracy, offering significant contributions to biomedical AI applications.

In Chapter 5, the book chapter affords brief and general information regarding Advancements in neuromorphic vision systems are transforming robotic automation. This chapter presents an AI-powered neuromorphic vision-based control system for robotic drilling applications, improving precision, speed, and adaptive learning. The authors discuss sensor integration, event-based vision processing, and real-time control strategies, making this work highly relevant to industrial robotics and automation.

In Chapter 6, autonomous vehicles require real-time decision-making models that mimic human cognitive functions. This chapter discusses neuromorphic AI frameworks that enhance path planning, perception, and adaptive control in self-driving cars. The proposed neural engineering architecture integrates spiking neural networks and reinforcement learning to improve vehicle maneuverability and collision avoidance.

In Chapter 7, brain-Computer Interfaces (BCI) enable direct neural communication with machines, leading to significant advancements in humanoid robotics and assistive technologies. This chapter introduces an adaptive BCI system for humanoid robot control, focusing on steady-state visual evoked potentials (SSVEPs) and real-time signal processing techniques for enhanced human-robot interaction.

In Chapter 8, decision-making is a fundamental AI application across industries. This chapter explores deep learning-based decision-making models that improve operational performance in business, healthcare, and logistics. The authors present an Artificial Neural Network (ANN)-based framework, focusing on predictive analytics, optimization, and intelligent automation.

In Chapter 9, speech recognition plays a critical role in human-computer interaction and automated language translation. This chapter presents an AI-powered speech recognition framework leveraging Natural Language Processing (NLP) and deep learning. The authors discuss acoustic modeling, error correction, and real-time voice scoring, highlighting practical applications in education and AI-driven assistants.

In Chapter 10, in this chapter user give AI-driven medical imaging has enhanced early detection of ocular diseases. This chapter introduces deep learning-based neurocomputing models for classifying ophthalmological disorders using Optical Coherence Tomography (OCT) images. The proposed YOLOv3 and ResNet50 architectures improve diagnostic accuracy, offering valuable insights for automated medical analysis.

In Chapter 11, data security is critical in modern communication systems. This chapter presents an innovative multi-image steganography

model using Deep Convolutional Neural Networks (CNNs). The approach introduces private keys for encrypted image transmission, ensuring high security, robustness against steganalysis, and effective information concealment.

In Chapter 12, biodiversity conservation benefits from AI-driven species classification models. This chapter presents a deep learning-based framework for automated honey bee subspecies identification, utilizing morphometric analysis and image processing. The proposed model significantly improves classification accuracy, demonstrating the potential of AI in entomology and ecological research.

In Chapter 13, neural networks have revolutionized speech recognition and acoustic modeling. This chapter explores spiking neural networks (SNNs) for automatic speech recognition (ASR), presenting models for large vocabulary speech processing and phoneme recognition. The authors analyze energy-efficient deep SNNs, making significant contributions to speech technology advancements.

In Chapter 14, this chapter engages in discusses Brain-Computer Interfaces (BCIs) enable direct neural interaction with humanoid robots, transforming rehabilitation and assistive technology. This chapter discusses a brainwave-controlled robotic system based on steady-state visual evoked potentials (SSVEPs), showcasing its applications in robotic control and cognitive computing.

In Chapter 15, this book chapter presents Medical data augmentation using Generative Adversarial Networks (GANs) improves diabetes prediction models. This chapter presents a GAN-based approach for simulating glucose monitoring data, enhancing machine learning models for hypoglycemia detection and personalized diabetes care.

In Chapter 16, in this study, Neuromorphic computing offers brain-inspired AI solutions for high-performance computing and edge intelligence. This chapter presents an in-depth analysis of spiking neural networks, reservoir computing, and quasi-backpropagation algorithms, highlighting their impact on neuromorphic hardware and AI applications.

In Chapter 17, this chapter explains the purpose of Quantum computing is reshaping AI by enabling parallel computation and probabilistic learning. This chapter explores the integration of quantum machine learning with neural networks, focusing on quantum-enhanced reinforcement learning, quantum annealing, and quantum convolutional networks (QCNNs).

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Integrating Fog Computing with AI Model on Decision Making for Distribution of Energy Management

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Abstract

New obstacles to effective energy organization for system process are emerging as the number of Internet of Things strategies and dispersed energy possessions in the next-generation spreading network continues to grow. One explanation is that the supervisory control and data achievement system has limited computing and storage capacity; thus, it cannot link all the large-scale resources. An innovative approach to energy management known as cloud-fog classified architecture is presented in this study as a means to meet the evolving demands of next-generation distribution networks. The utility and revenue model that developed based on this design included regular consumers, prosumers, and operators of the distribution system. Additionally, energy management might be automatically accomplished by integrating an AI module into the suggested design. This study employs neural networks at the fog computing layer to make regression predictions of power source output and energy use behavior. Moreover, at the network's cloud layer, a genetic algorithm was used to optimize prosumers' and customers' energy usage in accordance with the maximizing utility goal function. Results, including recorded

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customer use patterns and stakeholder income, show that the suggested strategies work with a sample of regular and prosumer consumers in a generic distribution network. Building next-generation distribution network real-time energy management systems may benefit significantly from this work as a reference.

Keywords: Internet of Things, energy management, regression, predictions, cloud layer

1.1 Introduction

Conventional power users who own these small-scale generating facilities are becoming prosumers due to the fast penetration of DERs into the distribution network (DN). This means that they use energy from the utility grid and produce it [1, 2]. More grid operating flexibility is being made possible by the rising number of active prosumers, who enable bidirectional energy flows. Both ecological concerns and the desire of home prosumers to reap the benefits of efficient energy transactions with the grid are propelling this shift [3, 4].

By 2020, experts predict that 26 billion gadgets will be linked to the Internet of Things (IoT). A new age has dawned with the advent of the Internet of Things (IoT), in which a wide variety of end devices and sensors are connected wirelessly or via wires using different forms of contemporary communication and the Internet [5–7]. An ever-increasing number of controllable units are a part of the DN's energy operation and management process, and the frequency of information and data exchange between various parties is on the rise due to the proliferation of IoT devices and the widespread use of energy cyberspace knowledge in the power grid [8, 9]. A new generation of distribution networks is possible because of the widespread adoption of smart devices and renewable energy sources (RES) in the distribution network [10, 11]. This next-generation delivery grid's real-time energy management is becoming increasingly important [12].

With the widespread use of distributed RES and the integration of massive Internet of Things (IoT) devices into next-generation distributed networks (DN), this study intends to tackle the problem of energy management and executive [13]. First, a hierarchical fog-cloud design is suggested for decision-making and energy management. AI technologies deployed independently in fog and cloud layers using the large-scale data created in DN may capture customers' consumption and RES production [14]. Users' energy consumption behavior may be captured by microeconomic theory as well [15]. The model encompasses several stakeholders, including regular customs, prosumers, and the distribution system operator (DSO).

Finally, the method's practicality is shown by optimizing retail power pricing and managing diverse DN stakeholders' income in real time [16, 17].

The paper is prepared like this. Section 1.2, lays down the groundwork for the cloud-fog hierarchical architecture that propose for DN energy management and explain how fog and cloud layer's function. Part 3 of the model describes the typical consumer, the prosumer, and the DSO. In Section 1.4, put the verification into action by incorporating AI technologies into the cloud and fog layers for energy organization and executive. At the fog layer, the main focus is on predicting power consumption and creating renewable energy sources (RES), while in the cloud, optimization of computations for particular objectives takes place. Optimal goal optimization with complete social welfare reproduction including ordinary users, prosumers, and DSO in a local DN based on utility and income models.

1.2 Methodology

1.2.1 Energy Management Using a Cloud-Fog Hierarchical Architecture

The suggested cloud-fog hierarchical architecture is mostly presented in this portion (see Figure 1.1). The fog computing deposits conduct gathering analysis and regression forecast by mining the fundamental data from the units of main consumers and prosumers in the DN. Using the cloud computation layer allows us to optimize the overall goal.

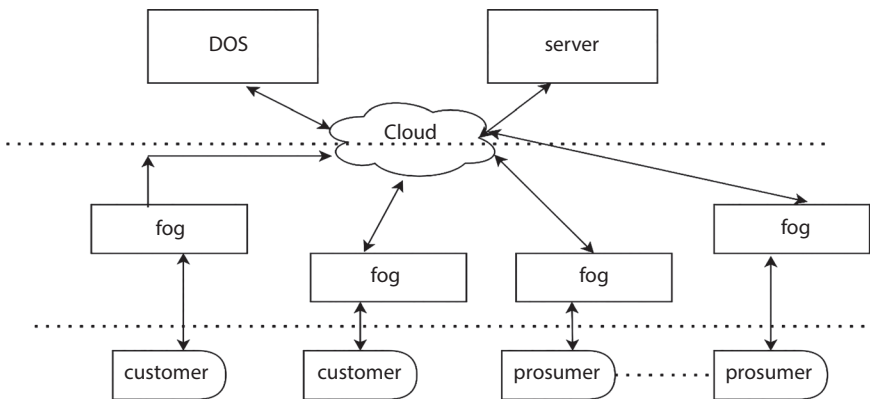


Figure 1.1 Energy management using cloud fog. Distribution operator.

1.2.2 Units Terminal

Customer or prosumer-installed DER (Internet of Things, photovoltaic, wind turbine, storage, etc.) and other IoT devices make up the terminal units of the next-generation DN. The communication and connectivity structure of the DN is shown in Figure 1.2. The database system stores data from clever meters and IoT devices. Fog layers, which are linked to the database systems, may conduct particular computational operations and prepare input for services supplied by higher layers. Wireless or wired protocols like Zigbee, 802.11, and 802.15 may facilitate communication between the device and the local area network gateway [18, 19]. Also, the gateway may gather data from utilities as well as Internet of Things devices; then, the terminal units and DN may communicate using the Open ADR protocol to operate the stated behaviors.

1.2.3 Operating Fog Layers

Fog computing involves placing databases and central processing units (CPUs) at the DN’s designated nodes to handle requirements from users and DN operators [20, 21]. By storing and managing the terminal information, fog computing may alleviate the strain on cloud data processing and latency. Figure 1.2 shows that the user’s smart meter and gateway may be communicated with by the fog computing nodes.

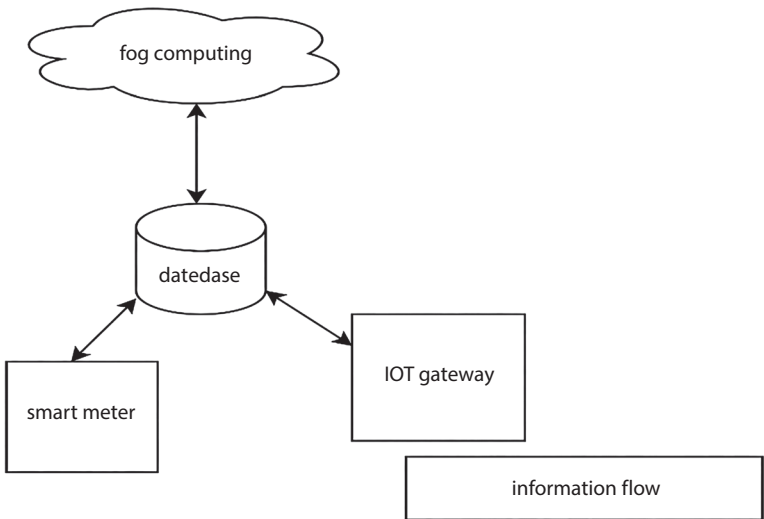


Figure 1.2 IoT device communication diagram.

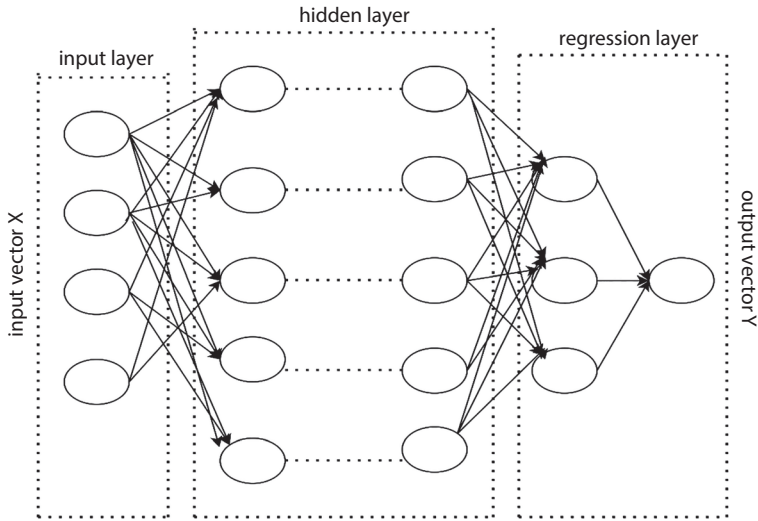


Figure 1.3 Neuronal network (NN) deployment diagram for fog layers.

Furthermore, under some scenarios, customers' power use behavior may be captured by AI modules put at the fog layers. As the amount of data continues to grow, artificial neural networks (ANN) have shown encouraging gains in machine learning and pattern recognition. Figure 1.3 shows how artificial NNs may be trained and utilized for regression analysis using sample data. A typical ANN has three types of input layers: hidden, regression, and general [22, 23]. For instance, in a regression study of a user's power consumption, the variables that may influence consumption behavior are the input data and the quantity of energy used is the output. Then, use NN's regression analysis to forecast how consumers and prosumers would consume. This lets distribution system operators get sufficient load management data from the fog computing layers. In addition, geographical data, weather reports, distributed power type, and other inputs may be used in reversion analysis using NN learning and exercise at fog layers using the outputs from RES for prosumers [24–26].

1.2.4 Operation of the Cloud Layer

Optimal scheduling, stability calculations, and market transaction participation are all responsibilities of the cloud layer, which makes decisions founded on data acquired from fog films and manages the energy consumption of the whole DN. A vast area network, like the Internet, may be

used to communicate with fog and provide command information. The best choice will be assisted by the AI algorithm that is implemented on the cloud [27–29].

In this paper, GA a method that consistently solves large-scale discrete and nonlinear problems—to take on the cloud-established global optimization issue. Through the use of the goal function, GA encodes all potential issue solutions into a vector, with each gene being a component of the vector. In a manner similar to how mutation, trade, and natural selection work in biology, this method ensures that only the strongest will remain. As seen in Figure 1.4, new generations are produced by various GA processes such as selection, exchanging, and mutation based on the degree of fitness.

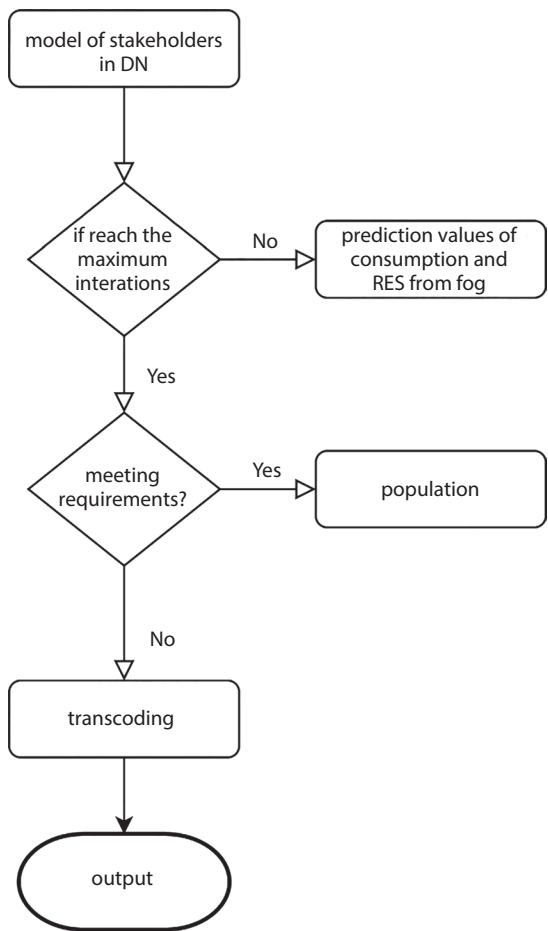


Figure 1.4 Graph showing how the genetic algorithm may optimize decision making.

1.3 Modelling of Different Distribution Network Stakeholders

1.3.1 Consumers' Usefulness Model

Users' tastes and patterns of power use are often unrelated. Using the Internet of Things (IoT), smart meters, and big data knowledge makes it feasible to record each user's power consumption patterns. Collecting data like infection, electricity price, energy time, power, etc., allows one to study the electrical habits of clients. Using microeconomics' functional idea, this research constructs a utility model for residential consumers. Various efficacy functions $U(XIT, \dot{u}IT)$ are chosen to represent the user's power level. The function represents customers' utility satisfaction. In this research, a quadratic equation function with diminishing bordering utility to define $U(XIT, \dot{u}IT)$.

$$U(X_I^T, W_I^T) = \left\{ W_I^T X_I^T - \frac{\alpha}{2} (X_I^T)^2 \right\}$$

Where it stands for the amount of energy the client uses at time slot T , ωIT describes how the user uses energy at time slot t , and $\alpha 0$, a predetermined value, denotes the unchanging circumstances.

Figure 1.5 displays how utility variations for different consumers as energy consumption increases. Additionally, it shows that, to varied

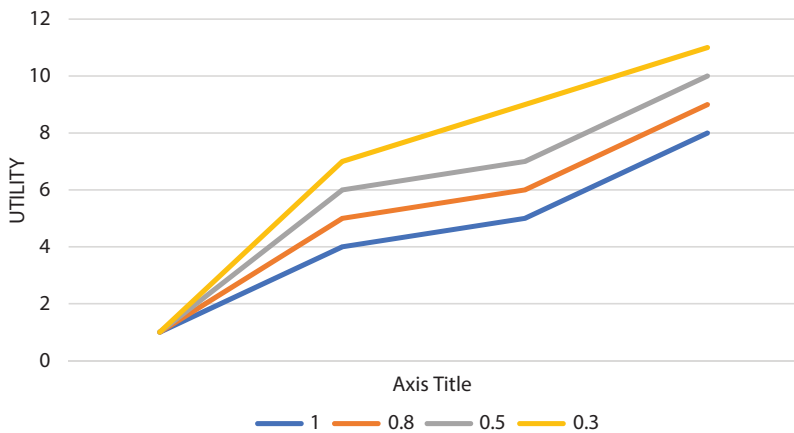


Figure 1.5 Energy consumption as a utility function for customers.

degrees, bordering utilities of all levels of pleasure are lessening. As an illustration of the declining impact, the marginal utility $\ddot{u} = 0.5$ is used.

The customer's utility and the cost of buying power make up the customer's overall income. This leads to the following expression for customer's comprehensive utility in time interval t :

$$R_{CUMSTOMERS, I = \sum_t^T [u(x_i^t, w_i)]$$

where x_{it} is the amount of energy used by client i at time slot t and $P_{tailert}$ is the real-time trade price for buying energy of consumers.

1.4 Results

This test utilizes a generic distributed network (DN) to spread 55 prosumers, each with a 20KW RES and 503 typical consumers. The suggested cloud-fog construction is used to optimize decision-making and execute energy management. Data generation rate and prosumer and customer locations dictate the placement and amount of fog nodes. Typically, the distribution grid's point of standard coupling (PCC) links the prosumers to a bus of the fundamental DN. Word trees and photovoltaics are the significant types of generators among prosumers. Tesla Powerwall's are used for storage, with a capital cost of ₹416250 INR and a lifespan of 15 years. Before calculating the real-time consumption characteristics $\ddot{u}$, prosumers and consumers may use energy management techniques such as flow, regression, and forecasting at the fog layers for renewable energy sources (RES) and loads. The cloud layer may also maximize the DN's retail price and the total quantity of energy bought from the wholesale market.

1.4.1 Operating a Fog Computing System

F fog layers utilize multi-layer feed-forward NNs trained using the Levenberg-Marquardt approach to track and understand how much electricity each customer uses. After that, forecasts are generated using regression analysis. This test makes use of the load data from blond buildings in Germany. This is a list of the NN parameters: The data supplies the following details: 1) the input data is the expected value of the clients' incessant load; 2) the output data is time, temperature, humidity, and lighting; 3) this NN has a single hidden layer with ten neurons; 4) training uses 70% of the data, validation 15%, and testing 15%. 5) A network's generalizability

being unaltered will cause NN training to end. This is where the regression analysis yielded its conclusions.

Figure 1.6 shows that after 34 generations of NN training, the root-mean-square error begins to meet the criterion, and after 40 iterations, it stops learning. A positive regression effect is often defined as a result greater than 0.9. With an R-value greater than 0.92, the reversion effect is considered adequate after training. Figure 1.7 shows the graph of normalized utility.

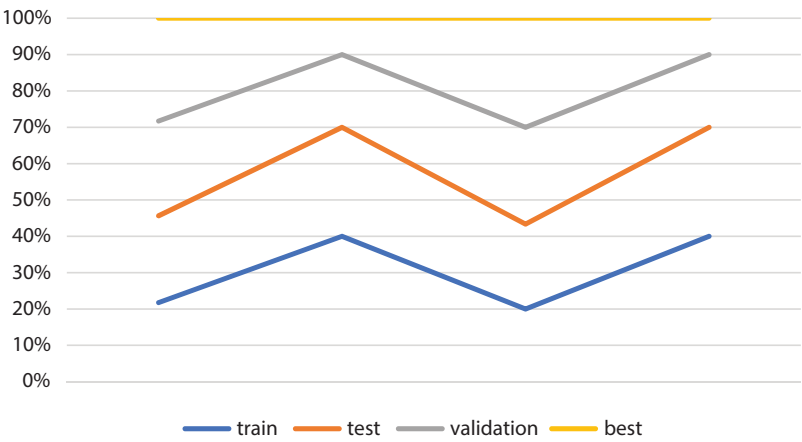


Figure 1.6 A trajectory for the generalization of NN learning.

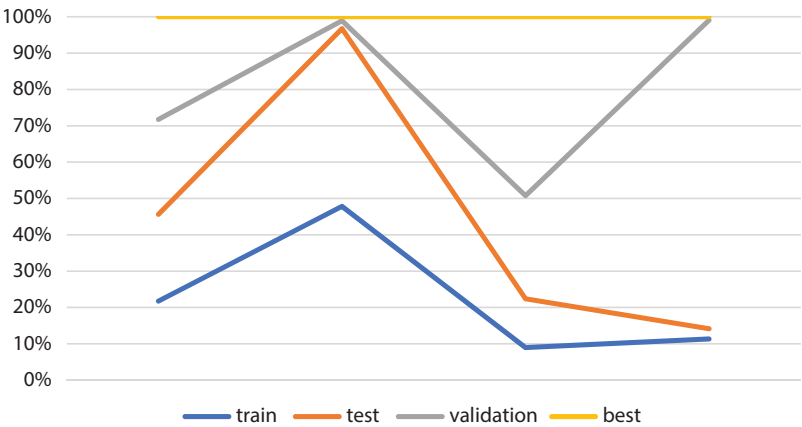


Figure 1.7 The utility function is available to customers in only 1 day.

Prosumers' RES output power may also be predicted using the NN incorporated in fog computing layers. Like load prediction by regression analysis, the procedure is straightforward. Even if they are not using NN to forecast RES output power here, since Another area of research is the use of NN for RES prediction; this test also includes a daily storage operation for arbitrage or prosumers. To make the test more efficient, the data of renewable energy sources that flow into the grid are taken straight from Open Energy Information (OpenEI).

1.4.2 Computing Operation Cloud

The goal of maximizing overall social welfare, as described in Section 4.1, is put into action at the cloud computation layer using data acquired from fog layers. Here are the specifics of the different parties involved:

Each time slot's $\ddot{u}$ is taken as v , the average value, when optimization is done in real-time at the cloud layer. On a global scale, in the cloud, the intelligent GA tool optimizes decision-making goals. The following parameters of GA are chosen:

- Cross-inheritance is set to 0.6.
- The mutation rate is 0.05.
- Maximum genetic algebra is 30.
- The population size is chosen as 40.

The input data of 13 hours to ensure the method is correct before computing the whole time (1–24 hours). The GA algorithm's convergence trajectory is seen in Figure 1.8.

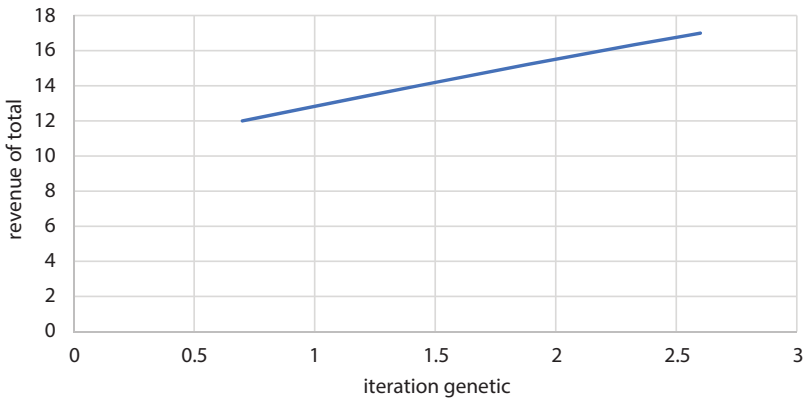


Figure 1.8 GA optimization convergence trace.