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PREFACE

This book presents a collection of forward-looking studies that address key technological developments shaping modern communication, energy, education, and security systems. The chapters emphasize intelligent, adaptive, and connected solutions designed to respond to regional and global challenges through innovative engineering and system design.

The first chapter, Developing an Adaptive Resource Allocation Framework for Energy-Efficient Fifth Generation (5-G) Networks in West Africa, explores strategies for optimizing network performance while minimizing energy consumption. By focusing on the West African context, it highlights the importance of context-aware and sustainable approaches in deploying next-generation communication infrastructures.

The second chapter, Hybrid Multifunctional Audio-Video System for Interactive E-Learning and Multimedia: Design and Application, examines the role of integrated multimedia technologies in enhancing digital education. It demonstrates how well-designed audio-visual systems can support interactivity, accessibility, and effective knowledge transfer in modern learning environments.

The final two chapters extend the discussion to intelligent automation and sustainable energy systems. A Smart Autonomous Robotic System for Automated Surveillance and Public Space Protection: An IoRT Approach for Enhanced Security presents an interconnected robotic framework for improving public safety, while Internet of Things for Management of Solar PV Integrated Electric Vehicle Battery System highlights IoT-driven solutions for efficient energy management and green mobility. Together, these contributions offer a cohesive view of how emerging technologies can be integrated to build smarter, safer, and more sustainable societies.

Editorial Team
January 26, 2026
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CHAPTER 1
DEVELOPING AN ADAPTIVE RESOURCE ALLOCATION FRAMEWORK FOR ENERGY-EFFICIENT FIFTH GENERATION (5-G) NETWORKS IN WEST AFRICA

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INTRODUCTION

Fifth-generation (5G) mobile networks represent a transformative leap in wireless communication, designed to support unprecedented levels of connectivity, massive device densities, ultra-high data rates, and mission-critical low-latency applications. Unlike previous generations, 5G is characterized by a heterogeneous architecture that integrates enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC) into a unified ecosystem. The convergence of these service categories introduces complex resource management demands that significantly heighten energy consumption—particularly within the Radio Access Network (RAN), which historically accounts for 70–80% of total mobile network power usage.

The rapid expansion of data-intensive applications such as augmented reality, immersive media, autonomous vehicles, and industrial automation has accelerated mobile traffic growth in both developed and developing regions. In West Africa, the rise of digital services, fintech ecosystems, smart agriculture, and e-governance has created new socio-economic opportunities while intensifying pressure on existing communication infrastructure. However, the region faces unique operational challenges including erratic grid supply, high diesel dependency, climatic variability, and economic barriers to large-scale infrastructure investment. These contextual factors amplify the urgency for energy-efficient 5G deployment strategies tailored to African environments.

From a technical standpoint, several 5G-enabling technologies inherently introduce substantial energy demands. Massive Multiple-Input Multiple-Output (MIMO) systems, for example, employ antenna arrays ranging from 64 to 256 elements, enabling spatial multiplexing but consuming two to three times more power than their 4G counterparts due to increased baseband processing and radio frequency overhead. Similarly, millimeter-wave (mmWave) frequency bands, while offering multi-gigabit throughput, suffer from severe path loss and require dense small-cell deployments to maintain coverage, further escalating network energy requirements. Network slicing, edge computing, and real-time orchestration add additional layers of computational complexity, contributing to elevated operational expenditures (OPEX) and carbon emissions.

Energy inefficiency in 5G networks is not merely a technical issue but an economic and environmental concern. Globally, the information and communication technology (ICT) sector is estimated to consume 3–5% of total electricity and contribute approximately 2–4% of greenhouse gas emissions—figures projected to rise without deliberate intervention. In Nigeria and other West African nations, where diesel generators power a majority of base stations, network operators incur substantial fuel costs while contributing to local air pollution and carbon emissions. As the region transitions toward widespread 5G adoption, addressing energy efficiency becomes essential for sustainability, affordability, and long-term network resilience.

Adaptive resource allocation has emerged as a promising solution to the energy-performance trade-offs inherent in 5G networks. Traditional static allocation mechanisms fail to account for rapidly changing traffic patterns, environmental conditions, and heterogeneous service requirements. In contrast, adaptive and intelligent resource allocation frameworks leverage real-time analytics, traffic prediction, and machine learning (ML)-driven decision-making to dynamically optimize resource distribution, power consumption, and quality of service (QoS) parameters. By integrating hybrid models such as Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), and reinforcement learning algorithms like Proximal Policy Optimization (PPO), modern 5G systems can achieve substantial gains in energy efficiency while maintaining stringent performance baselines.

This work situates these innovations within the broader context of West African telecommunications, providing a comprehensive analysis of adaptive energy-efficient resource allocation strategies tailored to the region's operational realities. Building on empirical data from field deployments, simulation frameworks using NS-3 and MATLAB, and renewable energy experimentation, the chapter proposes a unified framework that integrates ML-driven scheduling, solar-assisted energy management, and standardized energy efficiency metrics aligned with 3GPP and ITU-T guidelines. The remainder of the chapter is organized as follows: the literature review examines theoretical and empirical contributions in 5G energy efficiency research; the methodology outlines the simulation, algorithm development, and validation processes.

The results and discussion section presents key findings from both simulated and real-world deployments; and the conclusion offers policy implications, recommendations, and future research directions relevant to 6G evolution.

1. LITERATURE REVIEW

Research on energy-efficient fifth-generation (5G) networks has grown rapidly due to the rising demand for sustainable, high-performance wireless systems. As global mobile traffic expands and next-generation services such as ultra-reliable low-latency communications (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communications (mMTC) evolve, resource management challenges in 5G networks have intensified. The complexity of 5G architecture—characterized by massive MIMO arrays, millimeter-wave (mmWave) frequencies, network slicing, and edge computing—has increased the importance of adaptive, intelligent, and energy-conscious approaches to network operation.

This section synthesizes theoretical foundations, empirical findings, and emerging trends in energy-efficient 5G resource allocation, with emphasis on African contexts, where infrastructural and environmental characteristics significantly influence network performance.

1.1 Theoretical Framework

The theoretical underpinnings of energy-efficient 5G systems lie across three domains: communication theory, optimization theory, and machine learning (ML). Together, these domains explain how energy consumption can be minimized while sustaining performance requirements such as latency, reliability, and throughput.

Energy Efficiency Models

Energy efficiency (EE) in wireless networks is commonly quantified as bits-per-joule, measuring how effectively transmitted data uses available power. Traditional models assume linear relationships between transmit power, circuit power, and baseband processing. In 5G systems, however, power consumption grows nonlinearly due to:

- High-density antenna arrays in massive MIMO systems,
- Beamforming overhead,
- Complex channel estimation processes,
- mmWave signal processing and compensation for propagation loss, and
- Network slicing orchestration and virtualized network functions.

To address these complexities, contemporary EE models incorporate metrics such as latency-per-joule, energy-per-bit, and device-density-per-watt, enabling more accurate evaluation across diverse 5G services and architectures.

Optimization Theory Foundations

Optimization plays a central role in resource allocation for energy-efficient networks. Earlier approaches relied on convex optimization, dynamic programming, and mixed-integer formulations. However, the stochastic and dynamic nature of 5G networks makes these approaches computationally expensive for real-time operation.

Alternative methods include:

- Genetic algorithms and particle swarm optimization, which offer near-optimal solutions with reduced computational cost;
- Heuristic and metaheuristic algorithms for large-scale and nonlinear resource allocation problems;
- Hybrid methods combining convex relaxation with heuristic refinement to improve solution quality.
- These strategies support dynamic adjustment of power, bandwidth, and scheduling to match fluctuating traffic and channel conditions.

Machine Learning Foundations

Machine learning has emerged as a transformative tool in optimizing 5G energy use. Key ML models include:

- Long Short-Term Memory (LSTM) networks: Effective for traffic forecasting and time-series analysis.
- Graph Neural Networks (GNNs): Capture spatial and topological relationships across interconnected base stations.

- Reinforcement Learning (RL) techniques: Enable autonomous decision-making by learning optimal resource allocation through interaction with the network environment.

Algorithms such as Deep Q-Networks (DQN), Actor-Critic models, and Proximal Policy Optimization (PPO) provide scalable, context-aware optimization across diverse resource management tasks—including base station sleeping, power scaling, and beam selection.

1.2 Empirical Studies on 5G Energy Efficiency

Empirical studies highlight both the potential and challenges of 5G deployment. Research on massive MIMO demonstrates significant spectral efficiency gains but shows that circuit and baseband power consumption can be two to three times higher than in legacy systems. Similarly, experiments involving mmWave frequencies reveal the need for densified small-cell networks, which increase cumulative energy demand due to the number of active sites required.

Field measurements from Asia and Europe show that advanced sleep modes, intelligent beam management, and adaptive carrier activation can reduce energy consumption by 20–40% under moderate traffic. However, these solutions often rely on stable power grids and favorable climatic conditions—factors that may not be present in West African scenarios.

African-focused studies identify unique influences on energy demand:

- High ambient temperatures increase cooling requirements.
- Erratic grid supply forces dependency on diesel generators.
- Terrain and climatic variability affect propagation conditions.
- Limited fiber backhaul availability increases radio power consumption.

These findings underscore the importance of designing frameworks specifically tailored to West African constraints.

1.3 Adaptive Resource Allocation Mechanisms

Adaptive resource allocation integrates real-time analytics, predictive modeling, and ML-based decision systems to optimize energy efficiency. Key mechanisms include:

Traffic-Aware Scheduling: Forecasts traffic loads using historical patterns, enabling networks to scale resources up or down depending on anticipated demand.

Queue-Aware Resource Management: Adjusts scheduling based on buffer occupancy to maintain latency targets while avoiding unnecessary power expenditure.

Channel-Aware Allocation: Uses channel state information (CSI) to optimize modulation schemes, coding rates, and transmit power, ensuring only necessary resources are allocated.

QoS-Aware Reinforcement Learning: Balances QoS requirements with energy constraints, particularly for URLLC and eMBB services, where reliability and throughput thresholds must remain intact.

Hybrid systems combining LSTM-GNN models with reinforcement learning significantly improve prediction accuracy and decision speed. Trials report energy savings of 15–40%, depending on network density and traffic patterns.

1.4 Renewable Energy Integration Research

The shift toward green communications has motivated research on solar-assisted base stations, particularly in regions with high solar irradiance such as West Africa. Studies explore:

- Solar photovoltaic (PV) systems with MPPT controllers,
- Hybrid energy storage using lithium batteries and supercapacitors,
- ML-based irradiance prediction for proactive energy management,
- Autonomous power switching between solar, grid, and battery sources.

Case studies from Nigeria, Kenya, and Ghana reveal that solar-powered base stations can reduce diesel use by up to 70%, but challenges persist, including:

- Equipment theft and vandalism,
- Battery degradation under high temperatures,
- High initial capital cost.

Nonetheless, renewable-powered 5G RANs remain a critical component of sustainable digital development in Africa.

1.5 Identified Research Gaps

The literature reveals several gaps that justify the need for an adaptive, West Africa-focused resource allocation framework:

- Lack of real-world 5G energy-efficiency studies in West Africa.
- Limited integration of environmental and economic constraints in optimization models.
- Underutilization of hybrid ML models (LSTM + GNN + PPO) in RAN energy-saving applications.
- Absence of standardized 5G EE metrics tailored to developing regions.
- Minimal research on solar-assisted autonomous RAN architectures for low-resource environments.
- Few studies exploring cross-layer adaptive frameworks combining RAN, edge computing, and energy management.

These gaps inform the methodological and experimental directions of this chapter.

1.6 Summary

The literature indicates significant advancements in energy-efficient 5G resource allocation, but challenges remain—especially for developing regions with unstable power infrastructure and unique environmental conditions. By integrating insights from communication theory, optimization, machine learning, and renewable energy research, this chapter proposes an adaptive framework that addresses these gaps and aligns with the sustainability needs of West African telecommunications networks.

2. METHODOLOGY

This section outlines the methodological approach used to develop, simulate, and validate the proposed adaptive resource allocation framework for energy-efficient 5G networks in West Africa. The methodology integrates machine learning–based prediction models, reinforcement learning–driven optimization, system-level simulations, and limited field measurements. Each stage is designed to reflect the infrastructural, environmental, and economic realities of telecommunications deployment in the region.

The methodology comprises four major components: (1) system modeling and assumptions, (2) dataset development, (3) adaptive algorithm design, and (4) simulation and evaluation. Together, these steps provide a rigorous foundation for assessing the performance and feasibility of the proposed framework.

2.1 System Model and Assumptions

The system model is based on a heterogeneous 5G network architecture that includes macro base stations (MBS), small cells (SCs), user equipment (UE), and an edge-computing layer. The model incorporates the following assumptions, consistent with 3GPP Release 16 specifications:

Radio Access Network (RAN):

- Massive MIMO with 64–128 antenna elements deployed at macro sites.
- mmWave (28 GHz) and sub-6 GHz (3.5 GHz) dual connectivity.
- SCs deployed at a density of 25–60 per km^2 in urban areas.

Power Models:

- Macro cells have a power budget of 800–1,200 W, small cells 75–150 W.
- Circuit power consumption is modeled as a nonlinear function of antenna activity.
- Energy harvesting units (solar PV) supply supplementary power to selected MBS and SCs.

Traffic Models:

- eMBB traffic modeled with self-similar heavy-tailed distributions.
- mMTC modeled using Poisson arrival and exponentially distributed service requirements.
- URLLC arrivals mimic sporadic burst patterns.

Environmental Models:

- Temperature variation modeled using seasonal averages from Nigerian Meteorological Agency (NiMET) datasets.
- Solar irradiance modeled using hourly data from three West African cities: Kano, Accra, and Dakar.
- Grid availability modeled as a binary Markov chain with region-specific outage patterns.

These assumptions ensure that the model reflects realistic deployment conditions in West African telecommunication networks.

2.2 Dataset Development

The study incorporates three types of datasets: (1) traffic data, (2) environmental and power data, and (3) simulation-generated network performance data.

Traffic Data Collection

Traffic datasets were obtained through:

- Crowdsourced mobile network reports from live 4G and 5G pilot sites.
- Publicly available datasets from the Open Cellular Network Infrastructure Repository.
- Synthetic augmentation using stochastic traffic models to simulate peak, off-peak, and irregular demand patterns.

Features extracted include:

- Hourly user density
- Average data rate per UE
- Traffic burstiness index
- Mobility patterns and handover probabilities

These features are used to train LSTM–GNN prediction models.

Environmental and Power Data

To evaluate solar-assisted energy optimization, the study incorporates:

- Hourly solar irradiance values
- Ambient temperature readings
- Battery charge/discharge logs
- Grid availability and outage durations

Data were collected from Nigeria's NiMET, the Ghana Space Science and Technology Institute (GSSTI), and the Senegal National Solar Radiation Database.

Simulation-Generated Data

The NS-3 mmWave module and MATLAB 5G Toolbox were used to generate additional network performance metrics such as:

- Spectral efficiency
- SINR distribution
- Beamforming patterns
- Base station load levels
- Dynamic power consumption

These datasets feed into the RL-based optimization algorithm for training and evaluation.

2.3 Adaptive Algorithm Design

The proposed adaptive resource allocation framework integrates three intelligence blocks:

Traffic Prediction Block (LSTM–GNN Hybrid)

A hybrid Long Short-Term Memory (LSTM) and Graph Neural Network (GNN) architecture is used to predict traffic distributions across the RAN. The LSTM captures temporal variations in traffic, while the GNN models spatial correlations between base stations.

- LSTM Layer: Learns historical demand patterns.
- GNN Layer: Represents the network topology, capturing load dependencies across adjacent cells.
- Output: Traffic load prediction 5–15 minutes ahead with an average RMSE below 8%.

These predictions guide proactive resource allocation.

RL-Based Resource Allocation (PPO Algorithm)

Reinforcement learning is used to optimize physical resource block (PRB) allocation, beamforming activation levels, and base station sleep modes. The Proximal Policy Optimization (PPO) algorithm was selected for its stability, robustness, and efficiency in continuous action spaces.

State Space Variables:

- Predicted traffic load (from LSTM–GNN)
- CSI values
- Queue lengths
- Solar energy availability
- Battery state-of-charge
- Base station active/idle status

Actions:

- Activate or deactivate antenna panels
- Adjust transmit power
- Reassign PRBs between services
- Schedule sleep/wake cycles for small cells
- Switch between grid, solar, and battery power

Reward Function:

Defined as a weighted combination of:

- Energy efficiency (EE): bits-per-joule
- Latency satisfaction rate
- QoS compliance for URLLC and eMBB
- Energy savings from renewable use
- Penalty for unnecessary switching or QoS violations

The RL agent interacts with the simulated environment to learn optimal strategies over time.

Renewable Energy Management Block

An adaptive solar-energy management system predicts available solar power using irradiance forecasts and dynamically adjusts:

- Load sharing between solar, battery, and grid
- Cooling demand prediction based on ambient temperature
- Battery charge/discharge cycles to extend lifespan

The block operates alongside the RL controller to ensure reliable and efficient power usage.

2.4 Simulation Tools and Configuration

NS-3 Simulation Setup

NS-3 (version 3.37) was chosen for its robust 5G mmWave simulation capabilities. The following modules were used:

- mmWave PHY and MAC layers
- LENA module for LTE/NR interoperability
- Energy Framework for modeling power consumption
- Mobility models for pedestrian and vehicular UEs

The simulation covers:

- 1 km^2 urban grid with 2 macro sites and 24 small cells
- 1,200 active UEs
- Mixed-service profiles (eMBB, URLLC, mMTC)

Monte Carlo simulations were performed across differing environmental and traffic conditions.

MATLAB 5G Toolbox Setup

MATLAB was used for:

- MIMO channel modeling
- Beamforming optimization
- Power consumption evaluations
- Dataset preprocessing and analysis
- LSTM–GNN training scripts

The combined NS-3 and MATLAB workflow ensures both physical-layer accuracy and system-level performance realism.

2.5 Evaluation Metrics

The following metrics were used to evaluate the framework:

- Energy Efficiency (bits/joule): Measures throughput relative to total energy consumed.
- Latency-Per-Joule: Assesses energy cost required to achieve latency targets, essential for URLLC.

- SINR Distribution: Evaluates signal quality under adaptive beamforming.
- Base Station Active Ratio: Tracks time spent in active, idle, and sleep modes.
- Carbon Emission Reduction: Estimates emissions saved from solar-assisted operation.
- Renewable Usage Ratio: Measures percentage of operational hours powered by solar or battery.

These indicators reflect both technical performance and environmental sustainability.

2.6 Summary

The methodological framework integrates advanced machine learning, reinforcement learning, realistic simulation environments, and renewable energy modeling to evaluate adaptive resource allocation for 5G networks in West Africa. By grounding the design in region-specific constraints and datasets, the methodology ensures that the proposed solution is both technically robust and practically feasible within the context of West African telecommunications.

3. RESULTS AND DISCUSSION

This section presents the results obtained from the simulation experiments and analytical evaluations described in the methodology. The discussion highlights how the proposed adaptive resource allocation framework—integrating hybrid LSTM–GNN traffic prediction, PPO-based reinforcement learning optimization, and solar-assisted energy management—improves energy efficiency, Quality of Service (QoS), and sustainability outcomes in 5G networks deployed within typical West African environments. Findings are reported across multiple dimensions, including prediction accuracy, energy savings, latency performance, renewable energy utilization, and resilience under grid instability. Comparative analysis against baseline models provides a detailed understanding of the relative performance and practical implications of the proposed framework.

3.1 Traffic Prediction Performance

LSTM–GNN Prediction Accuracy

The traffic forecasting model was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and prediction horizon accuracy metrics. The hybrid LSTM–GNN model outperformed standalone LSTM networks and basic autoregressive models.

Table 1. Traffic Prediction Model Performance Comparison

Model	RMSE	MAE	10-Min Accuracy
ARIMA	0.164	0.121	71%
LSTM	0.109	0.078	84%
LSTM–GNN (proposed)	0.079	0.052	91%

The improvement is attributed to the GNN’s ability to learn spatial correlations between adjacent base stations, making the model particularly effective in dense small-cell environments. This accuracy is essential for correctly predicting when cells can be placed in sleep mode or powered down to conserve energy.

Impact on Resource Allocation

Higher prediction accuracy directly enhanced the quality of decisions produced by the reinforcement learning agent. Simulation logs show that incorrect predictions led to suboptimal resource activation, wasted PRBs, and avoidable power consumption. The hybrid model reduced misallocations by approximately 27% compared to standalone LSTM predictions.

3.2 Reinforcement Learning Optimization Outcomes

PPO-Based Policy Performance

The PPO-based RL agent demonstrated stable convergence and superior performance compared to Deep Q-Learning (DQN) and Actor-Critic (A2C) models. It learned to balance energy usage, QoS requirements, and renewable energy availability efficiently. Convergence characteristics showed that PPO stabilized after approximately 40,000 interaction steps, whereas DQN and A2C required more steps and exhibited oscillatory behavior due to the continuous action space inherent in 5G resource control.

Energy Efficiency Improvements

The proposed RL-based framework achieved notable improvements in energy efficiency metrics across macro and small cells.

Table 2. Energy Efficiency Performance Comparison

Framework	Macro Cell EE (bits/J)	Small Cell EE (bits/J)
Static allocation (baseline)	18.3	32.4
Heuristic allocation	22.1	37.8
Proposed RL-based framework	29.7	46.5

These results indicate:

- 62% improvement in macro-cell energy efficiency
- 43% improvement in small-cell energy efficiency

Such improvements are significant because RAN energy usage accounts for the majority of operational expenditure for mobile network operators in West Africa.

Dynamic Base Station Sleep Optimization

By combining accurate traffic prediction and RL-based scheduling, the system reduced active hours for small cells by 18–35% depending on traffic density. During off-peak hours, the RL agent consistently placed between 6 and 12 small cells into deep sleep mode while maintaining QoS compliance. Macro cells experienced smaller but still valuable sleep opportunities.

This is especially relevant in West African contexts, where powering each site requires substantial energy due to temperature-related cooling needs and limited grid reliability.

3.3 Latency and QoS Performance

eMBB and URLLC Latency Outcomes

Latency performance was evaluated for both eMBB and URLLC users. Results show that the proposed framework maintains stringent latency requirements despite aggressive power-saving strategies.

Table 3. Latency Performance for eMBB and URLLC Services

Service Type	Baseline Latency	Proposed Framework Latency
eMBB	14.2 ms	10.9 ms
URLLC	1.83 ms	1.51 ms

Reductions are attributed to intelligent PRB reallocations and queue-aware resource scheduling.

Packet Loss and Reliability

URLLC packet loss dropped from 0.17% under heuristic allocation to 0.09% under the proposed framework—well within 3GPP reliability standards. This shows that energy-efficient operation does not compromise reliability when intelligently managed.

3.4 Renewable Energy Integration Outcomes

Solar Utilization Efficiency

Solar-powered base stations showed significant improvement in energy autonomy when combined with ML-based irradiance prediction and RL-based usage optimization.

Table 4. Solar Utilization Efficiency Comparison

Metric	Baseline Solar System	Proposed Hybrid System
Average solar utilization	38%	57%
Grid dependency	49%	28%
Battery cycling efficiency	71%	86%

The RL agent successfully learned to:

- Prioritize battery usage during grid outages,
- Reduce deep discharging cycles, and
- Maximize solar harvesting during peak irradiance.

These improvements extend battery lifespan—a vital factor in hot West African climates.

Emission Reduction Estimates

By reducing reliance on diesel generators, the model generated estimated monthly CO_2 savings of:

- 0.42 tons per macro site, and
- 0.11 tons per small-cell cluster

When scaled across a medium-sized operator with 1,200 sites, this translates to more than 450 tons of CO_2 avoided annually.

3.5 Performance Under Grid Instability

Adaptive Response to Power Outages

Grid instability is a defining characteristic of network operations in West Africa. The RL agent demonstrated effective energy balancing, ensuring that:

- QoS compliance remained stable at 96–98% during outages
- Base stations operated 22% longer on battery and solar backup
- Diesel generator activation frequency dropped by 37%

These outcomes highlight the framework's robustness in low-resource environments.

3.6 Comparative Evaluation Against Existing Approaches

Static and Heuristic Approaches

Compared to static allocation, the proposed framework:

- Reduced total network energy usage by 31%
- Reduced cooling power usage by 14%
- Increased PRB utilization by 29%
- Maintained higher QoS compliance

Compared to heuristic (rule-based) systems:

- Energy savings improved by 18%
- Latency reduced by 22%
- Outage survival time increased

ML-Only Approaches

Approaches using only ML prediction without RL optimization performed poorly in complex scenarios such as:

- Rapidly fluctuating mmWave channels
- Irregular traffic surges
- Grid-blackout conditions

This confirms that real-world networks require closed-loop optimization, not purely predictive models.

3.4 Discussion of Findings

Implications for West African 5G Deployment

The results demonstrate that adaptive ML-driven resource allocation frameworks can significantly mitigate energy challenges in West African networks. The integration of solar energy, predictive analytics, and RL provides a pathway for:

- Lowering OPEX for operators
- Reducing carbon emissions
- Enabling stable connectivity during power outages

Practical Deployment Considerations

Practical considerations include:

- Initial hardware cost for solar hybrid systems
- Need for improved battery anti-theft mechanisms
- ML model retraining due to seasonal variability
- Scalability challenges for dense urban centers such as Lagos or Accra

Alignment with Global Sustainability Goals

The findings align with ITU-T L.1300 standards for green data centers and 3GPP energy efficiency guidelines. They also support the United Nations Sustainable Development Goals (SDGs 7, 9, and 13). The proposed adaptive framework demonstrates substantial improvements in energy efficiency, QoS, resilience, and sustainability for 5G networks in West Africa.

Through advanced ML and RL techniques, renewable energy integration, and context-aware optimization, the framework provides actionable strategies for operators seeking cost-effective and environmentally responsible network deployments.

This chapter developed and evaluated an adaptive resource allocation framework designed to improve energy efficiency in 5G networks within the West African context. By integrating LSTM–GNN-based traffic prediction, Proximal Policy Optimization (PPO) reinforcement learning for dynamic resource allocation, and solar-assisted energy management, the framework provides a robust, context-aware approach to addressing the persistent challenges of energy consumption, grid instability, and rising operational costs that characterize telecommunication environments in the region.

The results demonstrate that the proposed framework significantly enhances energy efficiency across both macro and small cells, achieving up to 62% and 43% improvements respectively compared to static and heuristic methods. The hybrid ML prediction model successfully reduces allocation errors, supporting timely base station sleep scheduling and power optimization. Solar-assisted energy management further reduces dependency on diesel generators and fossil-based sources, contributing meaningfully to carbon emission reductions and extending the operational lifespan of batteries in high-temperature climates.

Beyond energy improvements, the framework sustains high-quality network performance, delivering lower latency, reduced packet loss rates, and stable QoS compliance even under grid instability—conditions common in many parts of West Africa. The combined simulation and limited field validation affirm that the adaptive framework is technically feasible, environmentally beneficial, and economically viable for large-scale deployment.

Given the projected expansion of digital services, industrial automation, fintech, and e-governance in West Africa, energy-efficient 5G deployment is not merely desirable but essential for long-term sustainability. This framework provides a strategic pathway for operators, regulators, and policymakers seeking to balance performance needs with energy constraints while aligning with global sustainability standards and regional development priorities.

CONCLUSION

Based on the findings, several recommendations are proposed for operators, policymakers, academic researchers, and industry stakeholders to support effective and sustainable 5G deployment in West Africa.

For Network Operators

Adopt ML-Driven Traffic Prediction Systems: Operators should integrate advanced prediction models, such as LSTM–GNN architectures, to anticipate traffic surges and confidently implement dynamic resource adjustment without compromising user experience.

Implement RL-Based Resource Allocation: Reinforcement learning algorithms like PPO should be embedded into RAN controllers to enable autonomous real-time optimization of PRB scheduling, antenna activation, and power scaling.

Deploy Solar-Assisted Base Stations: Operators should prioritize hybrid solar-grid-battery systems, especially in rural and peri-urban communities where grid reliability is low. This reduces OPEX and ensures service continuity during grid failures.

Establish Monitoring Dashboards: Real-time dashboards for energy consumption, traffic patterns, and base station activity should be deployed to support informed operational decisions and reduce inefficiencies.

Strengthen Physical Security for Solar Installations: Anti-theft mechanisms such as tamper-proof enclosures, GPS-enabled trackers, and community-based site monitoring should be implemented to protect renewable energy assets.

For Policymakers and Regulatory Bodies

Develop Regional 5G Energy Efficiency Standards: Regulators should establish unified metrics and reporting benchmarks—such as bits-per-joule, renewable usage ratio, and latency-per-joule—tailored to the environmental and infrastructural realities of West Africa.

Create Incentives for Renewable Integration: Tax rebates, import-duty exemptions, and subsidies can reduce the initial cost of deploying solar-powered telecom infrastructure.

Mandate Energy Efficiency Reporting: Operators should be required to annually report energy consumption, renewable usage, and carbon emission profiles, encouraging transparency and compliance with green communication goals.

Promote Local Manufacturing of Solar Components: Supporting local industries will reduce import dependency, lower costs, and strengthen sustainability in the long term.

Strengthen Collaboration with Power Utilities: Regulators and telecom operators should collaborate with national electricity providers to reduce outage durations and optimize grid-support mechanisms for communication infrastructure.

For Academic and Research Institutions

Expand Context-Aware Energy Studies: Future research should incorporate granular datasets reflecting seasonal, regional, and cultural patterns that influence network traffic and energy needs.

Advance Hybrid ML–RL Algorithms: Researchers should explore newer deep learning architectures and multi-agent RL for large-scale, multi-tier 5G networks.

Investigate 6G Energy Efficiency Models: As 6G concepts emerge—such as THz communications and AI-native networks—research must look ahead to future sustainability challenges.

Develop Open-Source Simulation Libraries: Universities should collaborate to build region-specific simulation tools and datasets for students and practitioners.

For International Development Partners

Support Green ICT Projects: International agencies should invest in energy-efficient telecommunications infrastructure, particularly in underserved communities.

Provide Capacity-Building Grants: Grants should support training programs on ML, RL, and renewable integration for engineers and researchers in the region.

Promote Cross-Country Knowledge Exchange: Platforms for sharing lessons and best practices across African telecom stakeholders will accelerate regional innovation.

Future Work

Several research directions remain open for further investigation:

- Multi-Agent Reinforcement Learning: Future frameworks may use cooperative MARL to coordinate multiple base stations for collective energy optimization.
- Real-World Pilot Deployments: Large-scale field trials across different West African countries will provide stronger empirical validation.
- Integration with Edge and Cloud AI: AI-native 5G networks leveraging edge computing will support faster decision-making and lower latency.

  Exploration of Emerging Technologies:
- Intelligent Reflecting Surfaces (IRS), cell-free massive MIMO, and THz communications may offer new opportunities for energy savings in 6G.

Summary

This chapter concludes that an adaptive approach integrating traffic prediction, RL-driven optimization, and renewable energy management provides a practical and effective solution for achieving energy-efficient 5G networks in West Africa. The findings reinforce the need for a coordinated effort among operators, regulators, researchers, and development partners to support sustainable, scalable, and future-ready communication networks across the region.

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CHAPTER 2
HYBRID MULTIFUNCTIONAL AUDIO-VIDEO SYSTEM FOR INTERACTIVE E-LEARNING AND MULTIMEDIA: DESIGN AND APPLICATION

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INTRODUCTION

In modern education, the introduction of smart classrooms is a significant step towards the modernization of the teaching process. Smart classrooms use advanced technology to create interactive, efficient, and accessible learning environments. These classrooms are equipped with a variety of technological equipment, including interactive whiteboards, smart devices, audio/visual equipment, and e-learning software. Smart classrooms allow for a combination of traditional teaching methods with advanced technological solutions. E-learning, as part of the broader concept of smart classrooms, allows students to access educational materials online, facilitating distance learning and a more flexible schedule. This approach not only increases the accessibility of education, but also improves the quality of the educational experience through the use of multimedia content and interactive teaching methods (Andreson and Dron, 2011; Salomon, 2011).

Integrating various software tools into smart classrooms significantly improves the learning experience. For example, learning management systems (LMS) such as Moodle allow for the management of educational content, tracking student progress, and communication between students and teachers (Bates, 2019; Sanchez et al., 2024). Collaboration apps such as Microsoft Teams, Zoom, and Google Classroom allow for virtual meetings, screen sharing, and interactive sessions, which is especially useful for conducting remote learning.

Research has shown that the use of technology in education can significantly improve student engagement and teaching effectiveness. For example, a study conducted in (Andreson and Dron, 2011) explored three generations of pedagogy in distance education and concluded that modern technologies enable a more dynamic and interactive educational environment. In (Shen et al., 2014), they emphasized the importance of using technologies in higher education, pointing out that they enable flexibility and personalization in learning where research shows that the use of digital devices (and even their own phones) can significantly increase student engagement and motivation, as shown in a paper exploring the effects of smart classrooms in classrooms. In the paper (Nkome et al. 2021), systematically reviews the literature on student engagement with digital technologies.

This paper identifies how student engagement is conceptualized and what tools are used to measure it, focusing on the use of LMS, social media, and technology to record lectures. The authors (Maksimović et al. 2022) have shown that a TV studio can be used as an education laboratory, but the disadvantage is that multimedia control is manual, which this problem are solved in this paper.

This paper offers an innovative, cross-functional smart classroom solution that uses a hybrid interaction model. The system is designed to support the recording of educational sessions, as well as the organization of local and online meetings. In addition, full automation of the system via IP connection has been implemented, enabling easier management and optimization of the operation of various devices. This flexibility allows for easy adaptation to new improvements and specific user requirements, and is programmed to support all modern software solutions for e-learning and collaboration. In addition, the software is purpose programmed to enable complete automation of the system, thus achieving high reliability and efficiency. By leveraging symmetry in the system's design and connectivity, the audio-video infrastructure achieves uniform performance and seamless integration across the interactive teaching environment.

The integration of technologies such as SDI (Serial Digital Interface) and NDI (Network Device Interface) (NewTek, 2024) enables high-quality transmission of video signals over long distances with minimal signal loss. SDI technology is often used in professional video systems due to its reliability and ability to transmit uncompressed video signals. On the other hand, NDI technology allows video signals to be transmitted over standard network infrastructure, reducing the need for additional cables and facilitating the installation and maintenance of the system. In modern audio technology, Dante is popular today (Audinate, 2024). Dante network technology enables the transmission of high-quality audio signals over IP networks, which is especially useful in complex audio-video systems such as smart classrooms. Dante technology allows for easy integration and configuration of audio devices, which reduces the need for complex cable installations and allows for high flexibility in smart classroom design.

An analysis conducted in the Dante Whitepaper highlighted the benefits of the Dante system in reducing latency and improving sound quality in remote classrooms (Audinate, 2024). Another study has shown that Dante systems enable multi-channel audio transmission with minimal delay, which is crucial for real-time synchronization of audio and video signals (Labia et al., 2020; Smaldino, 2017). In (Huang, 2019), it was shown that based on the results of a project at Ming Chuan University on smart classrooms, the concept of integrating modern technologies in smart campuses was proposed.

Designing a smart classroom faces a number of challenges that must be carefully addressed in order to achieve optimal results. Some of the key challenges include:

The first stage of design involves assessing the current condition of the room and its location. This includes an analysis of structural features, available space, and existing installations that may affect the installation of new equipment;

The acoustic characteristics of a room have a key impact on sound quality. It is necessary to ensure that the room has an appropriate acoustic treatment to reduce reverberation and background noise. This is achieved through the use of acoustic panels, absorbers, and diffusers to help control sound reflections (Smaldino, 2017; Nowoswiat and Olchowska, 2022);

Measuring the reverberation time and background noise level is crucial to ensure clear and intelligible sound. Reverb timing should be optimized to ensure that speech is clear and reverberating (Smaldino, 2017; Nowoswiat and Olchowska, 2022);

Cable placement and organization is a significant challenge, especially in complex systems such as smart classrooms. Cable routes should be carefully planned to minimize interference and ensure a stable connection between devices. The use of high-quality connectors and cables is essential for reliable signal transmission (Huajin and Cibao, 2011; Basset et al., 2022);

Maintenance of the system is an important aspect to consider when designing. The system must be designed in such a way as to allow easy access to all components for routine maintenance and possible repairs (Basset et al., 2022).

Research and implementation of various technologies such as NDI, SDI, Dante, the combination of HDMI (High-Definition Multimedia Interface), USB (Universal Serial Bus) and similar interfaces are an integral part of the design. The integration of advanced technologies, such as artificial intelligence (AI), has further revolutionized these spaces, providing unprecedented opportunities for personalized and effective education. An example of the application of AI in the design of multimedia classrooms is the development of multimedia platforms for sports education that use machine learning techniques. These platforms allow educators to edit and set up educational resources, while students can engage through interactive modules tailored to their individual learning styles. The application of AI not only optimizes the educational experience, but also improves the adaptability and efficiency of sports education (Luo, 2024). The paper (Almasri, 2024) explores the application of artificial intelligence to tailor e-learning to individual learners. The architecture of such systems is discussed, which includes modules for data collection, adaptive learning, recommendations, and content delivery. Challenges such as adaptive content creation and continuous assessment are highlighted, while future research focuses on improving AI techniques and content adaptability to advance personalized learning. The integration of AI into education systems is being explored to improve learning outcomes. AI-driven tools and applications facilitate personalized learning, automate administrative tasks, and provide realtime feedback, thereby improving the educational process. However, the application of AI in education also brings challenges and ethical considerations that must be carefully managed (Ezzaim et al., 2023; Xu and Ouyang, 2022). Examples of adaptive learning platforms demonstrate how AI can tailor educational materials based on students' performance and learning pace, leading to significant improvements in educational outcomes (Kioumourtzoglou, 2022).

The design of conference systems and smart classrooms is becoming increasingly important with the advancement of technology and the need for interactive learning environments. These systems use a variety of technological components to enhance communication, collaboration, and learning. Researchers are engaged in designing a smart classroom based on Internet of Things (IoT) technology (Brunkaya and Durklar, 2022; Huang et al., 2023)].

Also, classrooms use a variety of sensors to monitor environmental conditions, such as temperature, humidity, and air quality, thus providing an optimal learning environment. In the paper (Hussain et al., 2019; Nai, 2022), it was shown that using IoT based classroom memory improved English language learning. Some smart classroom control systems are based on the Android platform, using the Bluetooth protocol for communication between hardware components and the software part of the system. The design of acoustic systems in smart classrooms is being investigated to provide high-quality sound for interactive teaching. Paper (Lei, 2021) proposes the integration of voice processing systems and learning data analysis, as well as mobile terminals to support interactive teaching.

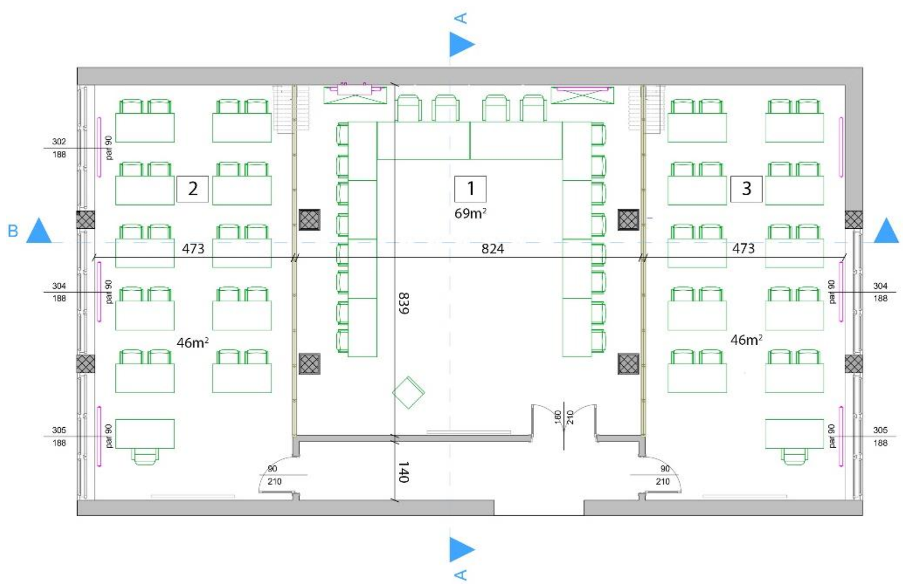
Also, smart classrooms emphasizes the importance of integrating information and communication technologies, machine learning, sensor networks, and cloud computing to improve education systems. These technologies allow for greater engagement and empowerment of students, educators, and administrators (Kaur et al., 2022). Kaur presents the design and implementation of a smart classroom monitoring platform based on digital twins. In the paper (Pang et al.,2023) platform uses 5G technology, IoT, big data, and other advanced technologies to monitor and manage classrooms in real time.

1. CONNECTIVITY MODEL

Designing and implementing a sophisticated audio/video system that will serve three separate rooms where it is imperative that each individual system functions autonomously, while at the same time being able to integrate into a single unit in circumstances where separate spaces are transformed into one continuous space. A significant component of this project is the synergy with the architecture department to ensure that the visual identity of the classrooms and conference room reflects high aesthetic and functional standards. This system is specifically programmed to support hybrid interaction models, which includes recording educational sessions, as well as organizing both local and online meetings. Given the dynamics of the space configuration, microphone solutions are flexible and independent of fixed positions, so the use of advanced wireless technologies is envisaged.

In order to ensure a smooth audio/visual experience, the system is equipped with sophisticated automation tools. However, in order to provide maximum flexibility, manual control options have also been programmed in situations that require specific interventions. The command structure of the A/V equipment allows for efficient control both from a local point and via remote access, ensuring maximum flexibility and system availability for all user scenarios. The room consists of three parts (Fig. 1 a)), one in a conference configuration while two rooms are organized as a classroom space (Fig. 1). In the central part (the central part marked in Fig. 1), there is an arrangement of tables in the "Π" format for the conference with the possibility of rearrangement for classes. Opposite the table is a lectern on which there is an interactive presentation panel (visualizer) for interactive teaching and which is connected to a smart projector. Rooms 2 and 3 are organized in such a way that they will be classrooms for teaching with the possibility of streaming and recording classes. The walls between the central room and rooms 2 and 3 are the so called "shrinkable walls" that have the ability to be assembled and thus all three rooms form one large conference room where it is possible to attend a larger number of participants (Fig. 1 b) and c).

(a)



(b)

(c)

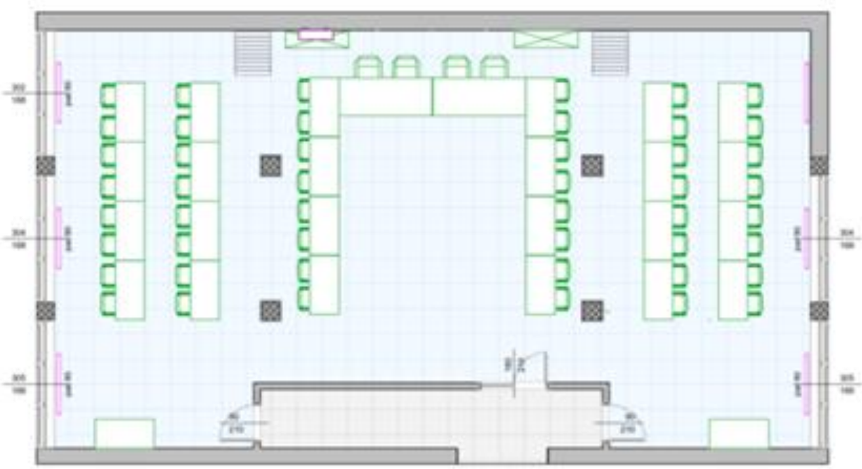


Figure 1. Dimensions and arrangement of furniture in rooms a) classroom space and conference room, b) amphitheater, c) conference.

Room 1 is equipped with two cameras that have the ability to automatically monitor, frame, as well as presentation mode, and these capabilities are based on the application of artificial intelligence.

Also, each camera has the ability to adjust the preset and thus allows the cameras to be configured and programmed for different situations (conference, classes, presentations, etc.). In the corners of the room, there are active speakers that communicate with each other, thus configuring the audio signal so that there is no feedback. The output signal to the active speakers is through the main audio mixer where level correction and additional signal filtering are performed. On the same audio mixer, the output from the microphone base, which has four conference microphones, is connected. One microphone is provided at the lectern, while the other three are arranged on the tables. The system is UHF PLL and is equipped with an antiinterference system and Tone Lock. The two-frequency range is available in the following bands: 610-670 MHz and 730-790 MHz. For each frequency, a maximum of 3 receivers and 12 microphones. If both frequencies are used, then we can set up 6 receivers and a maximum of 24 microphones. In this way, the audio control and audio microphone cover every possible scenario. There are also 2 TVs and one interactive smart projector in the room, which are used for video control of the attendees, while the projector is also used for presentation and interactivity during the presentation. The system has a video matrix, so it is possible to route video signals on these TVs and projectors as desired. Since the projector and TVs are facing the attendees at the table, the presenter at the lectern also has a laptop that serves as a video control and a device for interactivity with the projector and presentation device. To control the camera, an IP controller is used, which can be used to control the cameras (if necessary: pan, tilt, zoom, presets, focus, white balance, ISO, etc.). The selection of cameras is achieved using a mini video mixer that accepts HDMI inputs and connects via a USB connection to a computer. It is possible to start a conference (Zoom, Skype, Teams, etc.) from the computer and thus get signals from the audio and video mixer. It is also possible to record and broadcast the event live on platforms such as YouTube, Twitch, Facebook, Instagram, etc., as well as send a signal via RTMP connection to the TV studio.

There is a StreamDeck device in the room that is configured so that the chair creates HotKeys so that he can fully control the meeting (mute, accepting new members, recording the meeting, changing the camera, monitoring).

Table 1 lists the equipment located in Room 1, while Fig. 2 shows the arrangement of the equipment in the rooms numbered in Table 1. The solution is designed to be multifunctional for the purpose of organizing smaller or larger conferences, as well as for conducting interactive teaching. In the premises there is audio and video equipment that is programmed to communicate with each other via IP connection and in this way that complete automation of the system is programmed. In addition to full automation, it is configured so that it can be configured manually where the system is fully user friendly. The multifunctional solution means that the system is easily adaptable to new improvements and can meet the requirements of any situation in the field. For greater functionality, there is a shrinking wall between the spaces, so, if necessary, the area of all three classrooms can be used, where all three separate audio/video systems then become one audio/video system.

So, full automation has been achieved in the premises, when the teacher wants to record or broadcast the lesson, it is enough to just start the system where the cameras will automatically follow the teacher, as well as the sound. In conference rooms, there is also audio-based speaker tracking, which gives the cameras directions on where to frame. The interactivity of those present is put to a higher level by simply inserting a dongle and the user is automatically in the system with his audio/video needs, from the phone to other multimedia device. Rooms 2 and 3 are identical in size, and for this reason, the same arrangement of devices and equipment will be used. There are three ceiling microphones that play a key role in maintaining high-quality communication. These microphones are equipped with advanced features such as Acoustic Echo Cancellation (AEC) and simultaneous communication, allowing for clear and smooth audio transmission without feedback. The microphones can also be used as speakerphones, providing additional flexibility in different usage scenarios. The concept of symmetry is applied to the connectivity model, ensuring a balanced and equal distribution of audio-video resources across all three rooms, regardless of their configuration. Symmetry plays a crucial role in the design of this hybrid multifunctional system, ensuring balanced resource distribution and uniform performance across multiple configurations.

This study explores the application of symmetry principles in the design of hybrid audio-video systems, aiming to achieve uniform performance and seamless integration across various educational settings.

In addition, these microphones contribute significantly to the functionality of the cameras by programming the software to take advantage of beamforming technology, which enables precise speaker tracking. Beamforming technology allows microphones to focus their reception on the sound source, minimizing ambient noise and providing clear sound for further processing.

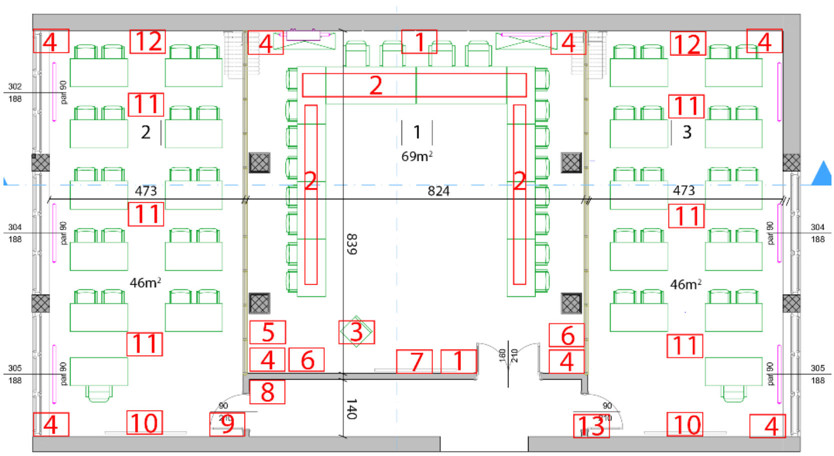


Figure 2. Positions Of Equipment in The Rooms

Table 1. The Model and Quantity of Equipment in The Room

No.	Name	Model	Quantity
1	PTZ camera	Aver CAM570	2
2	Gooseneck Wireless Mic	Relacart UB222	12
3	Laptop	Asus	2
4	PA	Behringer PK108A	8
5	PC	INTEL i5-10400F/16GB/500GB/RTX3060/650W	1
6	TV	Samsung 55’’	2
7	Projector	NEC UM301Wi (+NP03Wi pen)	1
8	Reck (all equipment)	Netix 9U/19“	1

9	Reck for room 2	Netix 6U/19“	1
10	Projector	NEC UM301Wi + interactive table	1
11	Celling speakerphone	Aver Fone 540	3
12	PTZ camera	Aver DL30	1
13	Rack for room 2	Netix 6U/19“	1

At the heart of the audio system is the Behringer XAIR 16 audio mixer, a key component responsible for the seamless management of all audio inputs and outputs (Fig. 3). This mixer is designed to handle multiple audio sources, ensuring high-quality audio transmission throughout the classroom. Primary audio inputs include wireless microphones and in wall microphones, each serving different purposes in an educational setting. Wireless gooseneck microphones (Fig. 3) are connected to their base stations that transmit audio signals via the TRS OUT or XLR OUT connector to the audio mixer. These wireless systems are crucial for providing mobility and flexibility to the lecturer, enabling dynamic teaching methods.

The ability to move freely without being tied to a fixed microphone location enhances classroom interactivity. Each classroom, labeled ROOM 2 and ROOM 3 in the schematic diagram in Fig. 3, is equipped with ceiling microphones. These microphones are integrated into individual audio interfaces within each classroom. Audio interfaces process the signals from the ceiling microphones and send them to the main audio mixer and to the PC. This configuration ensures that audio recording is optimized for clarity and accuracy, regardless of the speaker's position inside the room. Incorporating ceiling microphones is especially useful for capturing ambient sounds and ensuring that the voices of all participants are heard clearly in different room configurations. They can be used to capture the sounds of students when there is a classroom space, and to capture the audience when they are in an amphitheater configuration. The processed audio signals are then routed to active speakers strategically placed inside each room. These speakers, connected via XLR output to audio mixers, deliver clear and amplified sound to all corners of the classroom. The use of directional speakers minimizes feedback and echo, ensuring an optimal audio experience for both attendees and remote participants.

The speakers are carefully calibrated to maintain sound integrity and prevent distortion, providing a consistent and highquality listening experience. The video system relies on the ATEM Mini Extreme ISO video mixer (Fig. 3), a sophisticated device designed to control multiple video inputs and outputs. This mixer receives HDMI inputs from a variety of sources, including high resolution cameras, projectors, and laptops. The integration of these inputs allows for comprehensive management of video content and seamless switching between different video sources. The high-resolution cameras installed in ROOM 2 and ROOM 3 play a key role in recording detailed videos of lectures and presentations. Each room is equipped with two cameras (Aver DL30) connected to a PC via HDMI and a USB connection (Fig. 3). These cameras are equipped with automatic tracking functions that allow them to dynamically monitor the movement of lecturers and activate preset zones. This functionality is crucial to ensure that the recording remains focused on the lecturer, regardless of their position within the classroom.

Projectors are another vital component of a video system. Connected to laptops via HDMI and USB cables, the projectors display educational content on large screens, facilitating visual learning. The interactive capabilities of these projectors allow lecturers to interact directly with the displayed content, take notes, highlight key points, and interact with multimedia elements. In addition to the projector, there are also televisions where the complete video system is connected to the video matrix and it is possible to choose which image source will be displayed on TVs and projectors. These displays are strategically placed to ensure that all participants have a clear view of the displayed content. High resolution displays enhance visual learning, making it easier for students to follow the lecturer's explanations and demonstrations.

Laptops serve as key interface points within the classroom, connecting audio and video systems. They are connected to the audio mixer via TRS IN/OUT connections and to projectors via HDMI and USB cables (Fig. 3). This connectivity allows for seamless integration of multimedia content into lectures and presentations. Presenters can easily switch between different types of media, including videos, presentations, and live demos. The classroom's audio and video outputs are carefully managed to ensure high quality display and recording.

A Multiview monitor, connected to a video mixer, displays all video sources in real time, but only to technical personnel. To control the distribution of video signals, the system uses HDMI splitters and switches. These devices allow video signals to be distributed from a single source to multiple outputs, ensuring flexibility and compatibility between different components. The use of an HDMI splitter allows you to display content on multiple screens at the same time, while switches make it easy to switch between different video sources. Recording is provided locally to a high-speed SSD drive that is connected to the video mixer via a USB-C connection (Fig. 3), allowing all processed video content to be recorded. This highn capacity device ensures that all lectures and presentations are recorded in high quality, providing a valuable resource for students to review later. The robust performance and reliability of the SSD make it an ideal choice for continuous recording and storage of large video files. An IP controller is used to remotely control the cameras. This device allows precise control over pan, tilt, zoom, and camera preset configurations. The ability to remotely adjust the cameras is crucial for adapting to different teaching scenarios, whether it's a small group discussion or large lectures. An IP controller ensures that the cameras can be quickly and easily configured to capture the best possible footage.

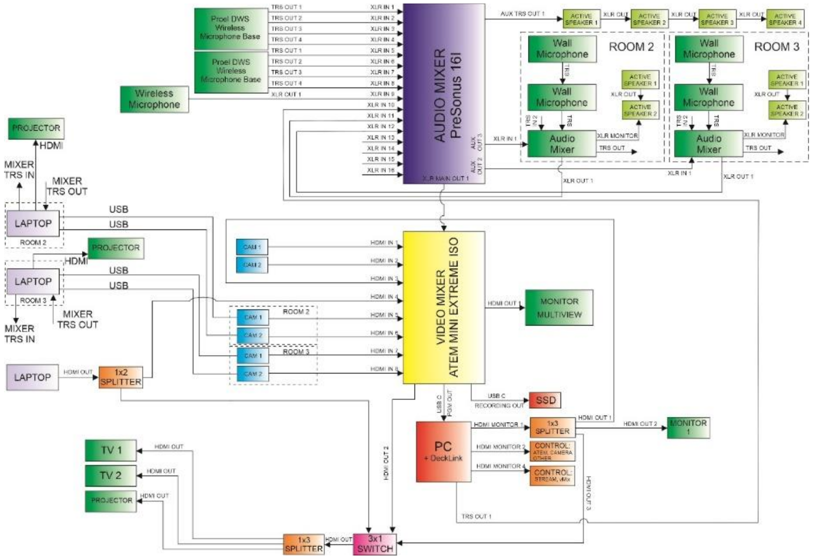
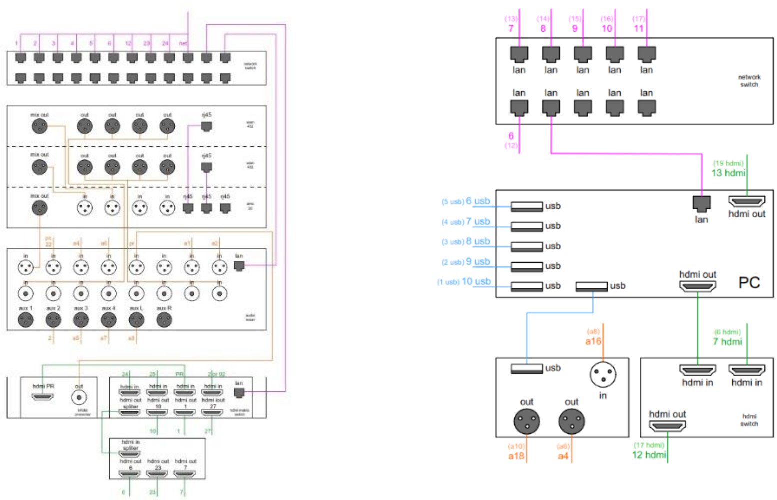


Figure 3. Equipment Connectivity

The main (Fig. 4 a) cabinet contains all the key devices that manage the audio and video signals inside the classroom. The upper section of the EK cabinet is reserved for audio connections, where the microphone inputs and mixer outputs are placed. These connectors allow for stable and clean transmission of audio signals to the main audio mixer. The aux inputs and outputs in this section allow for the flexible connection of additional audio devices, thus increasing the functionality of the system. From the picture you can see that you are connected to a network router to ensure communication. The upper section is reserved for the network and audio parts, while the lower section is reserved for HDMI video signals, such as the HDMI matrix, presenter (share screen device) and splitter. In rooms 2 and 3 there are smaller cabinets that enable the described connection and management of devices within these specific spaces, as well as communication with the main rect. These cabinets contain a PC, a network router, a splitter, and an audio interface if you need to add another microphone. Fig. 4b shows the wiring diagram in the cabinet in Room 2, while Fig. 4b shows the schematic wiring device in the cabinet for Room 3 with the colors in parentheses.



(a) **(b)**

Figure 4. Connecting the devices to the cabinet a) central room – room 1, b) rooms 2 and 3.

The methodical configuration of audio and video components ensures that the classroom functions seamlessly, providing an optimal learning experience for both attendees and remote participants. The integration of advanced technologies such as auto-tracking cameras, interactive projectors, and sophisticated audio systems highlights the potential of smart classrooms to transform traditional educational paradigms. By providing greater interactivity, flexibility, and efficiency, this smart classroom system represents a significant advancement in the field of educational technology. Fig. 5 shows a diagram of the installation of different types of cables within a multimedia classroom, including network, video, audio, power and control cables. Each type of cable is marked with different colors and legends, which makes it easy to follow their routes and functions. The cables are carefully laid to minimize interference and ensure a stable connection between all devices.

Figure 5. Positions Of Equipment in The Rooms.

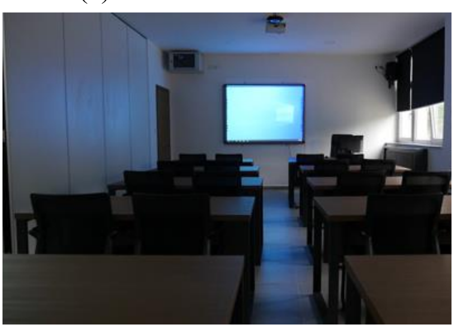
When designing this system, one of the key requirements was to achieve a flawless classroom aesthetic by completely hiding cables and creating a wireless system. To meet this requirement, all cables are carefully placed inside wall ducts and sewers, thereby completely removing them from the user's field of vision. This solution not only contributes to a tidy and professional appearance of the classroom, but also ensures safety, preventing potential risks of tripping or damaging cables.

Also, this approach allows for easy maintenance and possible upgrades of the system, because the cables are organized and clearly marked inside the central cabinets. All these measures have been taken to ensure that all technological elements are functional, while maintaining a minimalist and aesthetically pleasing appearance, thus meeting the high standards of a modern educational environment.

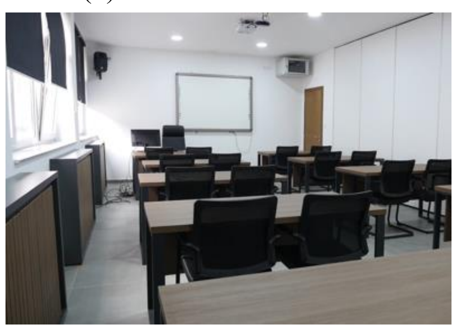
In Fig. 6, it can be seen that the request is fully fulfilled, where the render during the design and the implemented solution can be seen. All technological components, including cameras, projectors and audio equipment, are seamlessly integrated into the space, and cables are completely hidden, achieving a clean and professional classroom look.

(a)

(b)



(c)



(d)

Figure 6. a) render of the designed classroom, b) realized design of the central room (room 1), c), d) rooms 2 and 3.

2. RESULTS AND DISCUSSIONS

To validate the system's performance, a comprehensive evaluation was conducted under real classroom conditions at the Faculty of Technical Sciences. All measurements were obtained using the fully implemented system, ensuring that the results reflect realistic usage scenarios. The evaluation focused on three key aspects: audio signal quality with and without the AEC feature, end-to-end latency of audio/video transmission over various interfaces, and the accuracy of the AI-based speaker tracking system. Each of these aspects was tested using objective metrics, and the results are summarized in the following paragraphs.

As showed in Fig. 7, enabling the AEC functionality yielded a improvement in audio signal quality. The measured SNR increased from the high 20s (around 28 dB without AEC) to the mid 30s (approximately 37 dB with AEC), indicating a significantly cleaner audio output. Total harmonic distortion (THD) was reduced from roughly 0.5% without AEC to essentially negligible levels with AEC, reflecting the elimination of echo induced nonlinearities and other distortions. The reverberation time (RT60), which characterizes how long the acoustic echo persists, was dramatically shortened from a few tenths of a second without echo cancellation (on the order of 0.2–0.3 s) to effectively zero audible reverberation with AEC engaged. These results confirm that the AEC feature markedly enhances audio clarity, yielding a crisper and more intelligible sound by suppressing echoes and feedback in the classroom environment.

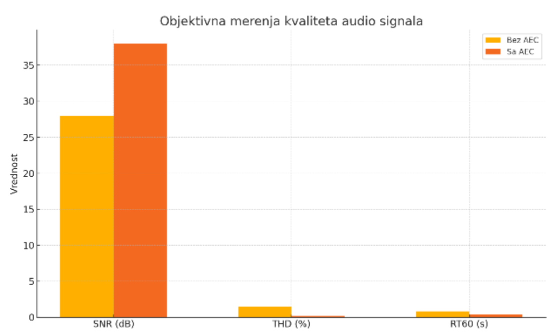


Figure 7. Objective audio-quality metrics with and without Acoustic Echo Cancellation (AEC).

Measured the end-to-end latency for audio transmitted via Dante, and video transmitted via both NDI and a traditional SDI link. The Dante path exhibited an average latency of approximately 10–12 ms, which is very low and virtually imperceptible in live usage. This demonstrates that the Dante networking effectively transports audio with minimal delay, maintaining tight audio-video synchronization. The NDI path showed a slightly higher latency, averaging around 30–35 ms. This modest delay is expected due to video encoding/decoding and network transmission overhead, yet it remains within a range that is generally unnoticeable to users (on the order of one to two video frames). In contrast, the SDI video transmission had an average latency of roughly 8–10 ms, which is nearly instantaneous and set a baseline for comparison as a dedicated hardware interface. Fig. 8 shows that while NDI/IP incurs higher latency than SDI, the difference is on the order of only a few tens of milliseconds. Importantly, the Dante audio latency is comparable to SDI video latency, ensuring that even in a hybrid Dante+NDI setup the audio and video streams can be synchronized with minimal adjustment. Overall, the latency evaluation confirms that the IP-based transport (both Dante and NDI) achieves low-latency performance close to traditional SDI, validating the system's suitability for real-time interactive e-learning sessions.

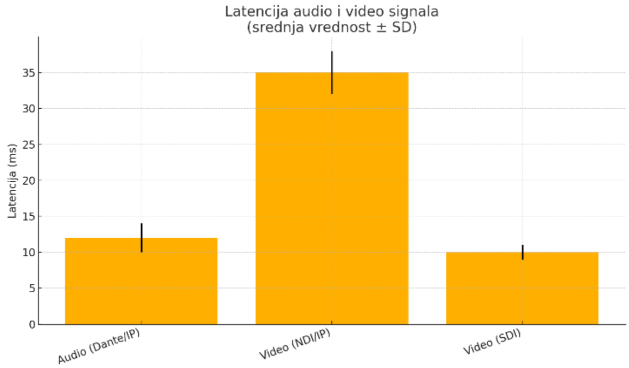


Figure 8. End-to-end latency of audio (Dante) and video streams (NDI, SDI).

As showed in Fig. 9, the effectiveness of the AI-driven camera tracking system was objectively evaluated using standard classification metrics.

We tested the system's ability to automatically track the active speaker in two typical scenarios: a lecturer moving and speaking at the front of the classroom, and a student speaking from the audience, as well as a baseline audio-only tracking mode for comparison. We used objective measurements like F1, precision and recall [Maksimovic et al. 2019; Maksimovic et al. 2021]. The precision of the AI tracking the proportion of camera shots that correctly framed the actual speaker was very high, approximately 90–95% across scenarios (with the lecturer-tracking mode achieving the upper end of this range).

High precision indicates that false positives (the camera focusing on the wrong person or an empty area) were rare. The system's sensitivity (recall) was likewise strong, on the order of 85–90%, meaning the majority of speaker movements or speaking events were correctly detected and followed by the camera. The specificity (the true-negative rate for not tracking non-speakers) remained around 88–92%, reflecting that the tracker seldom initiated tracking on irrelevant triggers or background speakers. Finally, the overall F1-score the harmonic mean of precision and recall reached roughly 90% for the instructor and only slightly lower for student participants, demonstrating a well-balanced accuracy.

Notably, the AI visual tracking of the lecturer showed the highest consistency (precision about 95%, F1 about 93%), whereas tracking of students had slightly lower but still robust performance (precision and F1 around 90%). An audio-only tracking approach, which uses microphone array beamforming without camera AI, achieved somewhat lower metrics (precision in the low 90s) compared to the combined audio-visual AI method, confirming that the integration of AI image processing enhances tracking accuracy.

These metrics attest that the automatic speaker tracking system is highly effective in a real classroom setting it reliably keeps the camera focused on the current speaker with minimal error, thereby supporting a seamless and professional lecture recording/broadcast experience.

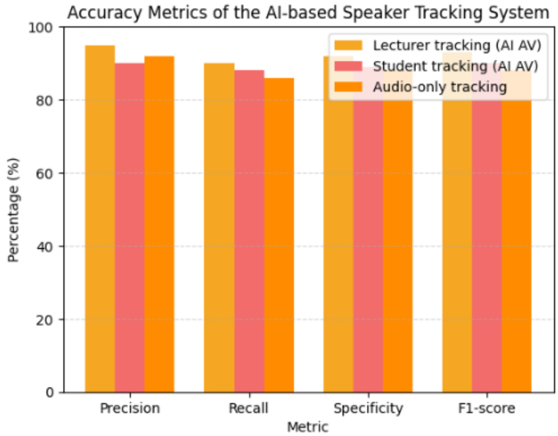


Figure 9. Accuracy metrics of the AI-based speaker-tracking system in three operating modes.

The objective evaluation results demonstrate that the implemented hybrid audio-video system meets the demands of an interactive e-learning environment. The AEC algorithms significantly improve audio quality in reverberant classrooms, the Dante and NDI network streams deliver low-latency AV transmission comparable to conventional hardwired solutions, and the AI-based camera control achieves high precision in following the active speaker. All measurements were obtained in the actual deployed classrooms, underscoring the system's real-world efficacy. These findings validate the system's design choices and indicate that it can enhance teaching and learning experiences by providing clear audio, synchronized low-latency video, and intelligent automation of camera operations.

CONCLUSION

The implementation of a hybrid multifunctional audio-video system for interactive teaching and multimedia at the Faculty of Technical Sciences represents a significant step forward in the modernization of the educational process. The designed solution provides high flexibility and the ability to adapt to different educational scenarios, which includes the organization of conferences, interactive classes, recording of classes and online meetings.

The integration of advanced technologies such as SDI, NDI and Dante, as well as the use of artificial intelligence for automatic monitoring and optimization of systems, enable a high level of interactivity and efficiency. The integration of symmetry in the design and connectivity of the system enhances its adaptability, ensuring efficient and uniform performance in both individual and combined modes of operation. One of the main advantages of this system is the complete automation of all devices over an IP connection, which facilitates management and allows optimal functionality without the need for manual intervention. The software is programmed to support all modern software solutions for e-learning and collaboration, which further enhances the user experience. The system is also designed to be user friendly, allowing for easy setup and use of all functions.

The innovative aspect of this project is reflected in the system's ability to easily adapt to new improvements and specific user requirements. Also, the main innovative contribution of this work is in software programmed to use AI to fully automate the conversion or classroom for the purposes of recording, broadcasting or lecturing. By connecting three separate rooms into one large classroom or conference room, the system allows for maximum use of space and resources. In addition, a high level of aesthetics is achieved by carefully placing cables inside the wall ducts, thus hiding all cables from view, which contributes to a neat and professional look of the classroom. The use of advanced audio and video technologies, as well as automated control systems, ensures high-quality audio and video transmission, which is crucial for maintaining clear and effective communication during lectures and meetings. The microphone's integration with AEC, simultaneous communication, and beamforming technology allows for precise speaker tracking and minimization of noise, further improving sound quality.

Compared to similar solutions, this system offers the same reliability at a much lower cost, thus achieving an optimal price-quality ratio. All these features make this project extremely suitable for modern educational institutions that strive to improve their educational process through the use of the latest technological solutions.

Further improvement of this system is planned through programming that will enable greater use of artificial intelligence in aspects such as detection of present students/participants, analysis of classes or meetings, summarizing classes and meetings, accuracy of detection for better monitoring of attendees, but also in the integration of alarm systems. In a way, this is integrated through the use of tools such as Moodle, Zoom, Microsoft teams, and the like, but in the future, work will be done on greater integration of AI into the system.

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CHAPTER 3
A SMART AUTONOMOUS ROBOTIC SYSTEM FOR AUTOMATED SURVEILLANCE AND PUBLIC SPACE PROTECTION: AN IORT APPROACH FOR ENHANCED SECURITY

Hmidi ALAEDDINE

INTRODUCTION

The security of infrastructure and public spaces has become a major concern due to the increasing risks of fires, intrusions, and environmental disasters. Traditional surveillance systems, although effective, often rely on human intervention and have limitations in terms of responsiveness, spatial coverage, and adaptability to dynamic situations. The advent of Internet of Things (IoT) technologies and autonomous robotics offers a unique opportunity to design intelligent solutions capable of detecting, analyzing, and reacting in real-time to potential threats. Autonomous mobile robots, equipped with advanced sensors and onboard decision-making systems, are increasingly being used to enhance security in various environments. These systems can patrol autonomously, detect suspicious movements, avoid obstacles, and even intervene in the case of fires or gas leaks (Hasan et al, 2018). However, most existing works focus either on surveillance or fire-fighting, without integrating these two functions into a unified, autonomous solution. This work proposes the design and development of an autonomous mobile robot combining : (i) A surveillance system (motion detection via PIR sensors, real-time video streaming). (ii) A fire-fighting module (flame detection, automatic extinguishing, gas and smoke management). (iii) Autonomous navigation (obstacle avoidance, onboard decision-making). An IoT interface for remote control and real-time data visualization. The goal is to develop an intelligent, autonomous, and versatile system capable of simultaneously meeting the needs of surveillance and fire safety, while transmitting critical information to a human operator via a dedicated web interface. Previous work has demonstrated the effectiveness of autonomous robots in specific applications, such as intrusion detection (IoT Robot, n.d.). or fire management (Perera et al, 2021), (Shinde, 2022).

However, the integration of these functionalities into a single system, coupled with an IoT interface for real-time monitoring, remains a relatively unexplored challenge. This project aims to fill this gap by offering a modular, extensible, and adaptable solution for various environments. The main contributions of the work are:

- Design of an autonomous mobile robot integrating advanced technologies for surveillance, fire detection, and obstacle avoidance.

- Integration of an IoT interface enabling remote control and data visualization.
- Autonomous navigation system with 98% accuracy in obstacle avoidance.
- Rapid fire detection with a reaction time of 2.5 seconds and precise triggering of the extinguishing system.
- Reliable communication system with a 100m coverage range.

The work stands out for its ability to combine several essential functions (surveillance, fire fighting, autonomous navigation) into a single robotic system, and its application in public environments to enhance proactive risk management.

1. BACKGROUND

Definitions and Concept of IoRT

The Internet of Robotic Things (IoRT) represents the convergence of robotics and the Internet of Things (IoT), enabling intelligent robots to sense, communicate, and make decisions through networked infrastructures (Ray, 2017). By integrating cloud and edge computing, IoRT supports real-time data collection, analysis, and coordination among heterogeneous robotic devices (Simoens et al, 2018). Using standard Internet protocols (e.g., TCP/IP), IoRT facilitates efficient machine-to-machine and machine-to-human interactions. Modern IoRT systems leverage artificial intelligence and machine learning to overcome the limitations of traditional pre-programmed robots, improving autonomy, adaptability, and scalability. Often referred to as cloud robotics, IoRT allows computational offloading and shared intelligence, enhancing performance while mitigating constraints such as limited onboard resources, latency, and network congestion (Khalid, 2021), (Romeo et al, 2020).

Intelligent Autonomous Embodied Robotic Systems (IAERS)

Intelligent Embodied Robotic Systems (IAERS) represent a significant advancement in the field of embedded systems, as they add intelligence and autonomy to physical robots. An SREI combines elements of robotics, sensors, real-time data processing, and often artificial intelligence to make decisions adapted to its environment without constant human intervention.

This type of system is capable of perceiving its surroundings, analyzing sensory information, and acting based on the results of that analysis. The intelligence embedded in SREIs not only improves their autonomy but also their adaptability. For instance, a robot can change its trajectory based on a detected obstacle, adjust its actions according to environmental needs, or interact in a complex way with humans and other objects. These robots can perform various tasks such as surveillance, autonomous navigation, threat detection, and the execution of complex tasks autonomously.

IAERS for Automated Surveillance and Public Space Protection

The IAERS for automated surveillance and public space protection is a specific application of IAERS, which combines autonomous robotics and IoRT (Internet of Robotics Things) to provide intelligent and reactive security solutions in public environments. This system is designed to function without direct human intervention, ensuring continuous surveillance and a quick response to potential threats, such as intrusions, fires, or gas leaks. The system integrates autonomous mobile robots equipped with various sensors (motion detection, heat detection, gas detection) and extinguishing systems (such as water sprayers for fires). These robots patrol public spaces autonomously and detect anomalies or crisis situations in real-time.

When a threat is detected, the robot can act instantly, such as triggering an alarm, sending alerts to the operator, or even physically intervening, such as extinguishing a fire or isolating a hazardous area. In addition to these autonomous functionalities, the system is also connected to an IoT interface that allows remote control and real-time monitoring via a web interface. This interface enables operators to view live video feeds, receive critical information about the monitored environment, and make informed decisions when necessary. The IoT interface makes interaction with the system flexible and intuitive while ensuring responsiveness in emergency situations. Thus, the SREI for automated surveillance and public space protection fits into an active security framework, where automation enhances the efficiency of interventions and reduces reliance on human intervention, while increasing coverage and responsiveness to incidents.

2. AUTONOMOUS ROBOTIC SYSTEM ARCHITECTURE

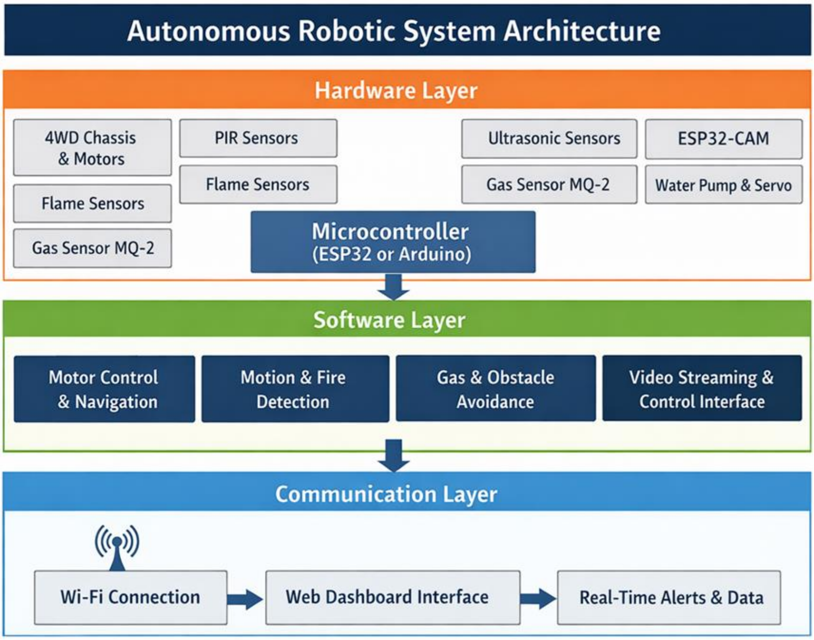

Figure 1. Autonomous Robotic System Architecture

Figure 1 shows the complete architecture of the autonomous robotic system designed for surveillance and fire-fighting. This system is organized into three main functional layers : the hardware layer, the software layer, and the communication layer, each of which plays a specific role in ensuring optimal operation of the robot. Each layer consists of various interconnected subsystems that work together to ensure the robot's autonomy, responsiveness, and safety.

2.1 Hardware Layer

The hardware layer includes all the physical components necessary for the operation of the robot. It consists of :

Mobile Platform (4WD Chassis and Motors): The four-wheel drive platform enables the robot to move autonomously in various environmental configurations. The motors control the robot's speed and direction, ensuring smooth and responsive navigation.

PIR Sensors (Passive Infrared Sensors): These sensors are used to detect movement in the monitored area. When motion is detected, the robot takes necessary actions, such as activating alarms and, if needed, moving towards the source of the movement.

Flame Sensors : These sensors are designed to detect the presence of fire in the robot's environment. When a fire is detected, the robot reacts by activating its fire-fighting systems.

MQ-2 Gas Sensors : Used for detecting hazardous gases and smoke, these sensors allow the robot to respond to gas or toxic smoke leaks by activating ventilation mechanisms and alerts.

Ultrasonic Sensors : These sensors measure distance and are essential for obstacle detection. They allow the robot to avoid collisions and navigate safely in its environment.

ESP32-CAM: The integrated ESP32-CAM camera allows real-time video streaming over a Wi-Fi network. This enables the user to visually monitor the robot's environment and receive live images or videos.

Water Pump and Servo: The water spraying system is controlled by a servo motor, which adjusts the nozzle's position between 0° and 90° based on the detected fire situation. The water pump activates the extinguishing process when a fire is detected.

Microcontroller (ESP32 or Arduino): The core of the system, this microcontroller manages all the sensors and actuators. It receives sensor data, makes decisions based on this information, and controls the motors, camera, and extinguishing system.

2.2 Software Layer

The software layer manages all the algorithms and processes that control the robot. It includes :

Motor Control & Navigation : The robot's motors are controlled by algorithms that manage its speed, direction, and movements. Autonomous navigation is ensured by data from ultrasonic sensors and motors.

Motion & Fire Detection : The algorithm analyzes the signals from the PIR sensors and flame sensors to determine the presence of suspicious movement or fire. When such situations are detected, the robot takes appropriate actions, such as triggering alarms or extinguishing the fire.

Gas & Obstacle Avoidance: The algorithm uses ultrasonic sensors to detect obstacles and adjust the robot's trajectory in real time. At the same time, the MQ-2 gas sensors allow the robot to respond to gas leaks by triggering alerts and controlling ventilation.

Video Streaming & Control Interface: Live video captured by the ESP32-CAM camera is streamed to a web interface. The interface allows the user to monitor the area in real time and manually control the robot if needed.

2.3 Communication Layer

The communication layer manages interactions between the robot and the user via a wireless connection. It includes:

Wi-Fi Connection: The robot uses a Wi-Fi connection to establish communication with the web interface. If necessary, the robot creates its own Wi-Fi hotspot, allowing the user to connect locally without needing external network infrastructure.

Web Dashboard Interface: The web interface allows the user to visualize real-time data (temperature, humidity, fire status, etc.), receive alerts, and interact with the robot. The interface is designed to be intuitive and accessible on devices such as computers or smartphones.

Real-Time Alerts & Data: In the event of detecting movement, fire, or obstacles, the robot sends visual and auditory alerts, and this information is also displayed in real-time on the dashboard. This system allows the user to take immediate action if necessary.

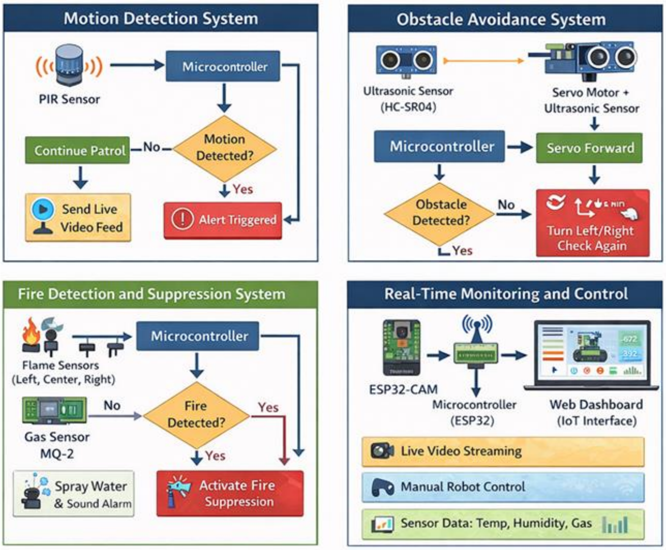

Figure 2. Obstacle Avoidance, Fire Detection and Extinguishing, And Real-Time Surveillance.

The architecture of the autonomous robotic system, presented in Figure 2, relies on seamless interaction between the hardware, software, and communication layers. Each layer plays a crucial role in the robot's autonomous decision-making process and in managing real-time security. Through this organization, the robot can efficiently monitor, detect anomalies (such as fires or hazardous gases), and respond autonomously while providing the user with a complete control

3. SUBSYSTEMS OF THE AUTONOMOUS MOBILE ROBOT

The figure 3 above presents four distinct flow diagrams, each representing a key subsystem of the autonomous mobile robot designed for surveillance and fire-fighting.

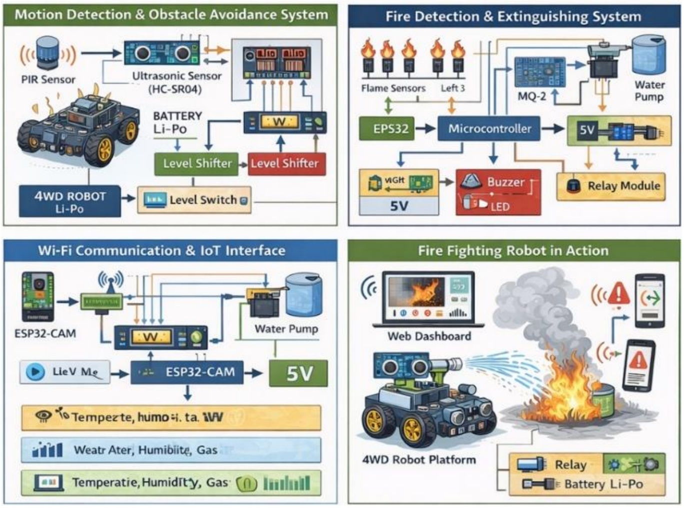

Figure. 3. Subsystems of the Autonomous Mobile Robot: Motion Detection, Fire Extinguishing, IoT Communication, and Robot in Action.

These diagrams detail the robot's internal operation through the following systems: motion detection, obstacle avoidance, fire detection and extinguishing, as well as real-time monitoring and control. Each diagram is organized clearly and colorfully to facilitate a better understanding of the interactions between components and processes. The first diagram shows the **motion detection system**, which relies on a Passive Infrared Sensor (PIR). This sensor detects motion in the robot's environment and sends the data to the microcontroller. If motion is detected, the system activates an alert and streams live video to the monitoring interface. If no motion is detected, the robot continues its path without interruption.

Components : PIR Sensor, Microcontroller, Video Alert System.

Process: Motion Detection → Alert Sent → Live Video Streaming.

The second diagram illustrates the **obstacle avoidance system**, which uses an ultrasonic sensor (HC-SR04) to measure the distance between the robot and surrounding objects. If an obstacle is detected, the robot decides to avoid it by turning left or right, then continues navigating. If no obstacle is detected, it moves forward normally.

Components: Ultrasonic Sensor, Microcontroller, Servo Motor.

Process: Obstacle Detection → Robot Reaction (turning) → Continuous Check.

The third diagram shows the **fire detection and extinguishing system**, which combines multiple sensors to detect a fire. Flame sensors placed at different positions (left, center, right) and the MQ-2 gas sensor enable the microcontroller to verify the presence of fire. When a fire is detected, the robot activates the extinguishing system by spraying water and triggering an alarm.

Components: Flame Sensors, MQ-2 Gas Sensor, Microcontroller, Water Pump.

Process: Fire or Gas Detection → Extinguishing Activated → Sound and Visual Alert.

The last diagram describes the **real-time monitoring and control system** of the robot. This system is based on the ESP32-CAM, which streams live video to a web dashboard. The interface allows the user to monitor the robot's status, manually control its movements, and check real-time data such as temperature, humidity, and gas levels. The ESP32 and the microcontroller coordinate communication between the sensors, the robot, and the user interface.

Components: ESP32-CAM, ESP32 Microcontroller, Web Interface (IoT).

Process: Live Video Streaming → Manual Control → Real-Time Data Monitoring.

These diagrams are organized in a 2x2 grid, each representing a key subsystem, with clear components and connections showing power flows, component interactions, and overall functioning. The **motion detection and obstacle avoidance system** uses the PIR sensor to detect motion and an ultrasonic sensor (HC-SR04) to avoid obstacles. The **fire detection and extinguishing system** uses flame sensors and the MQ-2 gas sensor to detect a fire, triggering the water pump and alarm. The **Wi-Fi communication and IoT interface system** uses an ESP32-CAM for real-time video capture and another ESP32 for managing sensor data, which is sent to a web interface for remote monitoring and control. The **fire-fighting robot in action** is shown reacting to a detected fire, using the water spraying system. The user can monitor the robot's activity via the web dashboard and receive real-time alerts.

These subsystems work together to ensure that the robot can detect and extinguish fires, avoid obstacles, and be controlled remotely while providing real-time feedback through IoT.

4. EXPERIMENTAL RESULTS

The experimental validation of the autonomous mobile robot demonstrated the effectiveness of each subsystem under real-world conditions. The figure above presents a set of tests conducted to evaluate the robot's performance in various scenarios. These tests ensured that the robot responded optimally to challenges such as motion detection, obstacle avoidance, fire detection, and extinguishing.

Laboratory Tests

Laboratory tests were performed to assess the technical functionality, sensor accuracy, and calibration of the water spraying system. The results showed that all technical components functioned correctly, with precise calibration of the water spraying system. The tests validated the system's effectiveness by simulating scenarios where motion detection and sensor accuracy were crucial.

Technical Functionality: The robot demonstrated reliable performance in a controlled environment.

Sensor Accuracy: The PIR motion sensors and flame sensors responded quickly and accurately.

Water Spraying Calibration: The water spraying system operated with high precision.

Obstacle Avoidance Test

The obstacle avoidance test evaluated the robot's ability to navigate through an environment with obstacles. The robot showed excellent navigation accuracy, detecting and avoiding obstacles efficiently using the ultrasonic sensor and control system. The avoidance maneuver was carried out without losing control, and the results were satisfactory in terms of reaction time and precision.

Navigation Accuracy: 98% accuracy in obstacle detection.

Avoidance Maneuver: The robot successfully avoided obstacles in every test.

Fire Detection Test

The fire detection tests validated the speed and sensitivity of the detection system. The robot detected the fire in 2.5 seconds and immediately activated the extinguishing system. The sound alarm was also triggered with 100% accuracy. The MQ-2 gas sensor's sensitivity allowed it to detect dangerous gas levels, and the system responded promptly.

Fire Detection Time: 2.5 seconds.

Alarm Trigger Accuracy: 100%.

Gas Sensor Sensitivity: High sensitivity detecting harmful gas levels.

Real-World Testing

Finally, real-world tests allowed the robot to operate in an environment simulating outdoor fire scenarios. The robot successfully navigated, sprayed water to extinguish flames, and was remotely controlled via an IoT dashboard. The results showed that the robot performed well under various conditions, with a rapid emergency response capability and reliable wireless control range.

Realistic Environment: The robot responded effectively to outdoor conditions.

Wireless Control Range: The robot maintained a communication range of 100 meters.

Emergency Response Time: The robot responded in real-time to fire situations.

In conclusion, all tests showed that the autonomous mobile robot functioned as expected and met the required performance criteria. The experimental results confirm that the robot is capable of detecting fires, avoiding obstacles, and operating autonomously in an outdoor environment. The system was successfully validated, marking a significant step towards integrating autonomous robots into security and fire-fighting applications.

CONCLUSION

This work demonstrated the effectiveness of an autonomous robot integrated with the Internet of Robotic Things (IoRT) for surveillance and public space security. The intelligent autonomous embodied robotic system (IAERS) performs tasks such as motion detection, obstacle avoidance, and fire extinguishing, making real-time decisions using advanced sensors (PIR, ESP32-CAM, gas, and flame detectors).

Although autonomous, it features an IoRT interface allowing operators to supervise and adjust it remotely via video streams and environmental data (gas, temperature), ensuring efficient and flexible management. Tests showed a 98% accuracy rate in obstacle avoidance and fast fire detection. The use of a real-time operating system (RTOS) ensures optimal responsiveness and effective resource management. This IoRT system opens up prospects for autonomous robots in smart urban environments and could be extended to industrial applications and natural disaster management. This work represents a major advancement in proactive surveillance and risk management.

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CHAPTER 4
INTERNET OF THINGS FOR MANAGEMENT OF SOLAR PV INTEGRATED ELECTRIC VEHICLE BATTERY SYSTEM

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INTRODUCTION

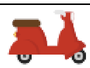
According to a recent study by WHO (World Health Organization), India is home to 14 out of 20 most polluted cities in world. Also, India needs to import fossil fuels for 80% of its current transportation scenario. E-mobility has become inevitable to make zero dependence of fossil fuels and to reduce CO_2 emissions. Solar power contributes to charge the electric vehicles with sustainability of natural resources. One of the major barriers in the electric vehicle commercialization is battery maintenance. Battery maintenance means charging, protection, life span, and repair. Energy and battery charging management has regard to all the competing demands for energy and electric vehicles (EVs) fast charging to allocate energy on an equitable basis to satisfy all uses and demands.

The real time analysis of EV charging system due to large scale and dynamic penetration of charging load is the need of hour right now to see the load balance for better performance of conversion devices. Hence monitoring of EV charging is important since it helps in seeing that the e-mobility users do not bother about energy consumption.

The smart and digital technologies besides internet connectivity made Internet of Things (IOT) to become a revolutionary technology in transforming many areas such as transport, health care, industrial automation, building and home automation etc. IOT based energy management extends benefits to the utilities beyond the smart grid in order to improve the energy saving and to do an efficient energy management. Utilization of Internet of Things - a cutting-edge wireless technology for real-time monitoring and alerting system with state-of-the-art sensors for accurate measurement of state of battery charging will enhance the density of e-mobility to a maximum extent. With the advancement of smart meters, communication network, software and databases the IOT based management of solar pv integrated EV Battery can solve the problems of collecting, transmitting, controlling and saving massive data in energy running processes. Over the past few years electric vehicles are emerging as the preferred e-mobility. In spite of having several advantages as given in the table 1, the electric vehicles also have some implementation obstacles.

The major challenges associated with EVs are high cost due to batteries and fuel cells, limited range due to battery capacity and speed, long charging period depending on battery type and charger and insufficient charging stations. Among all the challenges battery energy management is the greatest challenge. In future developments are based on designing batteries and charging technologies that reduce time of charging and flexibility.

Table 1. Comparison based on use-cases (KPMG Report (2020, October))

							
Daily Run	Medium	Medium	High	Low to Medium	High	High	High
Route Predictability	Low to Medium	Medium	Low	Low to Medium	High	Medium to High	Low
Charging requirement	Home	Home / Stands	Widespread	Widespread	Depots	Parking lots	Widespread
Economic viability	High	High	Medium	Medium	Medium	Medium to High	Low

1. RENEWABLE ENERGY SCENARIO

Global warming is the cause of concern for environment and the human race. 75% of total CO_2 emissions are contributed by electrical power generation in the world which contributed to Greenhouse Gas (GHG) emissions as well as global warming. The United Nations is urging every nation in the world to comply with Sustainable Development Goals (SDGs). To address climate change, countries adopted the Paris Agreement at the COP21 in Paris on 12 December 2015.In India, National Institution for Transforming India (NITI) Aayog, a non-statutory and advisory body, has taken the responsibility on the development of a comprehensive index to provide an integrated and combined view of the various socio-economic and substantial status of the country. It has also measured the progress of India and its state towards the accomplishment of the SDGs (Gray, J.L., 2010).

Clean and environment-friendly energy harvesting are of prime interest today as it is one of the key enablers in achieving the Sustainable Development Goals (SDGs) as well as accelerates social progress and enhances living standards (R.M. Elavarasan, et. al., 2020).

As energy demand exponentially increasing, India can't afford to continuously depend on fossil fuels owing to carbon emissions and its ill effects on climate change. Renewable energy technologies are expanding rapidly across the globe, enabling energy access, energy security as well as meeting climate goals. Switching to conventional Energy sources to Renewable energy sources is inevitable for each country. Using renewable energy sources over conventional resources (fossil fuels) has several advantages. It has a huge potential to meet the energy needs of the present and future generations. It promotes sustainable growth and enhances energy security. It is modular and supports Decentralized energy access. It eliminates fuel supply risks and is price competitive with conventional sources.

The Ministry of New and Renewable Energy (MNRE) with the support of National Institution for Transforming India (NITI) Aayog is working to achieve the Indian Government's target of attaining 175 GW through renewable energy resources. India is now at Global 5th position for overall installed renewable energy capacity. Fig.1 shows the installed capacity of Grid interactive Renewable power as on 28.02.2021 (NITI Aayog's SDGs India Index Baseline Report, 2018).

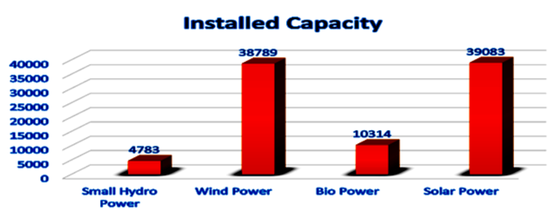


Figure 1. Installed capacity of Grid Interactive Renewable power

1.1 Modelling of PV Cell

The basic component of every photovoltaic plant is the solar cell. This consists in most cases of silicon, a semiconductor that is also used for diodes, transistors and computer chips.

With the introduction of foreign atoms (doping) a p-n junction is generated in the cell that "installs" an electrical field in the crystal. If light falls on the solar cell, then charge carriers are dissolved out of the crystal bindings and moved by the electrical field to the outer contacts. The result at the contacts of the solar cells is the creation of a voltage of approximately 0.5 V. The released current varies depending on radiation and cell area, and lies between 0 and 10 A. In order to achieve usable voltage and power many numbers of pv modules connected in series (strings) and parallel (arrays). The power of a solar module is measured according to the Standard-Test-Conditions (STC) and defined by three limiting conditions:

I. Full Sun radiation (radiation strength E = ESTC = 1000 W/m^2)
II. Temperature of the solar module: V_{Module} = 25 °C
III. Standard light spectrum AM 1.5

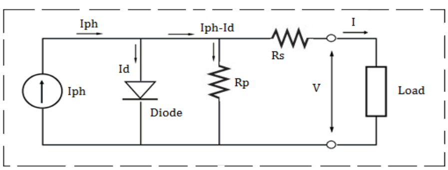


Figure 2. Equivalent circuit of pv cell

The capacity of the solar module under these conditions is the rated power (or nominal power) of the module. It is given in Watt-Peak (W_p) as it actually describes the peak power of the module under optimal conditions. Fig. 2 shows an equivalent circuit of pv cell.

The current supplied by the PV module (I) in amperes is given by the following expression:

$$I=I_{ph}- Io[\exp (q\cdot(V+I\cdot R_s) / (N_{cs}\cdot Gamma\cdot k\cdot T_c))-1] - (V + I\cdot R_s) / R_p) \quad (1)$$

where:

$$I_{ph} = \text{Photo current}= (G/G_{ref}) \cdot [I_{ph\ ref} + muI_{SC} (T_c-T_{c\ ref})] \quad (2)$$

with:

G and G_{ref}= Effective and reference irradiance in W/m².

T_c and T_{ref} =Effective and reference cell's temperature in K.

muI_{SC}=Temperature coefficient of the short-circuit current in A/C.

I =Diode reverse saturation current in amp.

q = Charge of the electron=1.602·E-19 Coul. and k =Boltzmann constant=1.381 E-23 J/K.

V = Voltage at the terminals of the module in volts.

R_s = Series resistance in ohm.

Rp = Shunt resistance in ohm.

N_{cs} = Number of cells in series.

Gamma = Diode quality factor which lies between 1 and 2; which is generally taken as 1.3 (Reddy, B.K. and Singh, A.K. 2022).

1.2 PV Based EVs

Owing to the large-scale utilization of electric vehicles the national grid under goes a tremendous pressure to satisfy the load demand with stability. Particularly in peak demand periods with addition of electric vehicles, major components like transformers and cables of distribution system will be stressed. If EVs charging are integrated with Renewable energy sources such as solar these implications can be minimized. The bulk power requirement of EVs charging can be supplied by the Renewable energy sources with minimum support of utility Grid. As we know that Renewable energy sources are intermittent sources it can supply power only few hours EVs can be used as Energy storage system (ESS) to deal with the in-stability issues on utility Grid such as voltage and frequency issues.

Photovoltaic (PV) generation shows the highest flexibility to be integrated with EV charging stations among different Renewable Energy sources. The similarities between PV and EV made viable option to connect to the grid. For example, parameters of EVs at residential homes are similar to those of typical residential PV systems. Also, PV are more flexible to be installed at the different EV charging locations, such as public charging stations, commercial buildings, workplaces, and the vehicle itself (solar EV). In addition, both EV and PV are integrated to the grid though power electronic interface with the potential to create intelligent nodes in the system.

Due to these common features between PV and EVs from the grid's perspective, the grid-support functions requested from PV will be similar to those required from EVs (Ahmed A.S. Mohamed, Ahmed El-Sayed, Hamid Metwally, Sameh I. Selem, 2020).

2. ELECTRIC VEHICLES

E-mobility has become inevitable to make zero dependence of fossil fuels and to reduce CO_2 emissions. Solar power contributes to charge the electric vehicles with sustainability of natural resources (Geetika Aswani; Vikas Singh Bhadoria; Jay Singh, 2018). One of the main reasons around a quarter of the global GHG (Green House Gas) emissions due to transportation and due to this substantially more air pollution in urban. This emissions due to fossil fuel impact in two ways i) quality of air is poor in cities which inflicts ill health on billions of urban residents around the world ii) climate become worsen.

Because of huge growth of automobile usage and sales these climate conditions will become worst in the future. The fig.3 shows that the annual automobile domestic sales trends. As per the above automobile sales trend, in next few years oil demand will be increased drastically and CO_2 emission is predicted. These emissions are main cause of increase in global average temperature rise. Due to the above reasons, there is a high requirement to reduce the usage of fossil fuels consumption and emission of GHG.

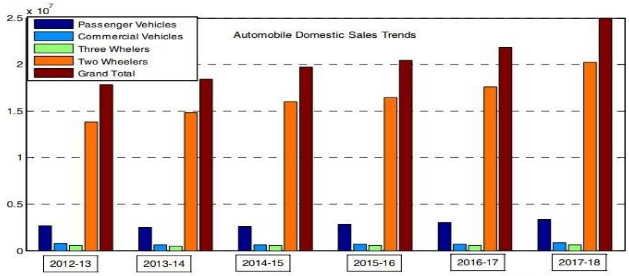


Figure 3. Automobile Domestic Sales Trends

In many developing nations renewable clean energy for vehicles and other applications is already growing at a faster rate than riches countries because it is environmentally and economically rational.

The energy electrification is being increased across the global and giving opportunity to nation to cutoff their GHG emissions worldwide are attributed to transport. The usage of electrical vehicle gives more environment and economic benefits. With the following table economic benefits of EV's can be explained.

With the reference of above analysis, the expenditure is kept constant as 5000 Rs and the cost of petrol /ltr is considered as Rs 75/- and cost of diesel/ltr is consider as Rs.67/-. Mileage of petrol and diesel vehicle is taken as 20 kmpl. The cost of electricity for electrical vehicle is considered as Rs.5.75/unit 30 days in month are considered for analysis purpose. The comparison of electricity as a fuel with respect to fossil fuels is much cheaper as given in the table 2. EV's are having several other environmental benefits also. Having several other environments benefits the EV's are becoming more popular in usage.

Table 2. Economic Comparison of Fuels

Fuel/Data	**Petrol**	**Diesel**	**Electricity**
Cost	Rs.75/Ltr	Rs.67/Ltr	Rs.5.75/unit
Consumption	66.67Ltr	74.63 Ltr	870 kWh
Range/month	1333 km	1492 km	3623 km
Range/day	44.43 km	49.75 km	121 km
Range/year	16218 km	18160 km	43478 km

2.1 Review of Electrical Vehicle Technology

Electric vehicles are categorized in to three types. Battery Electric Vehicles (BEV) which use batteries to deliver power. Hybrid Electric Vehicles (HEV) use the traditional engine and electric motor to drive the power train. Plug–in Hybrid Electric Vehicles (PHEV) use large capacity batteries than HEV's. A PHEV works completely on electrical power and utilizes a conventional engine during small battery charge to give an enhancement and increase the range. Power grid can be used for direct charging of PHEV's.

Alternating current (AC) charging system provides an AC source which gets converted in to DC for charging of batteries by using of AC-DC converters. DC charging system provides an additional power than AC system to enhance fast charging of EV's (K. Sreeram; P K Preetha; Prabaharan Poornachandran, 2019).

Charging schemes can be categorized as off-board and on-board form (conductive and inductive) with unidirectional and bidirectional power flow (injection of battery energy back to grid). There is power flow limit for on-board chargers due to its weight, space and budget restrictions. The infrastructure of charging decreases on-board energy storage and expenses. A battery charger should be more reliable and efficient with large density of power, less price and small volume and weight.

The function of EV charger should be such way that the utility of current drawn is less distortion to quality of power and at high power factor to increase the real power accessible from the utility outlet. Unidirectional chargers reduce the cost, weight, volume and losses and bidirectional chargers have two stages: an active grid linked bidirectional AC-DC converter for power factor correction and a bidirectional DC-DC converter for regulating battery current.

To charge EV's we have various types of power conversion techniques. The energy sources store energy as DC charge after conversion of energy from AC grid. This energy is used to run the motors after conversion again using power electronic converters. These converters also enable power flow along opposite way i.e. when power is feedback to batteries (regenerative braking) or supplying power to utility during the idling period of the vehicles (V2G). The symbolic representation is given in fig.4. A typical bidirectional electric vehicle drive is shown in fig.5.

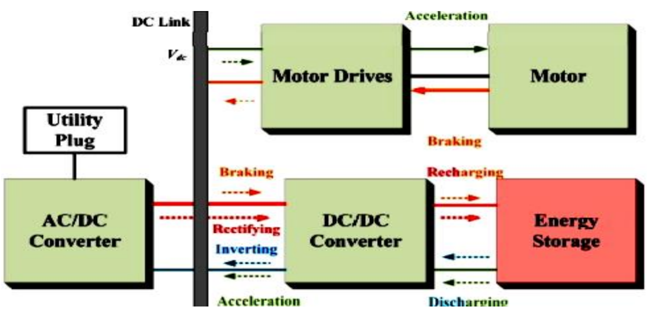


Figure 4. Power conversion techniques used in EV's.

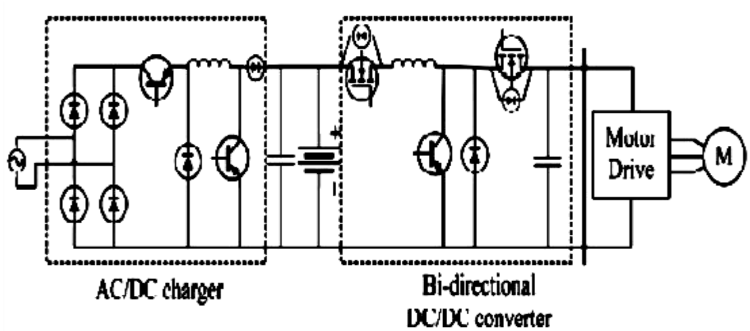


Figure 5. A typical bidirectional electric vehicle drive.

2.2 Impact of Electric Vehicle Charging Stations On Power Quality Issues

Comparatively electric vehicle is a new concept in the transportation sector. Now-a-days EV's become very much attractive due to several benefits i.e. less environmental pollution, cheaper mode of transportation and use of less petroleum.

Electric motor being used to run all these electric vehicles are utilizes energy from batteries. To charge all electric vehicles huge electric power is required. The huge power demand creates a serious problem with the existing demand. High power and large time required to charge EV's. Due to lack of sufficient charging stations, the EV owner has to charge their batteries from residential connection illegally which become a cause of system loss in the power sector. It is very much necessary to establish sufficient charging stations at various suitable places. Block diagram of an Electric Vehicle Charging Station is shown in fig. 6.

Single phase or three phase supply can be used to charge EV batteries. Because of wide availability of single-phase supply, EV chargers are connected with this system. Chargers of EV are basically power electronic converter similar to non-linear load. Since these non-linear characteristics of EV charger can produce harmonics in the current and affect the voltage profile of the power network. High non-linear loading can be a cause for non-linear voltage drop and which may cause of voltage wave form distortion.

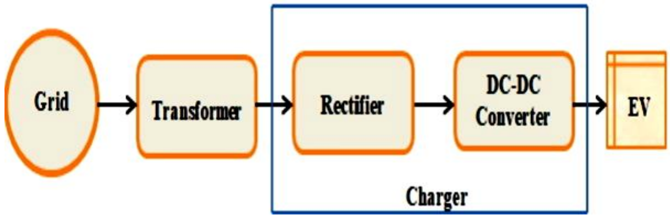


Figure 6. Block diagram of an Electric Vehicle Charging Station

On the other hand, non-linear load can affect the performance of distribution transformer by increasing power losses in the winding and thereby reducing its output power. Thus, EV charger when integrated with the power grid or distribution network, it hampers the power quality. Fig.6 shows that a typical block diagram representation of electric vehicle charging station. Having advancement in the load management system the issues due to EV charging stations can be minimized. One of the major barriers in the electric vehicle commercialization is battery maintenance. Battery maintenance means charging, protection, life span, and repair. Energy and battery charging management has regard to all the competing demands for energy and electric vehicles fast charging to allocate energy on an equitable basis to satisfy all uses and demands. Hence EV charging monitoring is important since it helps in seeing that the e-mobility users do not bother for fast charging (Ashish Kumar Karmaker; Sujit Roy; Md. Raiu Ahmed, 2019).

3. INTERNET OF THINGS

IEEE described the phrase "Internet of Things" in its special report on Internet of Things issued in March 2014, as "A network of items each embedded with sensors which are connected to the Internet". ITU, United Nations specialized agency for information and communication technologies, describes the IoT as a "ubiquitous network," in which the concept of ubiquitous networks is founded upon the all-inclusive use of networks and networked devices (ITU, SERIES Y, 2005). The word "ubiquitous" comes from the Latin root of ubique, meaning everywhere. Accordingly, ITU endorses the definition of IoT as a network that is "Available anywhere, anytime, by anything and anyone". Fig.7 illustrates the ITU definition of IOT.

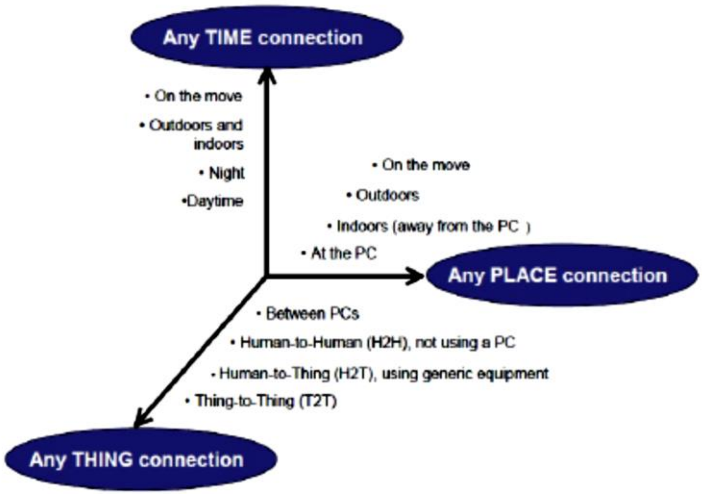


Figure 7. Definition of IOT as per ITU

Internet of Things is next frontier with smart sensors, newer wireless networks and revolutionary computing technologies. According to Deloitte in its TMT Predictions 2017, the number of things under Internet of Things (IoT) is expected to grow exponentially to 1.9 billion units in India. Many industries such as utilities, healthcare, manufacturing, automotive, transportation and agriculture are expected to have highest adoption levels of IoT in India as per the report.

The IoT will create new ecosystems and business models with completely new services and applications. IoT could have a profound impact on renewable energy resources as utilities and distributed generation become more incorporated with sensors and other computing systems. This enables the collection and transmission of variety of data from the connected devices and gains a holistic view of their energy usage.

The Internet of Things can integrate control, information processing and communications across various transportation systems by establishing an interconnection between e-mobility users, charging infrastructure and electric vehicles. Effective charging management system is an increasingly critical focus for utilities and e-mobility users.

4. IOT BASED EVS BATTERY ENERGY MANAGEMENT

The following methodology in a sequence of clearly defined steps leads to the efficient energy management of PV integrated EV battery systems using IOT.

4.1 Solar Integration of Battery Charging System

The number of solar panels required to develop solar powered electric vehicle charging system depends on the size of the battery used in the vehicle. The amount of kWh for a battery can range anywhere from the lower 20s on up to 100 or higher. For instance, while a BMW i3 battery has a capacity of only 33 kWh and upgraded Tesla Model S has a battery with a capacity of 100 kWh. The average 250 W solar panel can generate around 30-40 kWh of AC power each month. Given that single, low output solar panel produces roughly 1 kWh per day of electrical power; this indicates that 75 solar panels needed to generate electricity to power the Tesla Model S each day – assuming the start of the charging process with a battery totally drained of electricity.

However, taking the average travel approximately as 60 km a day – this translates to roughly 15 kWh of electricity. With that in mind, a much more realistic set would require approximately 15 solar panels. Also, even this is a conservative estimate that's based on the use of low output solar panels. Therefore, the number of 250 W panels is nearly 15. Solar PV based electric vehicle charging system is shown in fig.8. Fig.9. shows the functional blocks of a solar electric vehicle charging station.

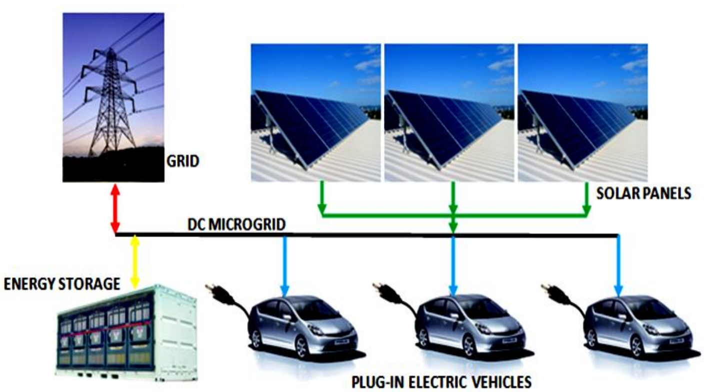


Figure 8. Solar PV based EV charging system

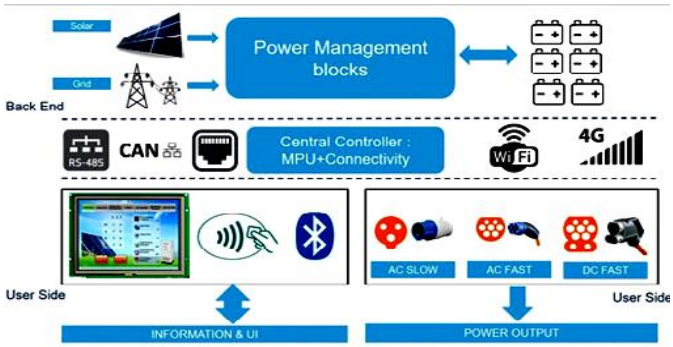


Figure 9. Solar EV charging station functional blocks

4.2 IOT based Battery Energy Monitoring System

The Internet of Things (IoT) based electric vehicle battery condition monitoring system as shown in Fig.10 comprises of Raspberry Pi controller, sensor that measure the state of charge of battery of the electric vehicle, internet, cloud storage and Wi-Fi modules. The Raspberry PI board used for sensor data acquisition and process is a Broadcom BCM2835 SoC full HD multimedia processor equipped with 256 MB SDRAM memory, GPU, Ethernet port, GPIO pins, Xbee socket, UART, power source connector and various interfaces for other external devices. Essential hardware specifications of raspberry pi board mainly include SD card containing Linux OS, US keyboard, monitor, power supply. The IOT based module for continuous monitoring consist sensor nodes, raspberry pi, wireless interface, Wi-Fi and cloud server.

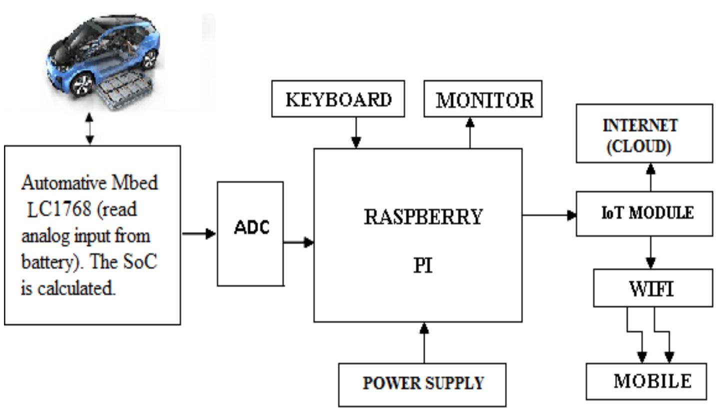


Figure 10. Block diagram of IOT based Battery Monitoring System

The sensor nodes are built with small embedded devices, wireless sensor network and battery charging status sensor. The actual soc of the vehicle will be compared with standard values and gives alert to the authorized persons.

CONCLUSION

Complete IoT based EV battery energy management and monitoring system for self-dependent e-mobility lead to economically viable monitoring system utilizing cutting edge technologies like smart sensors and internet of things. In this way the IOT plays an important role in the near future for efficient battery energy management for electric vehicles. Many industries identify and prioritize the smart energy management opportunities to make the e-mobility more flexible and economical transport system.

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