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Enhanced IoT Supply Chain Optimization through Two-Tier Spectral Clustering and Fuzzy-Logic Pathfinding

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ABSTRACT

Web of Things integrated with logistics needs a plenty of smart devices broadly distributed across total logistics systems to track resources and monitor environmental conditions. These internet enabled resources communicate wirelessly to convey logistical information to a central monitoring station, which then sends this information through internet for analysis. However, the huge rate of information transmission rapidly depletes the energy of monitoring devices, thereby reducing the functional life expectancy of the monitoring system. To overcome this issue, we propose an enhanced clustering and routing strategy known as the Fuzzy Spectral Clustering and Routing Algorithm (FSCRA). FSCRA influences the strengths of Signless Laplacian matrices to facilitate effective resource grouping and fuzzy logic to manage logistics uncertainties, for smart decision-making. Moreover, a dual-layer clustering basis is presented to split the logistic system into local and master tiers, which effectively distributes the communication load and justifying congestion in extensive global distributions. Also, A* algorithm is used in this work to identify optimal logistics paths among the master cluster heads to minimize functional costs and energy consumption. By combining these techniques, FSCRA not only ensures well-adjusted resource distribution among nodes but also improves the overall logistics visibility and performance. Wide-ranging simulations were conducted to assess the efficiency of FSCRA related to existing logistics management methodologies. The outcomes reveal that FSCRA suggestively improves key performance metrics, including packet delivery ratio, resource monitoring time, and energy consumption. This recommends that FSCRA stands as a strong and feasible solution for optimizing modern internet enabled logistics while maintaining high levels of data transmission reliability and efficiency.

1. Introduction.

The Web of Things in supply chain management has become a vital revolution for real-time resource monitoring, inventory management, and global logistics visibility. These networks consist of numerous Internet enabled sensors and monitoring devices distributed over a global logistic, each capable of sensing environmental conditions, processing logistics information, and transmitting status updates. As monitoring tags are typically power-driven by batteries with insufficient energy capacity, a key design challenge in IoT-driven logistics is reducing power usage. When internet enabled devices are attached to cargo or containers, the condition is often impossible to replace or recharge these batteries. This makes energy efficiency as a highest importance to ensure the monitoring system's longevity. Battery usage becomes even more serious in scenarios where information is relayed through multiple intermediary gateways before reaching the central logistics control centre. Multi-hop routing is necessary in large-scale logistics or when direct communication with the central hub is not feasible due to distances,

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obstacles, or interference. However, this approach can lead to quick reduction of the energy reserves of the nodes involved in transmitting data, thus reducing the system's functional life expectancy. Moreover, choosing an optimal logistics route is a challenging task, as it requires balancing the trade-offs between energy consumption, distribution delay, and logistic chain reliability.

To lighten these challenges, clustering has developed as one of the most effective and widely used routing strategies in logistics system. Clustering involves organizing internet enabled resources into distinct groups, or clusters, with each cluster managed by a designated Cluster Head (CH) such as a smart distribution container. The CH organizes local distribution group and regional center communication. Clustering simplifies logistics by reducing direct communication channels and data flow.

In a clustered logistic, resource tags send data to the CH instead of the main server. The CH collects data from all its resources, combines or processes it to reduce redundancy, and sends it to the central administration, sometimes through other CHs in a hierarchical logistical system. This aggregation minimizes communications, saving tag energy. Clustering also balances load by rotating the CH role among gateways in the cluster, preventing device battery drain. In large-scale worldwide installations, single-tier clustering sometimes causes the hotspot problem, as CHs near the central hub consume more energy due to relay traffic. A dual-layer clustering architecture is needed to separate local stocktaking collection from global backbone routing, improving logistic chain structural extensibility.

Clustering improves logistics versatility and management while increasing functional productivity. Clustering extends the monitoring system's life by localizing traffic within regional clusters and reducing direct transmissions to the monitoring station, making it ideal for extensive internet-enabled logistics that requires energy conservation. Spectral graph theory and spectral clustering can improve energy efficiency, logistics optimization, and system stability in internet-enabled logistics by clustering resources and partitioning networks. By using the logistics graph representation's spectrum features, spectral clustering creates stable, energy-efficient, and well-balanced logistics groups. Minimizing energy usage in monitoring networks requires efficient clustering. Signless Laplacian clustering can find internet-enabled devices close by route or location for energy-efficient communication. The Signless Laplacian is well-suited for graphs with weakly connected components, a common scenario in global logistics due to limited communication range and shipment gaps. By integrating a dual-layer approach, the Signless Laplacian can be exploited for macro-level partitioning of global trade routes, while fuzzy logic achieves micro-level leadership roles across different distribution tiers.

Fuzzy logic is an effective tool which is used for gateway selection. Fuzzy logic helps in combining factors like distance between the resource and the hub and the residual energy of the monitoring device to select the most suitable CH in a flexible and adaptive way. The A* algorithm is an excellent pathfinding technique which is used for optimum supply chain planning. By taking into account number of variables namely residual energy, distance between the transport vehicle and the destination, the A* algorithm helps in identifying the most efficient route from the source to destination.

In this work, a new fuzzy cluster-based routing algorithm based on fuzzy rules and spectral clustering has been proposed specifically for Enhanced IoT Supply Chain Optimization. The eigenvalues used in spectral clustering help in similarity measures leading to more accurate clustering of resources. This is supported by fuzzy rules for handling uncertainty in the logistics process with respect to cluster formation, CH selection, and A* algorithm-based optimal route discovery to ensure effective routing of data collected by the supply chain nodes.

2. Related Works.

In the literature, there are numerous research studies on group-based routing and on fuzzy logic [1-9]. Imad et al. in [10] combined Fuzzy logic and the A* algorithm in a novel way to adjust energy utilization among IoT devices, extending the monitoring system's life expectancy. Karkvandi et al. [11] introduced a lifetime criterion considering sensing spatial coverage as an IoT (WSN) operation criterion. They also calculated normalized network lifetime using an augmentation algorithm. Logambigai et. al. [12] have proposed a fuzzy-based unequal clustering approach where the Gateway was chosen using a fuzzy approach and then the remaining resource tags were joined with the Gateway to form a logistics cluster. The algorithm developed by Kim et al. in [13] extends the network lifetime utilizing fuzzy logic to calculate the likelihood of a resource acting as a head of the cluster. Thangaramya et al. [1] have proposed the use of spectral graph theory by following the approach of Clustering using Eigenvalues (CEV). In order to cluster the IoT nodes, they used a Laplacian matrix, and the eigenvalues and respective eigenvectors of the matrix were used to organize the devices.

In [14], Mhemed et al. proposed a fuzzy logic cluster formation protocol that forms clusters using a fuzzy inference system. Keyur M. Rana and Mukesh A Zavaeri in [15] proposed an A-star-based Energy-Efficient Routing algorithm to improve resource monitoring duration. To discover the best delivery route between the source and the destination, they utilized the A-Star method. Using the Fuzzy C-Means (FCM) procedure, Abdulzahra and Al-Qurabat [16] presented a clustering technique. A maximum energy level was introduced in their model to postulate the dependency of the Cluster Head (CH) on existing energy levels. Their approach merged fuzzy c-means, residual power, and the location of the node to select a CH. They have concluded that the presented approach helps in improving the life expectancy of the monitoring system. Whereas these single-tier fuzzy models excellently manage local energy, they habitually struggle with routing overhead in high-density industrial IoT.

Shahraki et al. in [17] made a study on challenges of large-scale IoT. In their review, they categorized and classified clustering algorithms based on objectives and network properties. Subramani et al. [18] presented a fuzzy-logic-based clustering model for IoT where they have chosen Gateways depending on the distance to the hub, the strength of the remaining nodes, and node compactness. Then the devices that weren't a Gateway were grouped and clusters were generated. They have concluded that the performance of the proposed method was at least 50% better. A hierarchical routing with optimal clustering utilizing a fuzzy system (HROCF) has been proposed by Kumaran et al. [19]. This method consisted of two phases; during the first phase, a Gateway was chosen with fuzzy inputs while in the second phase, hierarchical routing was employed for inter-hub communication. The move toward hierarchical structures suggests that multi-tier management is significant to balancing the load across nodes with varying distances from the central logistics sink. The energy-efficient distributed clustering algorithm (EEDCF) was proposed by Zhang et al. [20]. In this approach, they have considered non-uniform distribution and they have employed the Sugeno and Kang (TSK) fuzzy model to ensure the reasonability of the quantitative analysis.

LEACH-Fuzzy Clustering is an approach recommended by Lata et al. [21]. This approach utilized a centralized approach rather than a distributed (conveyed) approach to perform cluster arrangement and Gateway choice. An energy-efficient technique using fuzzy logic has been proposed by Toloueiashtian and Motameni [22] and they have considered three parameters for cluster formation namely the amount of connections in the Gateway, the power in the Gateway, and the distance from the Gateway to the central hub. Le-Ngoc et al. [23] have presented a multi-level scheme for clustering based on a Fuzzy Logic Controller (FLC). They have arranged the IoT network into multi-level clusters. Further, they have optimized the clustering using FLC. Authors in [24] suggested a brand-new routing protocol by encompassing LEACH. Using arbitrary power spreading and balancing the load, this model focuses on energy optimization. This approach is a widely used method for routing based on clusters described in the literature, and it rotates the Gateways according to the amount of energy that is available and left. The majority of IoT network systems compare their algorithm's energy efficiency with the LEACH energy level. As a result, the creation of this procedure represents a significant accomplishment for IoT routing. It is suggested in [25] to use the most well-liked clustering method, termed HEED. In this paper, the process of clustering IoT networks for energy efficiency is explained in detail. It also offers a suggestion for how nodes in ad hoc networks can elect a Gateway and form clusters.

In spite of these improvements, many existing protocols fail to integrate spectral partitioning with multi-tier hierarchy to address the supply chain congestion and hotspot problem effectively. Most modern models count on simple heuristic routing that does not account for the combined complexity of node connectivity and residual energy in a dual-layered environment. Recent studies such as those by Basavaraj et al. [27] and Wu et al. [28] have emphasized the restrictions of single-tier clustering in large-scale deployments, suggesting that dual-layer architectures are necessary to mitigate the hotspot problem.

In order to handle uncertainty in intricate IoT and environmental systems, [29,30] fuzzy-based mathematical models have been frequently used. The usefulness of such methods in practical applications is shown by fuzzy-grey modeling in IIoT contexts and vague-intellectual approaches for environmental analysis. Fuzzy -tree automata, which simulate structured information using tree-based representations, have been used to investigate hierarchical structures in fuzzy systems. In wireless sensor networks, where hierarchical communication structures are naturally formed by clustered topologies, such representations are pertinent.[31]. As a result, an improved routing approach using spectral graphs, fuzzy logic, and a dual-layer clustering framework is recommended for use in Enhanced IoT Logistic Optimization.

3. Preliminaries.

In this section, existing definitions, concepts, and findings that are fundamental to the development of our main contribution to IoT logistic optimization has been presented. These conventional theories and prior research efforts provide the necessary context and foundation for understanding the innovations and improvements proposed in this study.

3.1. Definition.

Let $G = (V, E)$ be a graph representing the logistic system, where the vertex set V *denotes IoT devices,* $V = \{v_1, v_2, \dots, v_n\}$ and edge set E denotes the communication or transit links between them, $E = \{e_1, e_2, \dots, e_m\}$. The adjacency matrix of A_G is defined by equation (1) [4]

$$a_{ij} = \begin{cases} 1, & \text{if } v_i \text{ and } v_j \text{ are adjacent,} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

3.2. Definition.

An(edge)-weighted graph is a graph G having non - zero weighted edges. In the context of logistics, there is a weight function $W : E \to R$ edge set $E(G)$ for this set of non-zero real numbers representing factors such as signal strength, transit distance, or fuel cost. It is denoted by (G, W). Let A_G be the *adjacency matrix* of a weighted graph G and is given by equation (2) [4]

$$A_G(i, j) = \begin{cases} w(i, j), & (i, j) \in E, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

where $w\,(i, j)$ represents the weight of the edge $(i, j)\,\epsilon E$

3.3. Definition.

A *path* in the logistic is a trail in which all the vertices (except possibly the first and last) are distinct representing a specific delivery or data relay route from an resource to a central hub.

3.4. Definition.

Let D_G be the *degree matrix* of a weighted graph G. In a logistics network, the degree of a node signifies its connectivity density within a warehouse or shipping lane. Its diagonal values are given by equation (3) [4].

$$D_G\,(j,\ j) = \sum_j A_G\,(j, k) \tag{3}$$

3.5. Definition.

Let S_L be the S*ignless Laplacian matrix* of a weighted graph G and it is defined by equation (4).

$$S_L = A_G + D_G \tag{4}$$

In the context of Enhanced IoT logistic Optimization, the Signless Laplacian is particularly effective for identifying the global skeleton of the logistics network, allowing for the separation of high-degree nodes that can serve as the pillar for the master cluster tier. This mathematical groundwork ensures that the most robust gateways are selected to manage the high-traffic backbone of the logistic.

4. System Model.

The basic system model of this work consists of IoT resource tags and gateways, which are deployed to monitor the logistics environment. The assumptions that are made in our work are:

1. The IoT supply chain network is composed of uniform monitoring devices with identical initial energy.
2. The deployment of IoT devices is discretionary across warehouses and transport vehicles.
3. After deployment, stationary gateways and the central logistics hub remain stationary.
4. After deployment, resource tags are left unattended and have limited energy throughout the transit period.
5. The intensity of the received signal is used to calculate the distance between IoT nodes.
6. The central logistics hub is situated outside of the immediate monitoring area.

A cluster of varying sizes is formed by the IoT devices in the supply chain. Each cluster has a Gateway or Cluster Head. The Gateway relays the data that the resource tags have detected to the central logistics sink. Every IoT node has the ability to function in either relay mode or sensing mode. When in relay mode, the Gateway collects data from its members, compresses it, and sends it to the central hub. We have focused a lot of attention on the monitoring node's energy optimization because the majority of its energy is lost during transmission over long-haul routes.

The energy model used in this work is comparable to that of the work existing in [11]. Moreover, its behavior is based on the equation (5) and (6). The Eelec, εfs and εmp are the electronics energy and the amplifier energy in free space and multipath respectively. The transmission energy needed for an l-bit message across a separation *dt* is as follows:

$$E_T(l, dt) = \begin{cases} l\,E_{\text{elec}} + l\,\varepsilon_{fs}\,dt^2, & \text{for } dt < d_0, \\ l\,E_{\text{elec}} + l\,\varepsilon_{mp}\,dt^4, & \text{for } dt \geq d_0. \end{cases} \tag{5}$$

where $d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$

The reception energy required for an l-bit message by a logistics gateway is as follows:

$$E_R(l) = l\,E_{elec} \tag{6}$$

5. Proposed Work.

The key objective of the proposed Fuzzy Spectral Clustering and Routing Algorithm (FSCRA) is to extend the life expectancy of IoT monitoring systems by optimizing both clustering and logistics data transmission processes. Unlike traditional single-tier models, FSCRA introduces a two-tier hierarchy to distribute the energy load more equitablyIn large logistics installations, hotspots are prevalent. This double-layer architecture separates the network into a Local Tier for warehouse-level information collecting and a Master Tier for global inter-hub relaying. FSCRA optimizes these operations using advanced methods to manage network energy. The Signless Laplacian matrix can be used to cluster resource tags based on connectivity, distance, and energy in internet-enabled logistics. Algorithm 1 shows the double-tier Fuzzy Spectral Clustering Algorithm phases. FSCRA uses the Signless Laplacian matrix from Spectral Graph Theory to cluster several IoT nodes. This method balances monitoring device loads in clusters, boosting network energy efficiency. The system ensures structural stability before tiered leadership elections by macro-level dividing global transit pathways using the Signless Laplacian. Fuzzy inference selects Gateways inside clusters. The cluster's space, each node's battery strength, and its degree (the amount of connections it has with other nodes) are considered by this method. The fuzzy inference method chooses the Gateway node based on these variables to optimize cluster performance and network energy efficiency. Master Cluster Heads (MCHs) from the gateway pool with higher remaining energy and closeness to the major logistical backbone route are selected by a secondary fuzzy selection procedure after local gateways are elected.

After selection, MCHs send aggregated logistical data to the central monitoring station. FSCRA uses Gateways from other clusters as relay nodes to preserve electricity since this transmission uses a lot of internet-enabled node energy. This multihop transmit technique minimizes node energy consumption, extending system life. The proposed work FSCRA uses Fuzzy A* to find the best logistics transmission route from the Gateway to the central monitoring center. This algorithm instantly finds the best path based on the network's state, ensuring low energy consumption and reliable communication.

Algorithm 1: Two-Tier Fuzzy Spectral Clustering and Routing Algorithm

Input:	*Total number of IoT nodes N, Initial Energy E_0, Central Hub coordinates (BS)*
Phase 1:	*Network Formation and Spectral Partitioning*
Step 1:	*Deploy N IoT nodes randomly in a logistics area.*
Step 2:	*Construct the Adjacency matrix and Degree matrix of the supply chain graph*
Step 3:	*Generate the Signless Laplacian Matrix (S_L) using equation (4)*
Step 4:	*Compute eigenvalues and their corresponding eigen Vectors.*
Step 5:	*Apply k-means clustering algorithm on eigenvectors to split the network into K regional clusters.*
Phase 2:	*Cluster Head (Two-Tier) Selection*
Step 6:	*In each cluster, Local Gateways are selected using Mamdani Fuzzy Inference System (FIS) by following rules given in Table 1.*
Step 7:	*From the selected Local Gateways, the Master Cluster Head (MCH) is selected using the FIS by following the rules given in Table 1.*
Phase 3:	*Heuristic Path Optimization*
Step 8:	*The central hub triggers the Fuzzy A* Algorithm to determine the optimal multi-hop path through the master cluster head.*
Step 9:	*For each MCH, calculate the evaluation function using equation (11)*
Step 10:	*The path with the minimum f(sn) value is identified as the optimal logistics route.*

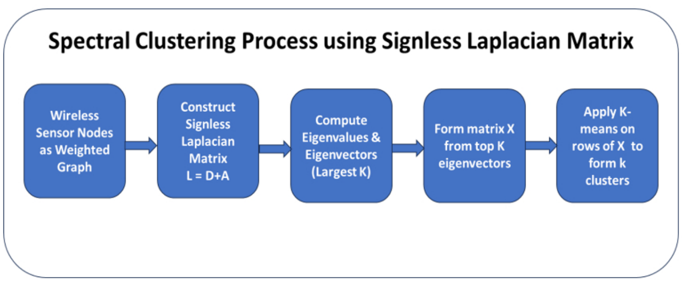
a. ***Formation of Clusters.***

Once the IoT monitoring devices are deployed, clusters are formed using Spectral Clustering as shown in Figure 1, which leverages the communication patterns between logistics resources to define the clusters. The process starts with constructing the Signless Laplacian Matrix (SL) utilizing the connectivity values obtained from the IoT devices. This matrix-based style is largely effective for large-scale logistic networks as it identifies weakly connected components that represent natural geographic or route-based partitions. The eigenvalues and eigenvectors of this framework are computed at that point. Using equation (7) as discussed in [26], the number of clusters, K, is determined.

$$K = \max \Delta_k = |\lambda_K - \lambda_{K-1}| \tag{7}$$

where λ_K and λ_{K-1} are consecutive eigenvalues of the Signless Laplacian matrix.

Figure 1: Spectral Cluster Formation in IoT Supply Chains.



Source: Authors.

Each IoT device identity i, is transformed into a tuple represents the corresponding values of the element i in the eigenvector. To construct the new matrix X, the largest K eigenvalues and their equivalent eigenvectors of the Laplacian matrix are used. In conclusion, the K-means method is applied to group each row of X into K distinct clusters, effectively partitioning the logistics resources into optimized clusters. By grouping resources based on shipment distance, the network ensures that data accumulation occurs at the most logical regional points, reducing long range transmission overhead.

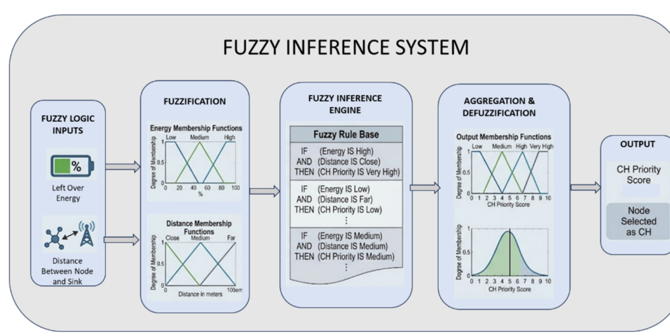
b. ***Selection of Logistics Gateway.***
The entire internet enabled logistic network system is divided into clusters using the spectral clustering technique, and the gateway is then selected using fuzzy logic. In this double-layer framework, specifically designed for Enhanced internet enabled Logistic Optimization, the fuzzy logic controller is applied twice: once for the election of Local Gateways and once for the designation of Master Kernals to ensure load balancing across logistics tiers. The most popular Mamdani fuzzy inference system [4], [11] and [12] is utilized in this work as shown in Figure 2. The reasoning engine takes two parameters namely distance between the IoT device and the central hub and the device's remaining battery level, as input. In a supply chain context, these parameters ensure that the most reliable and centrally located devices manage the data flow. The membership values for these two variables are low, average and high for battery levels and nearby, middle and far for the distance between the device and hub. Using the fuzzy rules listed in Table 1, the potential gateway values are calculated. The center of area (COA) method given in equation (10) is utilized for defuzzification, whereas the triangular and trapezoidal functions are utilized for fuzzification. The membership functions triangular and trapezoidal used in our fuzzy inference system are given in equation (8) and (9).

$$\mu_{A_1}(x_1) = \begin{cases} 0, & x_1 \le a_1, \\ \dfrac{x_1 - a_1}{b_1 - a_1}, & a_1 \le x_1 \le b_1, \\ \dfrac{c_1 - x_1}{c_1 - b_1}, & b_1 \le x_1 \le c_1, \\ 0, & c_1 \le x_1. \end{cases} \tag{8}$$

$$\mu_{A_2}(x_1) = \begin{cases} 0, & x_1 \le a_2, \\ \dfrac{x_1 - a_2}{b_2 - a_2}, & a_2 \le x_1 \le b_2, \\ 1, & b_2 \le x_1 \le c_2, \\ \dfrac{d_2 - x_1}{d_2 - c_2}, & c_2 \le x_1 \le d_2, \\ 0, & d_2 \le x_1. \end{cases} \tag{9}$$

$$COA = \frac{\displaystyle\int \mu_A(x_1)\, x_1\, dx}{\displaystyle\int \mu_A(x_1)\, dx} \tag{10}$$

Figure 2: Fuzzy Inference System for IoT Gateway Selection.



Source: Authors.

The extreme case rules are given below:
If the distance between IoT device and Hub is Nearby and High Battery Level, then the device has Very Strong chance of being a Gateway.
If the distance between IoT device and Hub is Far and Low Battery Leve, then the device has Very Weak chance of being a Gateway.

Table 1: Fuzzy Rules for Gateway Choice.

Distance between IoT Device and Hub	Device Battery Level	Gateway Priority
Nearby	High	Very Strong
Nearby	Average	High
Nearby	Low	Midrange
Middle	High	High
Middle	Average	Midrange
Middle	Low	Less
Far	High	Midrange
Far	Average	Less
Far	Low	Very Weak

Source: Authors.

c. ***Routing in IoT Supply Chains.***

This section explains the newly proposed routing technique for Enhanced IoT Supply Chain Optimization, utilizing fuzzy logic and A^* algorithm across logistics gateways to maximize the functional longevity of the monitoring system. The optimal path is determined here by routing through the Master Cluster Heads (MCHs) from the source to the destination, given the remaining battery capacity, and the gap between the IoT monitoring devices and the central logistics hub. The A^* algorithm is used here for transmitting logistics data to the Gateway from the neighboring resource tags. A fuzzy method has been used to determine the specific logistics node cost. The central logistics hub gathers information from each node within the transmission range. The best routing plan is calculated by the hub. Every round involves finding the best route, broadcasting it across the supply chain, and using this routing schedule to send data from local monitoring devices to the designated Gateway. After clustering, we use the A^* algorithm to find the optimal route from the source to destination and then send data to Gateway nodes in the inter-cluster backbone. Based on the evaluation function $f(sn)$ provided in equation (11), the IoT node is investigated.

$$f(sn) = NC(sn) + h(sn) \tag{11}$$

Where $NC(sn)$ is the logistics node cost, representing the actual cost of reaching node n from the source node. *NC(sn)* is computed using a fuzzy approach, and ranges from [0,1]. *h(sn)* is a heuristic function which estimates the cost from the current node to the final destination. By applying this evaluation function to the MCH tier, FSCRA ensures that the selected path maximizes residual energy while minimizing the Euclidean distance to the central hub. With the minimum $f(sn)$ cost, the A^* algorithm finds the path that balances data transmission consistency and energy efficiency. The chosen path is then used to forward resource monitoring packets from the source to the destination.

The Residual battery level of node n and Distance, the space between the central logistics hub and each IoT device of node *n,* are considered as fuzzy input variables to compute the best cost for node *n*. The fuzzy if-then rules for identifying the Node Cost within the supply chain are listed in Table 2.

Table 2: Fuzzy If-then Rules for Node Cost (NC) in IoT Supply Chains.

Battery Level (LE)	Distance to Hub (n)	Node Cost (NC)
Extremely less	Very less	Less
Extremely less	Less	Extremely less
Extremely less	Middle	Extremely less
Extremely less	Far	Extremely less
Extremely less	Very Far	Extremely less
Less	Very less	Midrange
Less	Less	Midrange
Less	Middle	Less
Less	Far	Less
Less	Very Far	Extremely less
Midrange	Very less	Large
Midrange	Less	Midrange
Midrange	Middle	Midrange
Midrange	Far	Less
Midrange	Very Far	Less
Huge	Very less	Very high
Huge	Less	Large
Huge	Middle	Large
Huge	Far	Midrange
Huge	Very Far	Midrange
Extremely large	Very less	Extremely large
Extremely large	Less	Extremely large
Extremely large	Middle	Extremely large
Extremely large	Far	Midrange
Extremely large	Very Far	Large

Source: Authors.

Using the defuzzification function Center - of - Gravity (CoG), NC(n) is obtained. The heuristic function $h(sn)$ is calculated by the Euclidean distance of the node to the destination hub.

6. Results and Discussions.

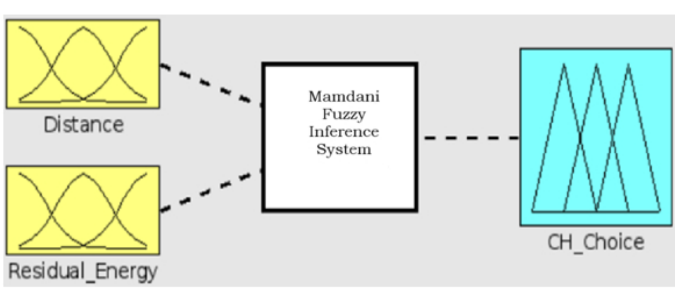
The proposed FSCRA algorithm has been evaluated using the MATLAB Fuzzy Toolbox, which runs the fuzzy functions provided in accordance with the fuzzy rules and mathematical framework established for logistics optimization. A total of 500 IoT monitoring devices were placed in the simulated logistics setup over a (100x100) m^2 area. An initial energy of 0.5J is assumed for each monitoring device. The suggested work is contrasted with various clustering techniques, including LEACH[23], CEV[5], A* and Fuzzy [9]. The algorithm initially tests with 100 to 500 IoT nodes. Figure 3 shows the Mamdani Fuzzy inference system for Gateway choice with 2 input variables Distance to Hub and Residual Energy, and 1 output variable Gateway Priority. Figure 4, 5 and 6 shows the fuzzy set values for the fuzzy input and output variable distance, residual energy and Gateway Priority respectively. The membership functions were further tuned to accommodate the selection of Master Hubs in the second layer of the hierarchy to manage transcontinental data flow.

Figure 7, 8 and 9 shows the fuzzy set values for the input variable Distance, Leftover energy and output variable Node Cost respectively, which are critical for calculating the most efficient transit paths.

Figure 10 presents a comparison of the IoT device functional duration across various routing algorithms, with the life expectancy measured in monitoring cycles. The graph clearly shows that the proposed Fuzzy Spectral Clustering and Routing Algorithm (FSCRA) significantly extends the logistic chain monitoring system's life expectancy compared to other existing routing algorithms. This extension is primarily attributed to the double-layered clustering approach, which prevents the hotspot problem by rotating the heavy relaying burden among a high-energy backbone of Master kernels.

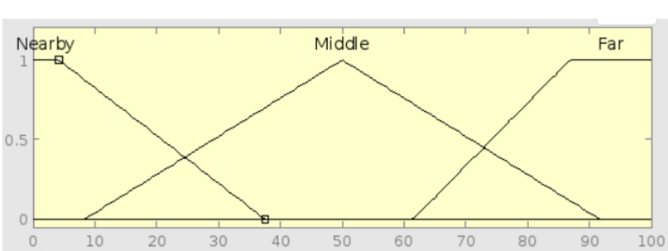
The trend observed in the graph indicates that as the number of tracked resources increases, the overall network life expectancy tends to decrease. This reduction in life expectancy is attributed to the increased energy consumption required to route a larger volume of logistics packets to the central kernel. However, FSCRA maintains a more stable deterioration curve than LEACH or CEV because the double-layer structure optimizes the load distribution, ensuring that local Gateways only perform short-range transmissions within the warehouse. More resources mean more data traffic, leading to more frequent transmissions and, consequently, higher energy disbursement.

Figure 3: Mamdani Fuzzy Inference System for Gateway Priority.



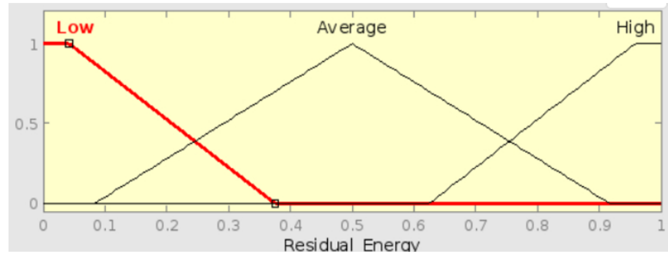
Source: Authors.

Figure 4: Fuzzy set for input variable Distance to Hub.



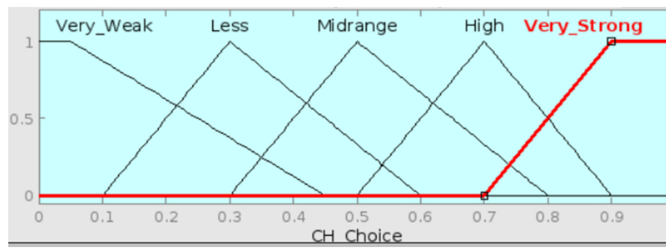
Source: Authors.

Figure 5: Fuzzy set for input variable Residual Energy of Monitoring Device.



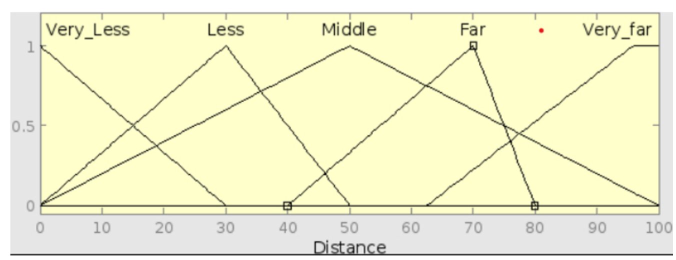
Source: Authors.

Figure 6: Fuzzy set for output variable Gateway Priority.



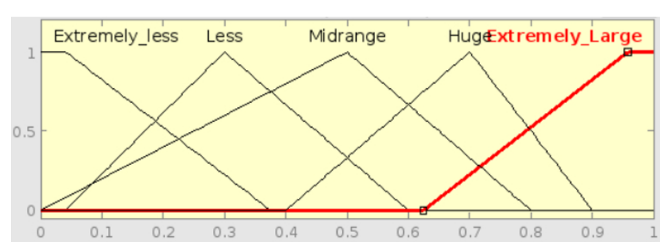
Source: Authors.

Figure 7: Fuzzy set for input variable Distance in Node cost evaluation.



Source: Authors.

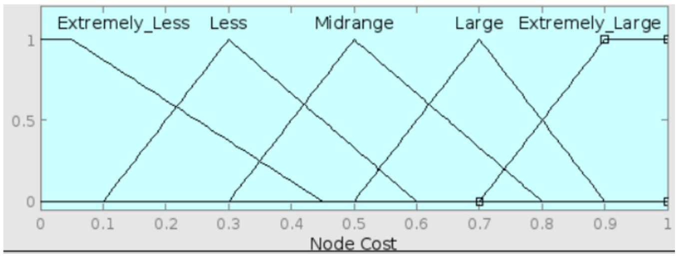
Figure 8: Fuzzy set for input variable Leftover Energy in Node cost evaluation.



Source: Authors.

Despite this general trend of decreasing life expectancy with an increasing number of monitoring devices, the FSCRA algorithm consistently outperforms other methods in terms of maintaining logistic network visibility. The effective use of the fuzzy

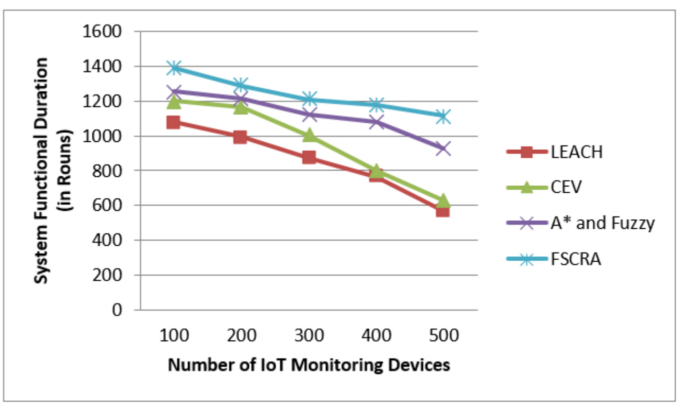
Figure 9: Fuzzy set for output variable Node cost.



Source: Authors.

logic and A* algorithm in the clustering-based routing strategy shows this superior performance. The proposed work FSCRA optimizes the routing paths and reduces unnecessary energy consumption by grouping resources into clusters and intelligently selecting Gateways based on their energy levels and closeness.

Figure 10: Number of IoT Monitoring Devices and System Functional Duration.



Source: Authors.

Moreover, the use of A* algorithm in this proposed work guarantees that the most energy-efficient paths are chosen for conveying real-time consignment from the Gateways to the monitoring station, which further enhances the monitoring system's energy efficiency. In consequence, even though the global logistics network grows in size and the routing process becomes more complex, FSCRA is able to manage energy consumption more effectively than other algorithms, thus extending the system's functional life.

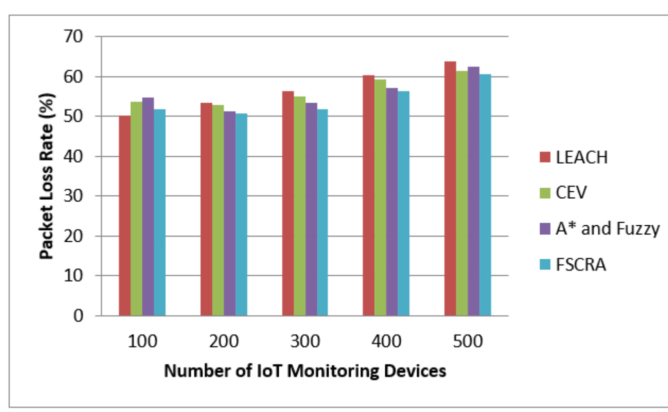
Figure 11 shows data transmission packet loss across a varied number of internet-enabled nodes. The results show that the suggested FSCRA has a much lower packet loss rate than competing methods. By structuring local and global information flow, the double-tier hierarchy decreases network congestion and packet failures during high-volume logistical reporting. Signal interference in industrial contexts, network congestion, and suboptimal routing paths cause packet loss in internet-enabled logistics. Monitoring devices exacerbate these issues, increasing packet loss rates. FSCRA solves these problems by using spectral clustering and the A* algorithm to transport data from warehouse to monitoring center reliably.

FSCRA groups internet-enabled logistic monitoring devices utilizing spectral clustering based on the Signless Laplacian matrix. This optimizes cluster formation, lowering the risk of resources being too far from their Local Gateways. The approach greatly decreases logistics status updates in the logistic network by using double-layer aggregation. A* was also used to find the best logistics channels for Gateway-to-central monitoring station data transmission. A* method uses device energy levels, shipping distance, and logistic chain architecture to find energy-efficient, dependable shipment routes. This thorough transmission channel selection reduces real-time cargo packet loss.

Even when the logistics network grows with more internet-enabled devices, the proposed approach FSCRA maintains a decreased packet loss rate through effective clustering and smart path selection using the A* algorithm. This is essential for logistic chain applications that require data integrity and reliability. Figure 12 shows that the suggested FSCRA method is more power efficient than current methods when comparing the average energy use of 100 IoT monitoring devices during different functional cycles. The optimum clustering of logistics resources utilizing spectral clustering reduces local communication energy with FSCRA algorithm. The suggested system prioritizes Gateways with lower connectivity using fuzzy logic, reducing energy consumption.

Additionally, the A* algorithm finds the most energy - efficient paths for logistical status transmission from Gateways to the central station, lowering energy use. FSCRA regulates and conserves energy, reducing energy use compared to other algorithms as the number of active internet - enabled nodes increases. By optimizing energy use across functional contexts, FSCRA can extend monitoring system life.

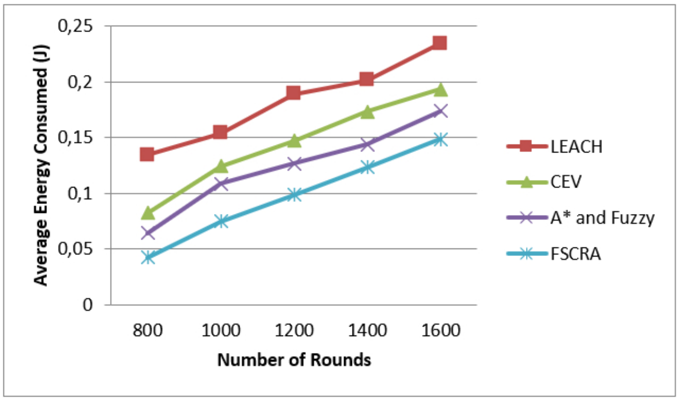
Figure 11: Packet Loss in IoT-Driven Logistics.



Source: Authors.

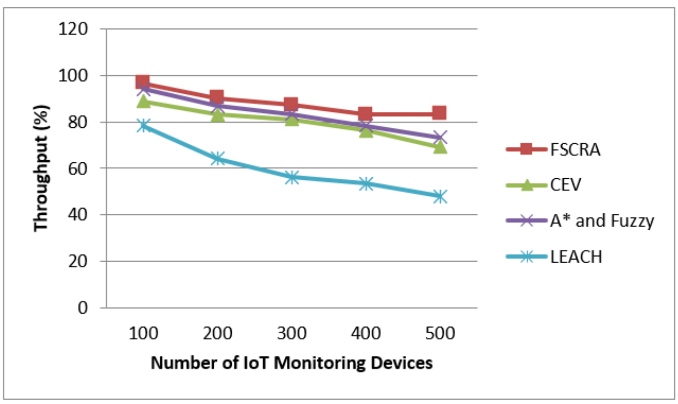
As IoT nodes proliferate, the proposed FSCRA algorithm outperforms existing techniques in throughput (Figure 13). By building a dedicated high-speed backbone through the Master kernels, the double-layer structure allows the logistic network to handle large traffic levels by delivering data from distant regional clusters to central logistics with little latency. Due to

Figure 12: Average Energy Consumption of IoT Resources.



Source: Authors.

Figure 13: Throughput in Smart Supply Chains.



Source: Authors.

FSCRA's efficient clustering and A* algorithm, which optimize logistics paths to avoid congestion and packet loss, throughput is increased. FSCRA distributes the increased data load evenly and selects optimal transmission pathways to preserve network throughput. The algorithm's ability to minimize packet loss increases data transmission success, enhancing throughput. FSCRA, a double-tier architecture, can handle expanding logistics sizes and achieve higher throughput than traditional approaches.

Conclusions.

The Fuzzy Spectral Clustering Routing Algorithm (FSCRA), a new algorithm for clustering and routing in Internet enabled logistic chains, has been put forth in this paper. In the proposed work, using Signless Laplacian cluster is used to form clusters, a Gateway is elected in each cluster using fuzzy logic, and the A* algorithm has been used for selecting the optimal path for the transmission of logistics data. A significant enhancement introduced in this work is the implementation of a dual-layer clustering mechanism, which partitions the network into local resource-level and master gateway tiers to balance the communication load across the logistics infrastructure. The suggested work was implemented and tested using MATLAB. By isolating the high-intensity routing tasks to a backbone of Master Hubs, FSCRA effectively addresses the energy hole problem common in dense industrial IoT deployments. According to the simulation results, the suggested work outperforms current methods regarding throughput, power efficiency, packet delivery ratio, and the life expectancy of the monitoring system. The integration of dual-tier management ensures that the network remains scalable and reliable even as resource density increases within a warehouse or transit lane. Future work can explore the use of Master Gateways as mobile nodes for use in mobility-based logistics applications.

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