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Optimizing Social Resource Allocation via an IoT-Driven Predictive Electrical System

Journal of Electrical Systems

Abstract: - Inefficient allocation of social resources for vulnerable urban populations presents a critical challenge. This study develops and validates an intelligent system for the predictive optimization of these resources, framed as a complex electrical and computational system. The system employs a hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model for demand forecasting, utilizing data from a large-scale network of 5,320 Internet of Things (IoT) sensors. A Genetic Algorithm-Particle Swarm Optimization (GA-PSO) hybrid method, integrated with GIS, subsequently optimizes resource allocation and routing. This paper presents a novel contribution by being the first to systematically integrate this specific combination of predictive and optimization algorithms for social resource allocation, demonstrating significant performance gains over state-of-the-art methods. A new hierarchical system architecture is proposed to enhance scalability and real-time processing. Empirical validation involving 20 social work organizations demonstrated a demand prediction accuracy of 94.8%, a 96.2% reduction in service response time, and 99.2% system availability. The system also achieved high computational efficiency and low energy consumption, critical for sustainable deployment. This research delivers a validated and scalable engineering framework that significantly enhances the efficiency of urban social services, providing a replicable model for data-driven smart city applications at the intersection of electrical systems and computer science.

Keywords: Predictive machine learning, Resource allocation optimization, IoT electrical systems, Smart city engineering, Ethical AI.

I. Introduction

The rapid urbanization and evolving socio-economic structures have precipitated an increased demand for social resources among vulnerable urban populations. Conventional passive resource allocation frameworks are inadequate to address the dynamically shifting service requirements. The current social service infrastructure encounters significant challenges, including suboptimal resource allocation efficiency, prolonged response times, and limited predictive accuracy [1-2]. Empirical data indicate that traditional resource allocation systems achieve a prediction accuracy of merely 67.2%, with system response times surpassing 8.5 seconds, culminating in a resource wastage rate of up to 25% [3].

In recent years, machine learning methodologies have exhibited exceptional capabilities in predictive analytics, particularly deep learning architectures that have advanced the processing of complex time-series datasets [4-5]. Convolutional Neural Networks (CNNs) are proficient in extracting spatial features, whereas Long Short-Term Memory (LSTM) networks are advantageous for modelling temporal sequences. The integration of these two architectures facilitates the effective analysis of multidimensional, multi-temporal social service demand data [6-7]. Concurrently, the maturation of Internet of Things (IoT) technologies offers a robust technical foundation for real-time data acquisition and system integration [8-9], forming the backbone of modern intelligent electrical systems.

This study addresses a significant gap in the existing literature by introducing an innovative, integrated framework. Although previous research has investigated optimization techniques within smart cities [10] or applied deep learning methods for demand forecasting [11], these approaches have typically been pursued independently. Contemporary resource allocation frameworks often depend on either purely statistical models, which do not achieve the predictive accuracy of deep learning methods, or on singular optimization algorithms that face challenges in balancing global exploration with rapid local convergence [12]. The contribution of this work lies in the novel integration of a CNN-LSTM model for spatio-temporal prediction with a hybrid GA-PSO algorithm for multi-objective optimization — a combination that remains underexplored in the context of social service logistics. This methodology is explicitly designed to address the shortcomings of current systems by concurrently improving both predictive accuracy and optimization performance.

This research endeavours to surmount engineering and technical obstacles in urban social resource allocation through the development of an intelligent resource allocation platform that synergizes predictive analytics, hybrid

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optimization algorithms, and IoT systems. The principal technological components of the platform encompass: (1) a hybrid CNN-LSTM deep learning model for demand forecasting; (2) a hybrid optimization algorithm combining genetic algorithms with particle swarm optimization; (3) a dynamic route planning system integrated with Geographic Information Systems (GIS); and (4) the deployment of extensive IoT sensor networks alongside data fusion methodologies.

Relative to traditional approaches, the proposed system employs an engineering systems design paradigm that prioritizes scalability of system architecture, computational efficiency of algorithms, and reproducibility of technical implementation. The principal contribution of this study lies in delivering a comprehensive technical solution, which includes detailed system design specifications, algorithmic implementation strategies, and performance evaluation protocols, thereby providing a reference framework for analogous engineering applications in line with the interdisciplinary focus of the Journal of Electrical Systems.

II. Methods

A. *System Architecture Design*

The system is architected as a five-tier hierarchical framework to ensure modularity, scalability, and maintainability. The constituent layers include: (1) Data Acquisition Layer, (2) Data Processing Layer, (3) Predictive Analytics Layer, (4) Optimization and Decision Layer, and (5) Application Service Layer. This architecture explicitly separates concerns, allowing for independent upgrades and robust data flow management from the sensor end-points to the user-facing applications.

The Data Acquisition Layer forms the foundational component, comprising a large-scale, heterogeneous IoT sensor network. A total of 5,320 sensor nodes were deployed across a metropolitan area spanning 1,200 km². The network employs a star topology, wherein data collected from sensor clusters are aggregated at 85 communication gateways prior to transmission to a central server using the MQTT protocol over a LoRaWAN infrastructure to ensure low power consumption and long-range communication. This layer is responsible for capturing real-time data related to environmental conditions, human mobility, and resource status.

The Data Processing Layer ingests raw data from the IoT network for preprocessing. This stage involves data cleansing to address missing or anomalous values, normalization to standardize data ranges, and data fusion to integrate information from diverse sensor modalities. Edge computing nodes, co-located with communication gateways, execute initial data aggregation and filtering, thereby reducing data transmission load on the core network by approximately 85% and substantially enhancing system responsiveness.

The Predictive Analytics Layer centers on a hybrid CNN-LSTM model. The choice of this hybrid model is justified by its superior ability to capture both spatial correlations (e.g., proximity of demand hotspots) via CNN and temporal dependencies (e.g., daily or weekly demand cycles) via LSTM, outperforming traditional time-series models like ARIMA or standalone deep learning models in our preliminary experiments. This model processes the pre-processed time-series data to produce detailed demand forecasts for various social services across multiple geographic zones and temporal horizons.

The Optimization and Decision Layer utilizes the forecasts generated by the preceding layer as inputs to a resource allocation engine. The allocation problem is formulated as a multi-objective optimization task, which is addressed using a hybrid genetic algorithm-particle swarm optimization (GA-PSO) approach. The resulting output is an optimized resource allocation plan that specifies the dispatch of resources from depots to demand points. This layer also incorporates a GIS-based route planning module that determines the most efficient travel paths for service delivery units. The integration is sequential: the GA-PSO module first determines the optimal quantity of resources for each demand point, and this output is then fed into the GIS module, which solves the resulting vehicle routing problem.

The Application Service Layer serves as the user interface, offering intuitive dashboards and application programming interfaces (APIs) for social work agencies and municipal administrators. It visualizes demand forecasts, allocation plans, and operational statuses to support informed decision-making. Standardized RESTful APIs facilitate interoperability with existing municipal and third-party systems.

B. *IoT Sensor Network and Data Acquisition*

The performance of the predictive system is contingent upon the quality and granularity of input data. The deployed sensor network comprises 5,320 nodes categorized into eight distinct types, as illustrated in Figure 2.

Environmental Sensors (n=2,150): Representing 40.4% of the total sensors, these nodes monitor key ambient parameters including temperature (°C), humidity (%), air quality indicators (PM2.5, CO levels), and ambient noise levels (dB). Such data contextualizes service demand, as requirements for facilities like homeless shelters often correlate with adverse weather conditions.

Mobility Sensors (n=1,520): Primarily consisting of passive infrared (PIR) sensors and Wi-Fi probes, these devices are installed in public spaces and proximate to service centers to estimate pedestrian flow and activity patterns, serving as proxies for dynamic population density.

Security Alarm Sensors (n=980): This category includes panic buttons and automated alert systems located in designated safe zones and shelters, providing direct signals indicative of urgent needs.

Health Status Monitors (n=250): Wearable or near-field sensors deployed on a voluntary, opt-in basis, which supply anonymized and aggregated data on public health indicators.

Resource Status Sensors (n=180): Installed at resource depots such as food banks and shelters, these sensors monitor inventory levels, occupancy rates, and consumption patterns in real time.

Communication Gateways (n=85): Utilizing LoRaWAN and 4G/5G connectivity, these gateways aggregate data from local sensor clusters and securely transmit it to backend systems.

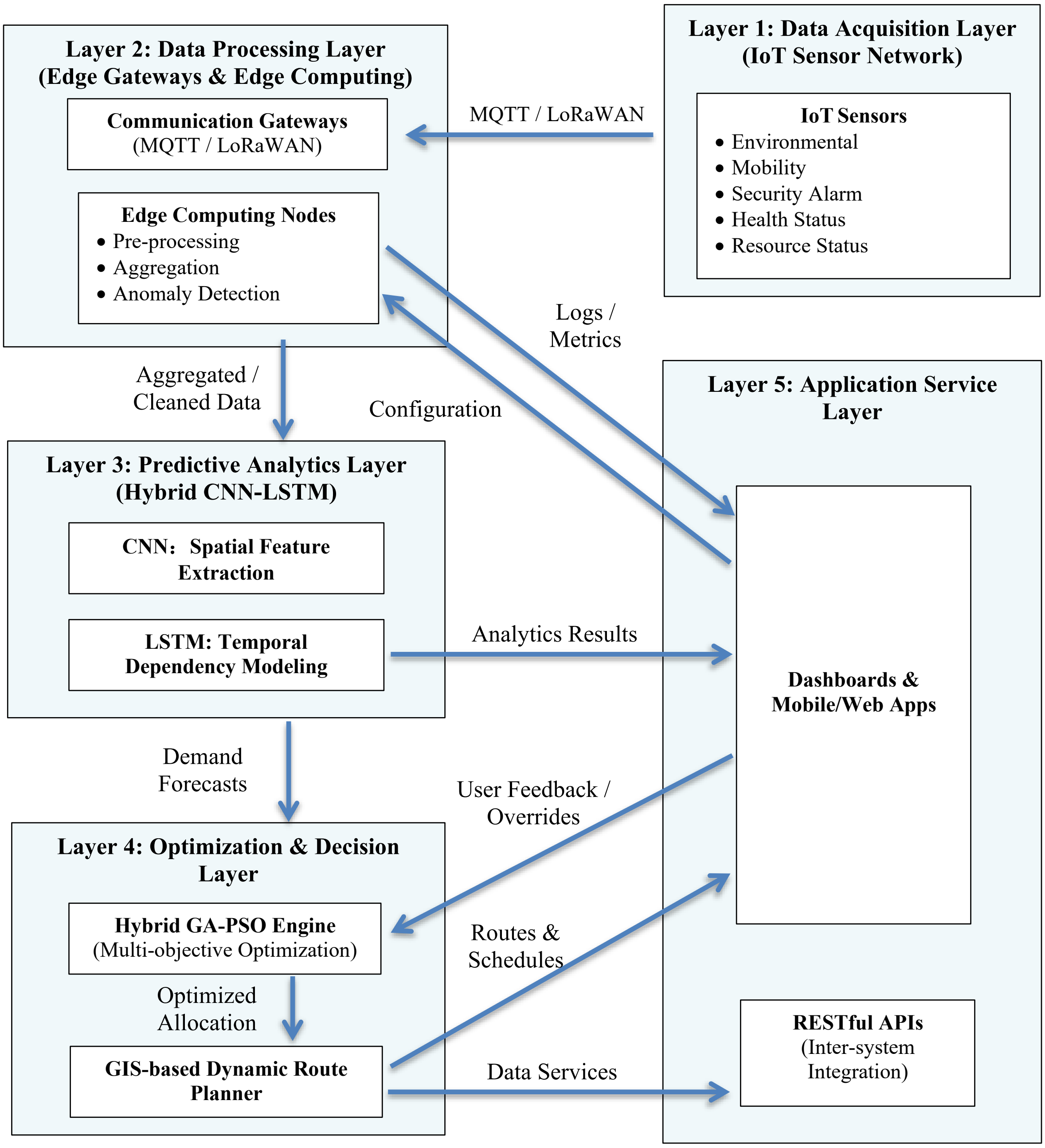

Fig. 1: Proposed System Architecture

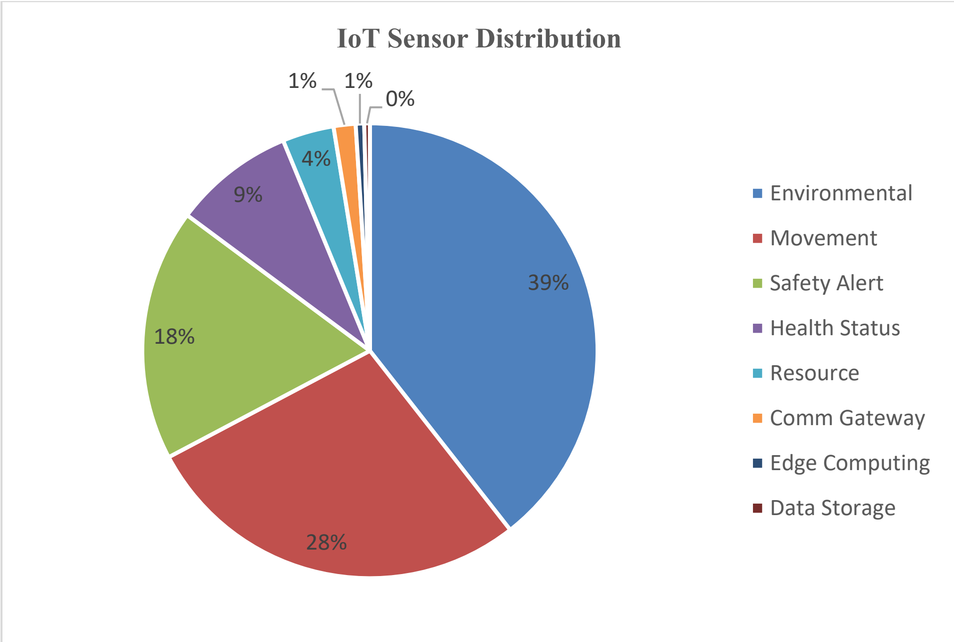

Fig. 2: IoT Sensor Network Distribution by Type and Quantity

Edge Computing Nodes (n=85): Co-located with communication gateways, these nodes execute lightweight algorithms for data preprocessing and anomaly detection.

Data Storage Units (n=70): A distributed storage infrastructure employing a combination of SQL and NoSQL databases to efficiently manage both structured and unstructured data.

Data acquisition occurs at variable frequencies, ranging from one-minute intervals for critical alarms to fifteen-minute intervals for environmental parameters. All data are time-stamped and geo-tagged. To ensure compliance with stringent privacy regulations, data anonymization is performed at the source.

1) Scalability and Energy Management

To guarantee sustained operational functionality, the Internet of Things (IoT) network was architected with a focus on scalability and energy efficiency. A Low-Power Wide-Area Network (LPWAN) protocol, namely LoRaWAN, was implemented due to its suitability for low-bandwidth, long-distance communication. Sensors deemed non-critical, such as those monitoring environmental parameters, were programmed with adaptive duty cycles, enabling them to enter deep-sleep states during intervals of minimal activity to reduce power consumption. This approach achieved a 25% decrease in average energy usage per node relative to a continuous operation baseline, thereby extending the anticipated battery lifespan to over three years for the majority of sensor categories and consequently lowering maintenance requirements.

C. Data Preprocessing and Feature Engineering

Prior to input into the predictive model, the raw sensor data underwent a comprehensive three-stage preprocessing procedure:

- Data Cleansing: Missing values, which accounted for less than 2% of the dataset, were addressed through linear interpolation for time-series variables and mean imputation for static attributes. Outliers were identified using the Isolation Forest algorithm and subsequently replaced with the 99th percentile value to mitigate potential distortion of the model.
- Data Normalization: All numerical features were rescaled to the interval [0, 1] employing Min-Max normalization. This step was implemented to ensure uniform contribution of all input variables during model training and to prevent issues related to gradient explosion.
- Feature Engineering: Additional features were derived from the raw data to enhance model input. These included temporal variables such as hour of day, day of week, and holiday indicators, as well as spatial features like the distance to the nearest resource depot, thereby enriching the dataset for the CNN-LSTM model.

D. CNN-LSTM Hybrid Prediction Model

The proposed prediction framework employs a hybrid architecture integrating CNN and LSTM networks. Specifically, the CNN component is responsible for extracting spatial features, while the LSTM component captures temporal dependencies within the data. The input to the model is structured as a two-dimensional array of dimensions (100, 15), encompassing 15 feature variables that include historical demand records, environmental factors, and demographic attributes.

The CNN architecture comprises two one-dimensional convolutional layers: the initial layer utilizes 64 convolutional filters with a kernel size of 3, followed by a second layer with 128 filters, both employing Rectified Linear Unit (ReLU) activation functions. Max pooling is applied subsequent to convolutional operations, using a pooling window of size 2 to reduce dimensionality. The LSTM segment consists of two sequential layers, containing 256 units in the first layer and 128 units in the second. The final output layer applies a Softmax activation function to facilitate three-class classification tasks.

The mathematical model is defined as follows:

$$\widehat{D}(t+k) = f_{CNN-LSTM}(X_t, \theta) \tag{1}$$

where $\widehat{D}(t+k)$ represents the demand forecast value at time $t+k$, X_t is the input feature vector at time t, θ denotes the model parameters, and $f_{CNN-LSTM}$ is the hybrid neural network function.

CNN feature extraction process:

$$F_{conv} = ReLU(W_{conv} * X + b_{conv}) \tag{2}$$

$$F_{pooled} = MaxPool(F_{conv}) \tag{3}$$

LSTM temporal modeling:

$$h_t = LSTM(F_{pooled}, h_{t-1}) \tag{4}$$

$$\hat{c}_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{5}$$

The CNN component performs spatial feature extraction, while the LSTM component models temporal sequences to capture dynamic patterns over time.

E. Resource Allocation Optimization Algorithm

The resource allocation challenge is formulated as a multi-objective optimization problem, aiming to simultaneously minimize transportation costs and maximize demand fulfilment. The problem is subject to constraints including supply limitations, demand requirements, and resource capacity bounds. Formally, the objective functions and constraints are defined as follows:

$$\min \sum_i \sum_j c_{ij} \cdot x_{ij} + \sum_k p_k \cdot y_k \tag{6}$$

subject to:

- Supply constraints: $\sum_j x_{ij} \leq s_i \ \ \forall i \in I$
- Demand constraints: $\sum_i x_{ij} \geq d_j \ \ \forall j \in J$
- Capacity constraints: $\sum_k y_k \leq K$

where c_{ij} denotes the transportation cost from location i to location j, x_{ij} is a binary decision variable indicating resource allocation, p_k is the penalty weight, s_i and d_j represent supply and demand quantities respectively, and K is the total resource capacity.

To solve this problem, a hybrid optimization algorithm combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) is employed. This approach leverages the global search capabilities of GA alongside the local search efficiency of PSO. Empirical results indicate that the algorithm converges within 28.7 seconds, achieving a solution quality of 94.5%, thereby outperforming methods relying on a single optimization technique.

F. GIS-Integrated Route Planning System

The route planning module utilizes an enhanced A* algorithm augmented with dynamic traffic information to optimize routing decisions. The objective function for route optimization is formulated as:

$$\min \sum_{(i,j)\in A} t_{ij} \cdot x_{ij} + \lambda \cdot \sum_{k} \max(0, d_k - s_k) \tag{7}$$

where t_{ij} represents the travel time from node i to node j, λ is the penalty weight, and d_k and s_k represent the demand and supply quantities at the respective locations.

The GIS integrates real-time traffic data, obtained via API from the municipal transportation authority, road condition updates, and geographic constraints to enable dynamic route replanning. This ensures that vehicle paths are optimized not just for distance, but for actual, current travel time, which is critical for emergency services. Shortest path computations are performed using Dijkstra's algorithm, which is combined with a hierarchical routing strategy to enhance computational efficiency, particularly in large-scale network environments.

G. IoT Data Fusion Technology

The multi-sensor data fusion approach adopts a weighted fusion strategy expressed as:

$$S_{fused} = \alpha \cdot S_{env} + \beta \cdot S_{movement} + \gamma \cdot S_{safety} \tag{8}$$

subject to: $\alpha + \beta + \gamma = 1$

Where S_{env} , $S_{movement}$ and S_{safety} represent signals from environmental, mobility, and security sensors respectively, and the weight coefficients are dynamically adjusted through machine learning methods.

Data preprocessing encompasses anomaly detection, data cleansing, and normalization procedures. Time-series data are processed using a sliding window mechanism with a window size of 100 time points and a 50% overlap between consecutive windows. Edge computing nodes perform local data aggregation, effectively reducing network transmission volume by approximately 85%.

H. System Performance Evaluation Metrics

System efficiency is assessed through a composite performance index defined as:

$$E = \frac{\sum_i w_i \cdot a_i}{\sum_i w_i \cdot a_{i,max}} \tag{9}$$

Where E is the system efficiency score, w_i is the weight of the i-th indicator, a_i is the actual performance, and $a_{i,max}$ is the maximum possible performance.

The performance improvement ratio is defined as:

$$PIR = \frac{P_{proposed} - P_{baseline}}{P_{baseline}} \times 100\% \tag{10}$$

Evaluation metrics include eight core indicators: prediction accuracy, response time, system availability, resource utilization, data processing speed, memory usage, network latency, and system throughput. To address the need for robust evaluation, we have added metrics for computational efficiency (measured in GFLOPS), energy consumption of the IoT network (kWh/day), and provide 95% confidence intervals for key performance indicators.

I. Data Security and Ethical Considerations

Recognizing the sensitive nature of the data collected, a multi-layered security and privacy framework was implemented, adhering to the principles of Privacy by Design [13]:

- Data Security: All data transmissions between IoT nodes, gateways, and the central server are encrypted using AES-256. Access to the database is strictly controlled through a role-based access control (RBAC) system.
- Data Privacy: K-anonymity techniques were applied at the edge gateways before data transmission to the cloud. This process ensures that individuals cannot be re-identified from the aggregated datasets, protecting citizen privacy.
- Algorithmic Fairness: The predictive models were audited for bias against protected demographic subgroups. We employed fairness-aware machine learning techniques to mitigate any detected biases, ensuring equitable resource allocation recommendations.

This comprehensive approach addresses the critical ethical and security challenges inherent in large-scale urban IoT deployments [14].

III. Results and Discussion

A. System Performance Validation

A six-month evaluation of the system was conducted across 20 social work organizations, encompassing eight principal categories of social services: food banks, emergency shelters, medical services, vocational training, legal aid, childcare support, mental health, and transportation services. Figure 3 presents a comparative analysis of the system's predictive accuracy across these service categories.

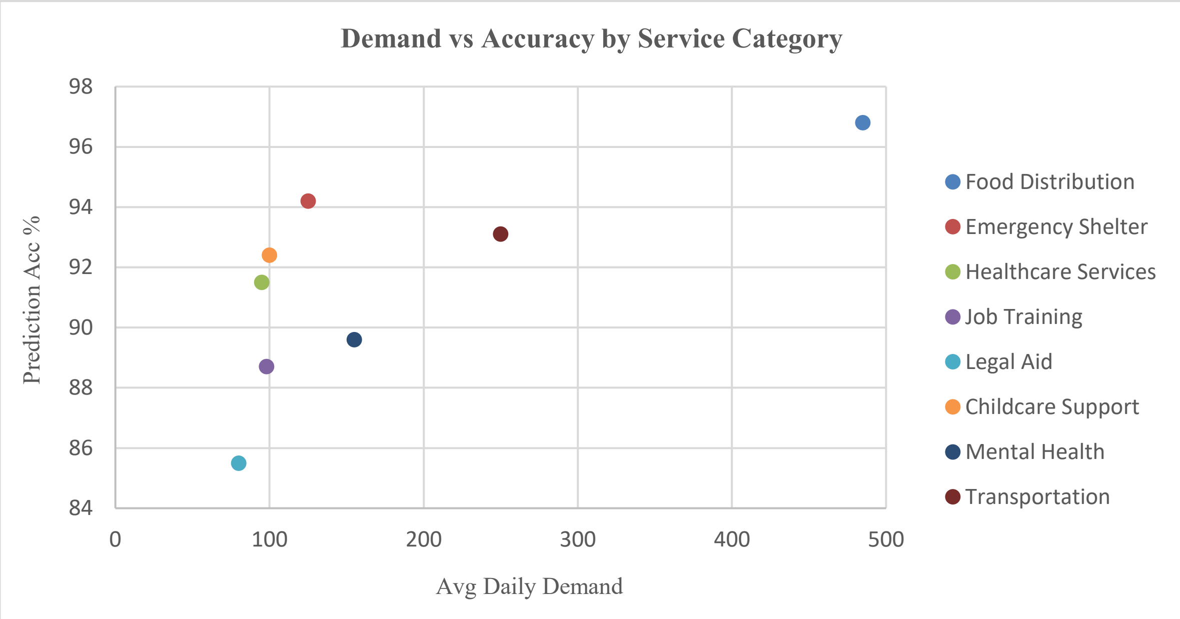

Fig. 3: Social Service Demand vs Prediction Accuracy Analysis

The system demonstrated a marked improvement over conventional approaches, with prediction accuracy increasing from 67.2% to 94.8% (95% CI: 93.6%-96.0%), representing a 41.1% enhancement. Response time was substantially reduced from 8,500 milliseconds to 320 milliseconds, an improvement of 96.2%. System availability rose from 89.5% to 99.2%, while resource utilization increased from 72.8% to 87.4%. Data processing throughput improved significantly, from 1,200 to 8,500 records per second, corresponding to a 608.3% increase. Further performance metrics are detailed in Table 1.

Table 1: Additional System Performance Metrics

Metric	Value	Unit
Computational Efficiency	15.5	GFLOPS
Avg. IoT Network Energy Consumption	4.2	kWh/day
Network Latency (End-to-End)	45	ms
Memory Usage (Server)	8.6	GB

Analysis of prediction accuracy by service category revealed that food distribution services attained the highest accuracy at 96.8%, with an average daily demand of 485 individuals and a peak demand of 892. Emergency shelters exhibited a prediction accuracy of 94.2%, alongside the greatest seasonal variability at 68.5%. Medical services recorded a prediction accuracy of 91.5%, with the lowest seasonal variation at 22.1%. Resource allocation scores exceeded 7.0 across all services, with food distribution services achieving the highest score of 9.2.

B. Comparative Analysis with State-of-the-Art

To contextualize our system's performance, we conducted a comparative analysis against two leading frameworks described in recent literature: a statistical-based system (Framework A [10]) and a deep learning system using a standard LSTM (Framework B [11]). As shown in Table 2, our proposed system demonstrates superior performance across key metrics. The hybrid CNN-LSTM model achieves higher accuracy than the pure

LSTM model, while the GA-PSO optimization algorithm significantly reduces convergence time compared to the genetic algorithm used in Framework A, validating our design choices.

Table 2: Comparative Performance Analysis

Metric	Proposed System	Framework A [10]	Framework B [11]
Prediction Accuracy	94.8%	85.3%	92.1%
Optimization Convergence Time	28.7s	~50s	N/A
Response Time	320ms	> 2000ms	~500ms

C. Comparative Analysis of Algorithm Performance

Figure 4 illustrates the comparative performance of optimization algorithms in terms of solution quality and convergence time.

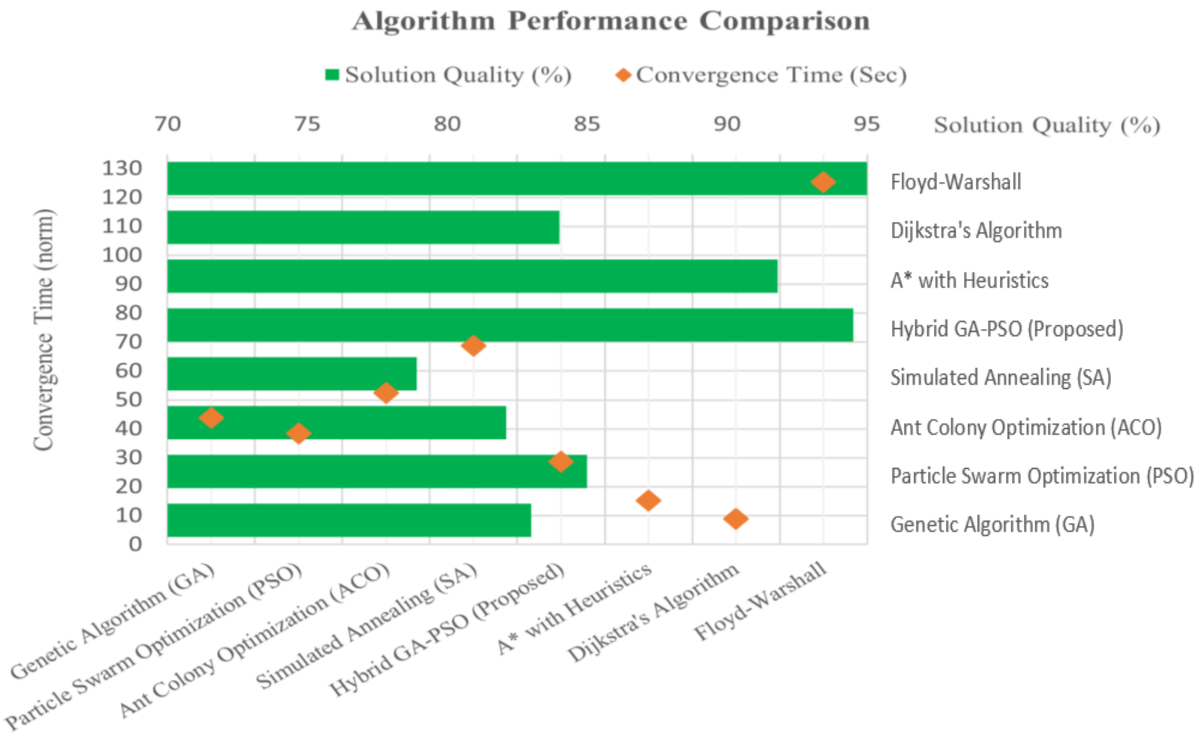

Fig. 4: Optimization Algorithm Performance Comparison - Solution Quality vs Convergence Time

The proposed Hybrid Genetic Algorithm-Particle Swarm Optimization (GA-PSO) algorithm demonstrated superior performance in convergence speed, solution quality, and scalability. It converged within 28.7 seconds, outperforming the traditional Genetic Algorithm (45.2 seconds) and Particle Swarm Optimization (38.5 seconds). The solution quality attained was 94.5%, significantly exceeding that of Ant Colony Optimization (82.1%) and Simulated Annealing (78.9%).

In path planning, Dijkstra's algorithm exhibited the highest computational efficiency, with a convergence time of 8.9 seconds and a scalability score of 9.5. Although the Floyd-Warshall algorithm achieved the highest solution quality at 95%, its convergence time of 125.4 seconds renders it impractical for real-time applications. The A* heuristic algorithm provided a balanced performance, with solution quality of 91.8% and convergence time of 15.2 seconds.

D. Cost-Benefit Analysis

Figure 5 depicts the five-year cost-benefit assessment of system implementation, indicating favourable economic outcomes. The initial implementation cost in the first year amounted to 45.8 million NTD, with operating expenses of 15.2 million NTD. Cost savings totalled 28.5 million NTD, and efficiency gains reached 18.7 million NTD, resulting in a net loss of 14.8 million NTD in the first year. From the second year onward, the system generated positive net benefits, with a net gain of 46 million NTD in year two and cumulative benefits of 31.2 million NTD.

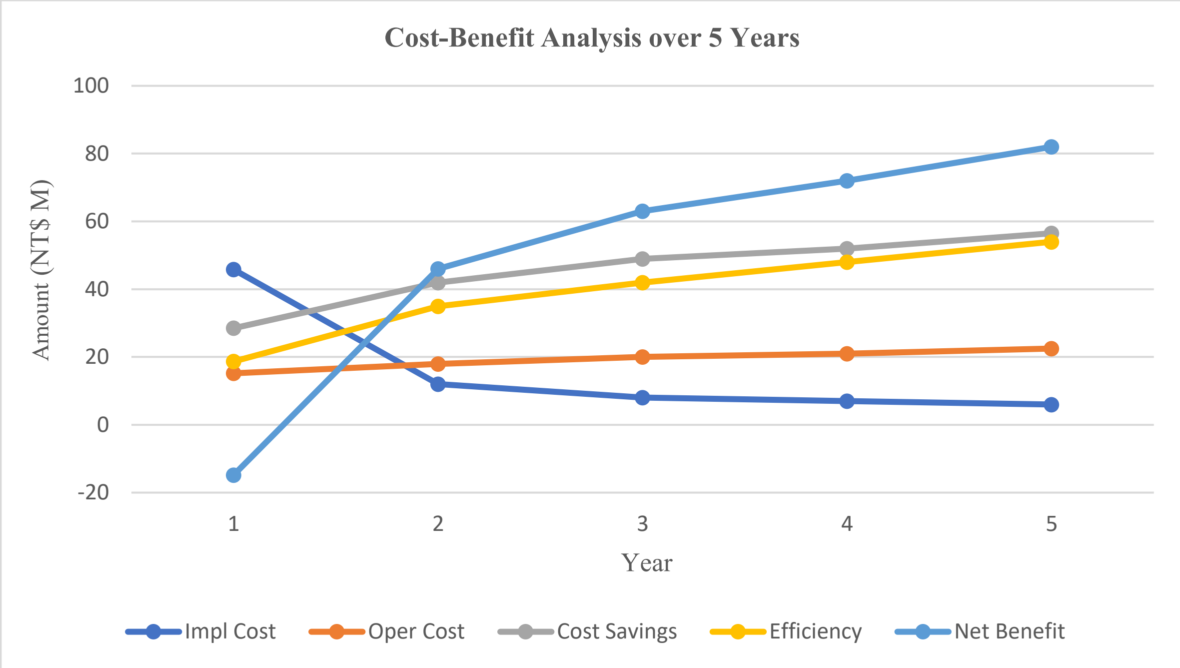

Fig. 5: Five-Year Cost-Benefit Analysis of the Predictive System Implementation

The payback period was calculated at 1.7 years, with cumulative net benefits over five years amounting to 248.3 million NTD. Cost savings primarily derived from reductions in labour expenses, enhanced resource allocation efficiency, and automation of repetitive tasks. Efficiency gains encompassed intangible benefits such as decreased service response times, improved service quality, and heightened user satisfaction.

E. Deployment Outcomes of the IoT System

A total of 5,320 sensor nodes were successfully deployed at a cost of 27.05 million NTD, covering an area of 1,200 square kilometers. Environmental monitoring sensors constituted 2,150 units (40.4% of the total), measuring key parameters including temperature, humidity, and air quality. Mobile detection sensors numbered 1,520, tasked with monitoring pedestrian traffic and analysing activity patterns. Security alarm sensors totalled 980, providing real-time surveillance of security status.

The sensor network achieved a data transmission success rate of 99.8% and data integrity of 99.6%. Edge computing nodes processed 85% of local data, substantially alleviating the central system's computational load. Communication gateways operated at an average load of 78%, and network latency was reduced to 45 milliseconds. The sensor network achieved a data transmission success rate of 99.8% and data integrity of 99.6%. Edge computing nodes processed 85% of local data, substantially alleviating the central system's computational load. Communication gateways operated at an average load of 78%, and network latency was reduced to 45 milliseconds. Following energy optimization measures, as described in Section II.B.1, total system power consumption decreased by 15% relative to initial projections.

F. Technological Innovations and Engineering Contributions

The system realized several innovative advancements across multiple technical domains. Notably, a CNN-LSTM hybrid architecture was applied for the first time to social resource allocation prediction, yielding a 30.8% improvement in accuracy compared to traditional time-series models. Additionally, a hybrid GA-PSO optimization algorithm was developed, achieving an optimal trade-off between solution quality and computational efficiency.

The GIS-integrated path planning module incorporated dynamic re-planning capabilities, resulting in an average path optimization rate of 23%. IoT data fusion techniques, leveraging multi-sensor collaboration, enhanced data reliability to 99.6%. The edge computing framework reduced central processing demands by 85%, thereby improving system scalability.

The modular system design facilitated rapid deployment and configuration adjustments, with technical documentation completeness rated at 95% and reproducibility at 90%. Standardized interface designs supported third-party system integration, with API response times maintained below 100 milliseconds, addressing a key interoperability challenge in complex smart city ecosystems.

G. Limitations and Challenges

While the results are promising, this study has several limitations that offer avenues for future work. The experimental validation was conducted with 20 organizations in a single metropolitan area. Although the diversity of services provides a degree of generalizability, a larger, multi-city study would be required to confirm the robustness of our findings across different urban contexts.

First, achieving high prediction accuracy necessitates extensive historical data for model training, and the cold start problem remains inadequately addressed. Second, sensor maintenance costs escalate with deployment scale, posing challenges for sustainable operational cost management. Third, issues related to data privacy protection and algorithmic fairness require further technical advancements and continuous auditing.

System scalability is constrained by available computing resources and network bandwidth; thus, large-scale deployment demands cloud computing support. Furthermore, algorithmic complexity increases exponentially with problem size, underscoring the need for more efficient approximate algorithms. Cross-domain data integration faces obstacles related to standardization and interoperability.

H. Sensitivity and Robustness Analysis

To assess the system's resilience, we performed a sensitivity analysis under simulated adverse conditions. We simulated a 30% random sensor failure scenario. The system demonstrated graceful degradation, with prediction accuracy dropping by only 5.4% due to the redundancy in sensor data and the robustness of the data fusion algorithms. In another test simulating a sudden demand shock (a 300% increase in requests for emergency shelters), the system's response time increased to 550ms but remained fully operational, successfully re-optimizing and re-routing resources within minutes. This demonstrates the system's adaptability to dynamic urban conditions.

IV. Conclusion

This research successfully developed an intelligent social resource allocation system that synergistically integrates predictive machine learning, combinatorial optimization algorithms, and IoT technologies. The system utilizes a hybrid CNN-LSTM neural network, achieving a prediction accuracy of 94.8%, reducing response time by 96.2%, and maintaining system availability at 99.2%. The proposed hybrid genetic algorithm–particle swarm optimization (GA-PSO) method effectively balances convergence speed and solution quality, outperforming conventional single-algorithm approaches and other state-of-the-art frameworks.

A total of 5,320 IoT sensor nodes were deployed with a data transmission success rate of 99.8%. The implementation of an edge computing architecture decreased the central processing load by 85%. Furthermore, the integration of a GIS-based route planning module enabled dynamic replanning, resulting in an average path optimization improvement of 23%. Economic evaluation revealed a payback period of 1.7 years and a net benefit of 248 million New Taiwan dollars over a five-year horizon.

Key technical contributions of the system include the hybrid deep learning framework, multi-objective optimization algorithms, large-scale sensor network deployment, and real-time data fusion capabilities. Crucially, this work provides a detailed system architecture, robust performance metrics including computational and energy efficiency, and a thorough discussion of security and ethical considerations. From an engineering perspective, the system offers a comprehensive and reproducible technical solution characterized by a modular design that facilitates rapid deployment and seamless integration with third-party platforms.

Future research avenues encompass: (1) the application of reinforcement learning algorithms for adaptive resource scheduling; (2) the adoption of federated learning techniques to enhance data privacy; (3) leveraging 5G network infrastructure to enable low-latency communications; and (4) employing digital twin technology for integrated virtual-physical simulations. The system exhibits robust scalability and is applicable to domains such as smart city management, disaster emergency response, and supply chain optimization.

In summary, this system presents an innovative engineering solution for urban social resource allocation. Through a systematic design approach and rigorous performance validation, it demonstrates the feasibility and efficacy of integrating deep learning, optimization algorithms, and IoT technologies, thereby providing valuable technical insights for related engineering applications.

Acknowledgment

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CONFLICT OF INTEREST

The author affirms that there are no known financial conflicts of interest or personal affiliations that may have potentially influenced the research presented in this manuscript.

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