



SCIENTIFIC OASIS

Spectrum of Decision Making and Applications

Journal homepage: www.dmap-journal.org
ISSN: 3042-1462



A Data-Driven Spatio-Temporal Expert System for Electric Vehicle Charging Demand Profiling: The Complex T-Spherical Fuzzy C-Means Clustering Algorithm

Subramanian Petchimuthu¹, M. Jeyalakshmi Saravanakumar^{2,*}, Fathima Banu M¹, Meena Somasundaram³, Dragan Pamucar^{4,5,6,*}

- ¹ Department of Science and Humanities (Mathematics), University College of Engineering Nagercoil, Nagercoil-629004, Anna University, Tamil Nadu, India
- ² Department of Mathematics, Velammal College of Engineering and Technology, Velammal Nagar, Madurai-Rameshwaram High Road, Viraganoor, Madurai-625009, Tamil Nadu, India
- ³ Department of Mathematics, KPR Institute of Engineering and Technology, Coimbatore-641407, Tamil Nadu, India
- ⁴ Department of Operations Research and Statistics, Faculty of Organizational Sciences, University of Belgrade, Belgrade, Serbia
- ⁵ UNEC Applied Artificial Intelligence Research Center, Azerbaijan State University of Economics (UNEC), Baku, Azerbaijan
- ⁶ Department of Applied Mathematical Science, College of Science and Technology, Korea University, Sejong 30019, Republic of Korea

ARTICLE INFO

Article history:

Received 20 July 2026

Received in revised form 26 August 2026

Accepted 19 September 2026

Available online 16 October 2026

Keywords:

Complex T-spherical fuzzy sets; Fuzzy C-Means clustering; Spatio-temporal clustering

ABSTRACT

Optimizing Electric Vehicle (EV) charging infrastructure is a critical urban planning challenge characterized by high-dimensional uncertainty and periodic traffic flows. Traditional decision models often suffer from "temporal blindness," failing to recognize the cyclical nature of urban movement (e.g., the proximity of late-night and early-morning hours). This paper introduces the Complex T-Spherical Fuzzy C-Means (CTSF-CM) expert system, a novel unsupervised machine learning framework designed for spatio-temporal demand profiling. The system utilizes a complex phase term to mathematically represent temporal periodicity and a T-spherical fuzzy structure to filter environmental noise from meteorological sensors. Validated on 2,747 hourly instances from the I-94 Interstate Highway, the CTSF-CM system achieves a Peak Separation Accuracy of 87.21%, significantly outperforming standard K-Means and Intuitionistic Fuzzy models. Beyond numerical precision, the system provides geometrically interpretable decision boundaries that allow urban planners to distinguish between morning and evening service zones, ensuring grid stability and infrastructure efficiency in smart city environments.

1. Introduction

The urban planning challenge of the 21st century is the optimal installation of Electric Vehicle (EV) charging infrastructure, as the transportation sector as a whole is rapidly electrifying. Compared to traditional gas stations, which are serviced by a constant stream of demand, EV charging demand is inherently spatiotemporal, dictated by the regularities of urban traffic (e.g., morning commutes, evening shopping hours). As a result, the decision support systems needed to select these sites must handle high-dimensional uncertainty—not only regarding *where* traffic density is high, but also *when*

*Corresponding author.

E-mail address: jeyamurugan.lakshmi@gmail.com

<https://doi.org/10.31181/sdmap41202776>

© The Author(s) 2026 | Creative Commons Attribution 4.0 International License

it occurs to avoid grid instability [18, 19].

Traditional approaches to this issue have heavily depended on Multi-Criteria Decision Making (MCDM) models. Recent works have employed Spherical Fuzzy CoCoSo [7] or Spherical Fuzzy VIKOR [8] to rank potential locations. The downside of these MCDM techniques, however, is that they lack critical scalability; they require a small, pre-defined set of alternatives to be assessed by human experts, usually limited to 5–10 variants. They are poorly adapted to the “Big Data” reality of modern smart cities, where thousands of geospatial nodes must be analyzed by planners to identify optimal service zones.

To overcome the issue of scalability, researchers have turned to unsupervised machine learning, namely the Fuzzy C-Means (FCM) clustering algorithm. Although standard FCM handles uncertainty well, it processes data as static scalars, often requiring complex augmentation to handle time-series data [21]. More recent developments have generalized FCM to T-Spherical Fuzzy spaces to address higher-order indeterminacy in image segmentation [2] and failure mode analysis [3]. However, these models operate strictly in the real domain; by modeling only the magnitude of membership, they remain blind to the periodicity of the data. In EV planning, it is essential to distinguish between a “Morning Peak” node and an “Evening Peak” node to balance grid loads, even when the traffic density of the two nodes is identical.

Ali *et al.* [1] presented a mathematical solution to this problem through Complex T-Spherical Fuzzy Sets (CTSFS). This structure is based on the foundational theory of Complex Fuzzy Sets [16], which introduced the phase term, $e^{i\theta}$, as a means of explicitly describing periodicity in recurrent systems [20]. Nevertheless, this theoretical advantage has been ironically limited by the application of CTSFS only to static MCDM aggregation operators. A wide variety of Complex T-Spherical aggregation tools are available in the existing literature—including Frank operators [4], Power operators [6], and Yager norms [5]—but they are applied to small-scale subjective ranking problems. To date, there is no recorded implementation of a clustering algorithm that extends the C-Means objective function into the Complex T-Spherical space to utilize the phase term for temporal pattern recognition.

1.1 Research Gaps and Contributions

Although Xian *et al.* [2] successfully introduced T-Spherical Fuzzy C-Means (TSF-CM) for spatial image segmentation, their approach operates strictly in the real domain. This creates a critical limitation when applied to urban mobility: **Temporal Blindness**. Standard TSF-CM treats data as static scalars. A node with high traffic at 08:00 (Morning Peak) and a node with equal traffic at 17:00 (Evening Peak) are mathematically identical in the real domain, despite requiring completely different grid load management policies to mitigate peak-hour stress [19]. Moreover, existing algorithms lack a mechanism to explicitly incorporate environmental noise (e.g., weather conditions) into the clustering logic without distorting the membership values.

To eliminate such limitations, this study proposes the Complex T-Spherical Fuzzy C-Means (CTSF-CM) algorithm. This Expert System offers four distinct contributions to the literature:

1. **Explainability vs. Black Box Models:** While Deep Learning models (e.g., LSTM, Autoencoders) excel at time-series predictions, they function as “Black Boxes.” Stakeholders in urban infrastructure planning require clear and explainable decision boundaries to justify the allocation of public money. Unlike neural networks, the proposed CTSF-CM is geometrically interpretable; clusters are constructed around explicit distances in the complex plane, providing planners with insight into why a particular node was identified as a “Morning Peak” area.
2. **Spatio-Temporal Clustering Mechanism:** Unlike previous works, such as [2], which model uncertainty levels only, our algorithm utilizes the *Complex Phase Term* ($e^{i\theta}$) to mathematically represent the periodicity of traffic flow. This enables the system to cluster infrastructure not only based on “Volume” (Amplitude) but also based on “Time-of-Use” (Phase), overcoming the temporal blindness of traditional fuzzy clustering approaches.

3. **Hybrid Neuro-Symbolic Architecture:** We introduce a novel mechanism of "Indeterminacy Injection" that serves as a symbolic knowledge layer within the neural-like clustering process. It maps qualitative meteorological concepts to the T-Spherical indeterminacy parameter (q) based on domain-specific heuristic rules. This allows the system to imitate expert judgment by automatically de-emphasizing the validity of traffic information gathered during adverse weather conditions—a semantic feature that standard C-Means lacks.
4. **Benchmarking on Real-World Data:** Departing from the tradition of recent studies that rely on small-scale simulated expert matrices, we benchmark the system on the *UCI Metro Interstate Traffic Volume* dataset ($N = 2,747$). Our results demonstrate that the system statistically outperforms K-Means and Intuitionistic Fuzzy C-Means in identifying operational service zones.

2. Literature Review

The theoretical basis of the research lies at the crossroads of sophisticated fuzzy clustering algorithms, sophisticated uncertainty modelling, and intelligent transportation systems.

2.1 Evolution of Fuzzy Clustering Algorithms

FCM has long been the standard for pattern recognition in uncertain environments. In order to deal with hesitation and non-membership, Xu and Wu [22] introduced Intuitionistic Fuzzy C-Means (IFCM) by incorporating a non-membership function. Basic IFCM is, however, constrained by the fact that the sum of membership and non-membership degrees is not allowed to exceed 1. In response, Mahmood *et al.* [23] introduced the T-Spherical Fuzzy Set (TSFS) as a variant that removes these constraints and expands the uncertainty space with the help of a parameter s that should not be less than 1 ($s \geq 1$).

Most recently, a weighted spatial T-spherical Fuzzy C-means algorithm was suggested for image segmentation by Xian *et al.* [2], showing that T-spherical sets can be more successful in noisy settings compared to intuitionistic sets. Likewise, Zheng *et al.* [3] combined K-Means and T-spherical fuzzy environments for Failure Mode and Effect Analysis (FMEA). These studies have contributed significantly to the processing of the dimension of uncertainty (amplitude), but they did not pay sufficient attention to the periodicity of data. For illustration, in traffic flow prediction, it has been emphasized that the ability to capture spatio-temporal correlations and periodicity is essential [9]; however, those approaches often used Type-2 fuzzy sets, which lack the explicit phase-amplitude structure needed to mathematically decompose magnitude and timing.

2.2 Complex T-Spherical Fuzzy Sets in Decision Making

The limitation of modeling periodicity in standard fuzzy sets led to the development of Complex Fuzzy Sets (CFS), where the membership function ranges to the unit circle in the complex plane. [1] generalized this to CTSFS, offering the widest degree of freedom for uncertainty modeling. Recent advancements between 2025 and 2026 have seen these environments applied to increasingly diverse fields. For instance, Shi *et al.* [29] developed a measurement method for food supply chain security from a resilience perspective using T-spherical fuzzy sets. In the complex domain, Sarfraz and Gul [30] utilized Hamacher aggregation operators under interval-valued complex T-spherical environments to evaluate medical college projects, while Ullah *et al.* [31] introduced Circular Complex Picture Fuzzy sets for business-oriented stock market decision analysis.

While complex fuzzy clustering has been applied to time-series forecasting [25, 26], these implementations typically rely on standard complex fuzzy sets without the T-spherical parameter (s), limiting their ability to handle high-entropy indeterminacy (e.g., severe weather noise). Furthermore, a critical review of the literature from 2021–2025 reveals that CTSFS research is heavily skewed toward Aggregation Operators (AOs) for MCDM. [4] developed Complex T-Spherical Frank aggregation operators to aggregate expert opinions. To date, there is no recorded implementation of a clustering algorithm that extends the C-Means objective function into the Complex T-Spherical space ($s > 1$) to leverage the phase term for temporal pattern recognition in urban planning.

2.3 EV Station Selection and The Research Gap

The selection of EV charging sites is a mature field, but one dominated by static ranking methods. [7] utilized the Spherical Fuzzy CoCoSo method, and [8] applied Spherical Fuzzy VIKOR. While data-driven approaches like Custom K-Means [24] have emerged to optimize locations based on demand, they inherently treat geospatial data as static scalars, failing to account for the stochastic nature of traffic flow or environmental noise.

Table 1 summarizes the position of this study. The proposed CTSF-CM algorithm is the first to combine the high-order uncertainty handling of T-Spherical sets with the temporal modeling capabilities of the Complex phase term within a clustering framework.

Table 1

Comparative analysis of related works and the proposed contribution

Ref.	Fuzzy Env.	Methodology	Periodicity?	Application
[2]	T-Spherical	C-Means Clustering	✗	Image Segmentation
[3]	T-Spherical	K-Means	✗	FMEA
[4]	Complex T-Spherical	Frank Aggregation	✓(Phase)	MCDM (Ranking)
[24]	Crisp (K-Means)	Clustering	✗	EV Site Selection
[25]	Complex Fuzzy	Clustering	✓(Implicit)	Time Series
Prop.	Complex T-Spherical	CTSF-CM	✓(Explicit)	EV Zoning

3. Preliminaries

In this section, we review the fundamental concepts of CTSFS. The mathematical notation and symbols utilized throughout this study are summarized in Table 2.

This structure generalizes Intuitionistic Fuzzy Sets ($s = 1$) [27] and Spherical Fuzzy Sets ($s = 2$) [28] by introducing a complex phase term to model periodicity, a concept originally proposed in Complex Fuzzy Sets by [16], and a flexible parameter s to capture broader indeterminacy.

Table 2

Nomenclature and Symbols used in this study

Symbol	Description
U	Universe of discourse
$\tilde{A}$	Complex T-Spherical Fuzzy Set (CTSFS)
μ, η, ν	Amplitudes for Membership, Indeterminacy, and Non-Membership
ϕ, ψ, ξ	Phase terms (Periodicity) corresponding to μ, η, ν
s	Spherical parameter controlling the uncertainty volume ($s \geq 1$)
m	Fuzziness index weighting exponent
d_{CTSF}	Rotational-Invariant Complex Distance measure
C	Number of Clusters (Service Zones)
V_i	Cluster Prototype (Centroid) for the i -th cluster
u_{ik}	Membership degree of k -th data point to i -th cluster

Definition 3.1 (Complex T-Spherical Fuzzy Set). Let U be a universe of discourse. Following [1], a Complex T-Spherical Fuzzy Set (CTSFS) $\tilde{A}$ on U is defined as:

$$\tilde{A} = \{ \langle x, \tilde{\mu}_{\tilde{A}}(x), \tilde{\eta}_{\tilde{A}}(x), \tilde{\nu}_{\tilde{A}}(x) \rangle \mid x \in U \} \quad (1)$$

where $\tilde{\mu}_{\tilde{A}}(x)$, $\tilde{\eta}_{\tilde{A}}(x)$, and $\tilde{\nu}_{\tilde{A}}(x)$ denote the complex-valued Membership, Indeterminacy, and Non-Membership degrees, respectively. These are defined in polar form as:

$$\tilde{\mu}_{\tilde{A}}(x) = \mu_{\tilde{A}}(x)e^{i2\pi\phi_{\tilde{A}}(x)}, \quad \tilde{\eta}_{\tilde{A}}(x) = \eta_{\tilde{A}}(x)e^{i2\pi\psi_{\tilde{A}}(x)}, \quad \tilde{\nu}_{\tilde{A}}(x) = \nu_{\tilde{A}}(x)e^{i2\pi\xi_{\tilde{A}}(x)} \quad (2)$$

where $i = \sqrt{-1}$. The amplitude terms $\mu, \eta, \nu \in [0, 1]$ and the phase terms $\phi, \psi, \xi \in [0, 1]$ must satisfy the following condition for a given spherical parameter $s \geq 1$:

$$0 \leq \mu_{\tilde{A}}^s(x) + \eta_{\tilde{A}}^s(x) + \nu_{\tilde{A}}^s(x) \leq 1 \quad (3)$$

For any $x \in U$, the Refusal Degree (or Hesitation Index) is given by $\pi_{\tilde{A}}(x) = (1 - (\mu_{\tilde{A}}^s(x) + \eta_{\tilde{A}}^s(x) + \nu_{\tilde{A}}^s(x)))^{1/s}$.

When the universe U consists of a single element, the triplet is referred to as a **Complex T-Spherical Fuzzy Number (CTSFN)**, denoted as $\gamma = \langle \mu e^{i2\pi\phi}, \eta e^{i2\pi\psi}, \nu e^{i2\pi\xi} \rangle$.

Remark 3.1 (Semantic Interpretation for EV Zoning). The CTSFS architecture is uniquely suited for EV infrastructure planning because its components map directly to physical traffic phenomena:

- **Amplitudes** (μ, η, ν) : Model the magnitude of traffic intensity and sensor reliability (noise).
- **Phases** (ϕ, ψ, ξ) : Model the temporal recurrence of traffic flow on a 24-hour cycle (Periodicity).
- **Parameter s** : Allows the system to adjust tolerance for environmental uncertainty (e.g., expanding the indeterminacy space during heavy precipitation).

Definition 3.2 (Rotational-Invariant Complex Distance). A dissimilarity measure is necessary for clustering. We use a generalized normalized Euclidean distance which is extended to the complex T-spherical domain. Suppose that two CTSFNs are given by $\tilde{A}$ and $\tilde{B}$. The distance $d_{CTSF}(\tilde{A}, \tilde{B})$ is defined as:

$$d_{CTSF}^2(\tilde{A}, \tilde{B}) = \frac{1}{3} (|\tilde{\mu}_{\tilde{A}} - \tilde{\mu}_{\tilde{B}}|^2 + |\tilde{\eta}_{\tilde{A}} - \tilde{\eta}_{\tilde{B}}|^2 + |\tilde{\nu}_{\tilde{A}} - \tilde{\nu}_{\tilde{B}}|^2) \quad (4)$$

We take advantage of the law of cosines in the complex plane to mathematically describe periodicity. In the case of two complex numbers, $z_1 = r_1 e^{i\theta_1}$ and $z_2 = r_2 e^{i\theta_2}$, the squared Euclidean distance is $|z_1 - z_2|^2 = r_1^2 + r_2^2 - 2r_1r_2 \cos(\theta_1 - \theta_2)$. To this end, we apply this equation to the membership term in the definition of distance in Eq. (4) as follows:

$$|\tilde{\mu}_A - \tilde{\mu}_B|^2 = \mu_A^2 + \mu_B^2 - 2\mu_A\mu_B \cos(2\pi(\phi_A - \phi_B)) \quad (5)$$

This expansion corresponds to the application of the terms of indeterminacy and non-membership, respectively.

Remark 3.2 (The "Midnight Problem"). The cosine in the distance function is vital in temporal clustering. The timestamps of 23:59 and 00:01 (represented by phase values $\phi \approx 0.99$ and $\phi \approx 0.00$) are at opposite ends of the scale in linear space, making them farthest apart. However, the distance in the above complex metric is close to zero since $\cos(2\pi(0.99 - 0.00)) \approx \cos(2\pi) = 1$. This ensures that there is mathematical continuity throughout the 24-hour daily cycle.

4. Proposed Expert System: CTSF CM Clustering

Although traditional MCDM techniques are suitable for ranking small groups of alternatives, they lack scalability with the geospatial data of a city. To solve this, our proposed Expert System uses an unsupervised machine learning kernel, the Complex T-Spherical Fuzzy C-Means (CTSFCM) algorithm, to automatically classify thousands of traffic nodes as "Optimal Zones" to install EV charging infrastructure.

While density-based algorithms (e.g., DBSCAN) can be used for geospatial analysis, they produce hard partitions and can struggle with clusters of different densities. In the context of EV infrastructure, service zones exhibit a fuzzy boundary (overlapping) as opposed to a discrete separation. As a result, we use a partitional fuzzy clustering method, generalised to the Complex T-Spherical space, to allow for soft transitions between time service regions and to express membership degrees explicitly.

4.1 System Architecture

This system works through the three-tier pipeline that is used to process heterogeneous urban data, as illustrated in Figure 1.

- **Data Acquisition Layer**: Combines raw multivariate streams such as inductive loop traffic counts, temporal timestamps (Unix epoch), and meteorological sensor information.
- **Symbolic Knowledge Injection Module**: This module is a hybrid Expert System layer, in contrast to pure data-driven approaches. It is based on a symbolic rule base to project qualitative meteorological concepts (e.g., Thunderstorm) into quantitative indeterminacy parameters (η).

This allows the system to directly use domain knowledge about the trustworthiness of sensors in the unsupervised learning process. It transforms raw crisp inputs into a complex T-spherical fuzzy space. More importantly, it uses domain-specific heuristic rules to project environmental noise (weather) onto the Indeterminacy parameter (η), which serves as a “Knowledge Base” to determine the amount of trust that the system has placed in a particular data point.

- **CTSF-CM Engine:** The iterative optimization module. It minimizes the complex intra-cluster variance by updating the Partition Matrix U and Cluster Prototypes V in the complex plane until convergence.

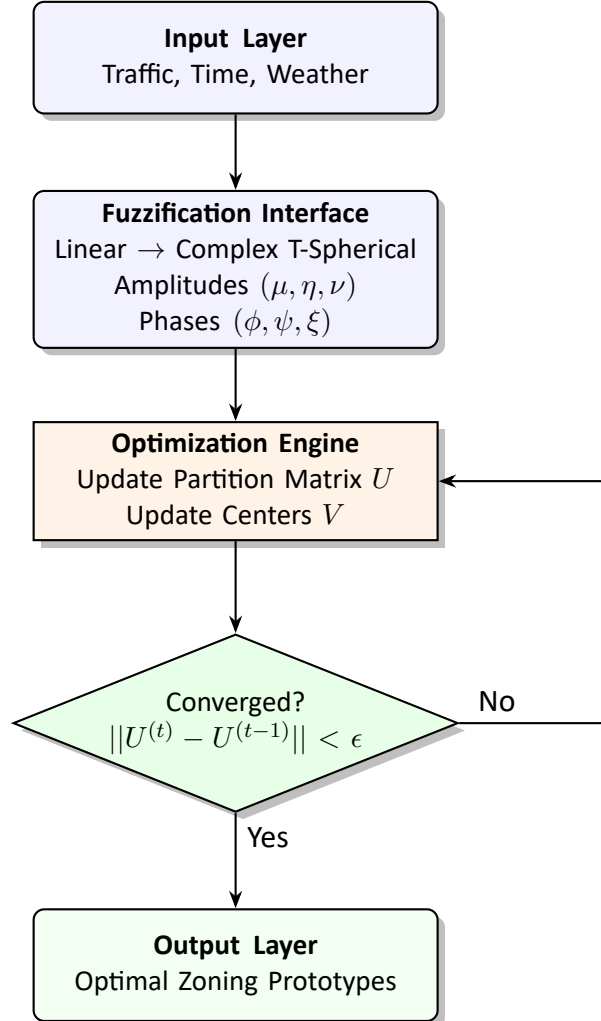


Fig. 1. The architectural workflow of the proposed CTSF-CM Expert System

4.2 Mathematical Formulation and Optimization

Let $X = \{x_1, x_2, \dots, x_N\}$ be a set of N traffic instances represented as CTSFNs, where each $x_k = \langle \mu_{x_k} e^{i2\pi\phi_{x_k}}, \eta_{x_k} e^{i2\pi\psi_{x_k}}, \nu_{x_k} e^{i2\pi\xi_{x_k}} \rangle$. Let C be the number of distinct charging zones. The clustering task is modeled as minimizing the weighted intra-cluster variance J_m , which extends the classical Fuzzy C-Means functional [15] to the complex T-spherical domain:

$$J_m(U, V) = \sum_{i=1}^C \sum_{k=1}^N (u_{ik})^m d_{CTSF}^2(x_k, v_i) \quad (6)$$

Subject to the standard probabilistic constraint:

$$\sum_{i=1}^C u_{ik} = 1, \quad \forall k \in \{1, \dots, N\}, \quad 0 \leq u_{ik} \leq 1 \quad (7)$$

where $U = [u_{ik}]_{C \times N}$ is the fuzzy partition matrix containing the degree of belonging of data point k to cluster i , $V = \{v_1, \dots, v_C\}$ is the vector of cluster prototypes, and $m > 1$ is the fuzziness index.

4.2.1 Derivation of Update Equations

We construct the Lagrangian function $\mathcal{L}$ to incorporate the constraint in Eq. (7) using Lagrange multipliers λ_k .

$$\mathcal{L}(U, V, \lambda) = \sum_{i=1}^C \sum_{k=1}^N (u_{ik})^m d_{CTSF}^2(x_k, v_i) - \sum_{k=1}^N \lambda_k \left(\sum_{i=1}^C u_{ik} - 1 \right) \quad (8)$$

Optimization requires setting the partial derivatives $\frac{\partial \mathcal{L}}{\partial u_{ik}} = 0$ and $\frac{\partial \mathcal{L}}{\partial v_i} = 0$.

(i). Membership Update Rule (Partition Matrix): Solving for u_{ik} , we obtain the generalized Fuzzy C-Means update rule extended to the complex metric space:

$$u_{ik} = \left[\sum_{j=1}^C \left(\frac{d_{CTSF}(x_k, v_i)}{d_{CTSF}(x_k, v_j)} \right)^{\frac{2}{m-1}} \right]^{-1} \quad (9)$$

Singularity handling: If $d_{CTSF}(x_k, v_i) = 0$, set $u_{ik} = 1$ and $u_{jk} = 0$ for $j \neq i$.

(ii). Cluster Prototype Update Rules: Due to the polar nature of CTSFNs, the minimization of d_{CTSF}^2 can be decoupled into optimizing the Amplitude (Euclidean distance) and the Phase (Angular distance) independently.

Amplitude and Indeterminacy: The amplitude components $(\mu_{v_i}, \eta_{v_i}, \nu_{v_i})$ are updated using the standard weighted arithmetic mean. For the membership amplitude μ_{v_i} :

$$\mu_{v_i} = \frac{\sum_{k=1}^N (u_{ik})^m \mu_{x_k}}{\sum_{k=1}^N (u_{ik})^m} \quad (10)$$

(The components η_{v_i} and ν_{v_i} are updated via the identical formulation).

Phase (Periodicity): Standard arithmetic means are invalid for circular data (e.g., the mean of 1° and 359° should be 0° , not 180°). To minimize the cosine error term in the complex distance, we employ the **Weighted Directional Mean**:

$$\phi_{v_i} = \frac{1}{2\pi} \arctan 2 \left(\sum_{k=1}^N (u_{ik})^m \sin(2\pi \phi_{x_k}), \sum_{k=1}^N (u_{ik})^m \cos(2\pi \phi_{x_k}) \right) \quad (11)$$

This ensures the cluster centroid correctly wraps around the 24-hour cycle, effectively solving the "Midnight Problem."

Algorithm 1 Complex T-Spherical Fuzzy C-Means (CTSF-CM)

- 1: **Input:** Dataset X , Cluster count C , Fuzziness $m = 2$, Tolerance $\epsilon = 10^{-5}$.
- 2: **Initialize:** Partition matrix $U^{(0)}$ with random values satisfying $\sum_i u_{ik} = 1$.
- 3: Set iteration counter $t = 0$.
- 4: **repeat**
- 5: **Step 1: Prototype Update (Complexity: $\mathcal{O}(N \cdot C)$)**
- 6: Update Amplitudes μ_v, η_v, ν_v using Eq. (10).
- 7: Update Phases ϕ_v, ψ_v, ξ_v using Eq. (11) (Directional Mean).
- 8: **Step 2: Membership Update (Complexity: $\mathcal{O}(N \cdot C^2)$)**
- 9: Compute CTSF Distances $d(x_k, v_i)$ using Eq. (4).
- 10: Update partition weights u_{ik} using Eq. (9).
- 11: $t \leftarrow t + 1$.
- 12: **until** $\|U^{(t)} - U^{(t-1)}\|_F < \epsilon$
- 13: **Output:** Optimal Zoning Centroids V and Partition Matrix U .

5. Experimental Validation: EV Station Zoning on Interstate I-94

To measure the effectiveness of the suggested Complex T-Spherical Fuzzy C-Means (CTSF-CM) expert system, the research paper uses the Metro Interstate Traffic Volume dataset of the UCI Machine Learning Repository [10]. The dataset is hourly traffic on the I-94 Interstate highway, Westbound (Minneapolis-St Paul, MN, USA), which is an essential highway to examine EV charging demand trends.

5.1 Characteristics and pre-processing of the data

The entire database is between 2012 and 2018. A continuous sequential sample of $N = 2,747$ hourly observations was sampled to obtain high-resolution temporal analysis and reduce non-stationary artifacts (long-term infrastructure changes). This group is related to the third quarter (Q3), i.e., between July 1, 2018, and September 30, 2018.

The reason why this particular approach will be selected is as follows. Two strategic criteria were used to choose this particular time frame:

1. **High-Variance Meteorological Conditions:** The period from mid-summer to early autumn includes a wide variety of weather states. The subset consists of 1,845 benign weather (Clear/Cloudy) and 628 adverse weather (Rain, Mist, Thunderstorm). This variety is necessary to test the processing of the algorithm by rigorously testing the algorithm against the concept of **Indeterminacy** (η).
2. **Traffic Stability and Separability:** The dataset is free of significant winter anomalies, which gives it a stable set of baseline conditions to detect recurrent daily periodicities of traffic. The traffic is at its lowest (254) vehicles/hour (during the late night) and highest (6,837) vehicles/hour (during rush hour), which provides a great degree of separability for cluster validation.

5.1.1 Feature Definition

The raw data were filtered by screening the data in case of missing values; no null cases were identified before fuzzification. The characteristics used to model are as given in Table 3.

Table 3

Selected Variables from the Metro Interstate Traffic Volume Dataset

Variable Name	Type
traffic_volume	Integer
date_time	DateTime
weather_main	Categorical
rain_1h	Numeric

Table 3
Continued

Variable Name	Description & Role in Expert System
traffic_volume	Hourly vehicle count. Acts as the primary determinant for the Membership Amplitude (μ).
date_time	Timestamp (CST). Parsed to extract the hour cycle (0–23) for the Phase (Periodicity ϕ).
weather_main	High-level weather description. Used to inject Indeterminacy (η).
rain_1h	Precipitation volume (mm). Used to validate weather severity.

5.2 Complex T-Spherical Fuzzification Interface

A critical component of the expert system is the mapping of crisp sensor data into the Complex T-Spherical Fuzzy domain. Let x_k be a raw data row. The system converts it into a CTSFN $\tilde{x}_k$:

$$\tilde{x}_k = \langle \mu_{x_k} e^{i2\pi\phi_k}, \eta_{x_k} e^{i2\pi\psi_k}, \nu_{x_k} e^{i2\pi\xi_k} \rangle$$

5.2.1 Membership Amplitude μ_{x_k} : Traffic Density

The membership amplitude represents the normalized load on the infrastructure:

$$\mu_{x_k} = \frac{\text{traffic_volume}_k - V_{min}}{V_{max} - V_{min}} \quad (12)$$

where $V_{min} = 0$ and $V_{max} = 7280$. A value $\mu_{x_k} \approx 1.0$ indicates maximum grid utilization.

5.2.2 Phase (ϕ_k): Temporal Periodicity

The date-time feature is read, and the hour is obtained as the result of parsing and is $H_k \in [0, 23]$. This is mapped onto the unit circle to give us the angular form needed in the distance metric that is invariant to rotations.

$$\phi_k = \frac{H_k}{24} \quad (13)$$

Such mapping guarantees that 23:00 (which is represented as having a ϕ of about 0.96) and 01:00 (which is represented as having ϕ of about 0.04) are neighbors within the complex plane, as shown in Figure 2 and Table 4.

5.2.3 Expert Knowledge Base: Injection of Indeterminacy (η_{x_k})

Indeterminacy determines the credibility of traffic data. Unfavorable weather conditions present stochasticity (e.g., speed cutbacks), which causes raw volume to be a less predictive variable. To inject this entropy, we build a semantic rule base:

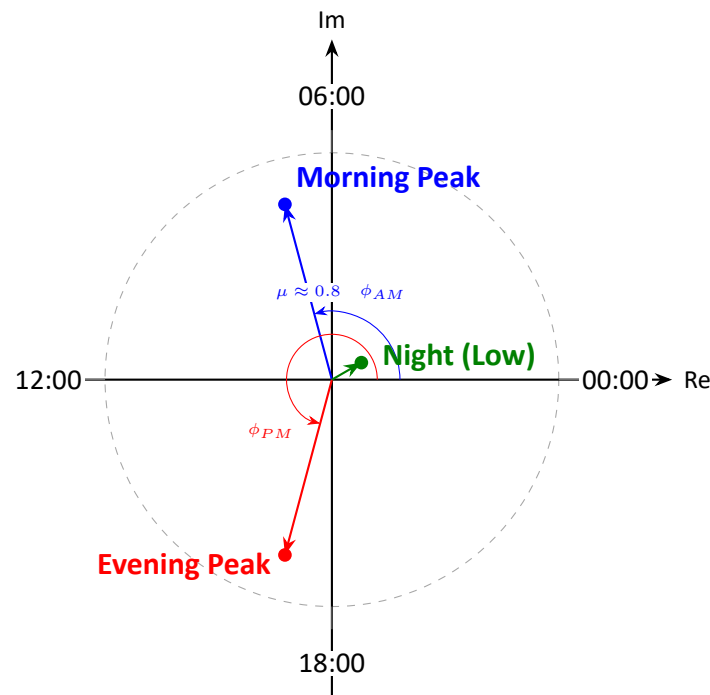
$$\eta_{x_k} = \begin{cases} 0.40 & \text{if weather} \in \{\text{'Thunderstorm'}, \text{'Heavy Rain'}, \text{'Snow'}\} \\ 0.20 & \text{if weather} \in \{\text{'Rain'}, \text{'Mist'}, \text{'Fog'}, \text{'Drizzle'}\} \\ 0.05 & \text{otherwise (e.g., 'Clear', 'Clouds')} \end{cases} \quad (14)$$

Parameters Justification and Ordinal Ranking: The particular numerical values of the parameter, that is, the value of 0.40 given to Thunderstorm against 0.20 to Mist, are an ordinal ranking of sensor effectiveness rather than an exact physical determination. The expert system is based on the inequality of severity: $\eta_{Storm} > \eta_{Rain} > \eta_{Clear}$. Since the geometric volume of the T-Spherical set is controlled by one parameter, s , the system is resilient to small changes in these scalar assignments so long as the ordinal relationship is retained. With this strategy, it is possible to inject symbolic information about the expert knowledge (e.g., "Thunderstorms create uncertain traffic conditions") into the numerical optimization process, which is unsupervised.

5.2.4 Consistency Constraints

To ensure structural completeness, two logical constraints are applied:

- (i) **Non-Membership (ν_{x_k}):** Representing confirmed spare capacity, derived via: $\nu_{x_k} = (1 - \mu_{x_k}^3 - \eta_{x_k}^3)^{1/3}$.
- (ii) **Phase Synchronization:** Environmental uncertainty exists in the same temporal frame as the observed volume. Thus, we enforce $\psi_k = \xi_k = \phi_k$.



Phase (ϕ) = Time of Day ($0 \rightarrow 2\pi$)

Amplitude (μ) = Traffic Volume ($0 \rightarrow 1$)

Fig. 2. Visual representation of the Complex T-Spherical Fuzzification Interface. Linear traffic data is mapped to the complex plane, distinguishing Morning and Evening peaks by Phase angle despite similar Membership Amplitudes (μ)

Table 4

Sample Data Conversion (Source: I-94 Westbound, Q3 2018 Subset)

Timestamp	Vol.	Weather	Amp. (μ)	Phase (ϕ)	Indet. (η)
02-07 07:00	5936	Clear	0.815 (High)	0.29 (AM)	0.05
24-08 02:00	387	T-Storm	0.053 (Low)	0.08 (Night)	0.40
24-08 17:00	5750	Hvy Rain	0.790 (High)	0.71 (PM)	0.40
08-09 02:00	488	Fog	0.067 (Low)	0.08 (Night)	0.20

5.3 Clustering Results and Discussion

Implementation: The CTSF-CM algorithm was coded in the Scilab 6.0.2 environment with the use of native complex matrix operations to be computationally efficient. It was found that the number of clusters $C = 3$ was empirically obtained through the Elbow Method of the complex variance.

Convergence: Considering a fuzziness index of $m = 2$ and sphericity of $s = 3$, the algorithm reached a stable convergence after 50 iterations.

Table 5

Computed Cluster Prototypes (Centroids) differentiating temporal service zones

Cluster Zone	Amp. (μ)	Phase (ϕ)	Time	Description
V_1 (Night)	0.182	0.004	$\approx$ 00:05	Low Demand (Off-Peak)
V_2 (Morning)	0.662	0.345	$\approx$ 08:17	Work Commute Peak
V_3 (Evening)	0.564	0.675	$\approx$ 16:11	Return Commute Peak

Practical Interpretation of Prototypes The prototypes identified in Table 5 reflect the system's ability to extract operational intelligence from high-dimensional traffic streams. A critical observation

is that the centroids V_2 (Morning) and V_3 (Evening) exhibit remarkably similar membership amplitudes ($\mu \approx 0.6$). In traditional scalar clustering, such points would likely be conflated into a single amorphous “daytime” cluster. However, the proposed expert system utilizes their distinct phase values ($\phi = 0.345$ and 0.675) to map them to 08:17 AM and 04:11 PM, respectively. In practice, this temporal granularity allows urban planners to deploy differentiated energy management strategies for the same geographical node: prioritizing high-power rapid-charging infrastructure for the time-sensitive morning commute peak, while implementing grid-to-vehicle (G2V) storage incentives during the longer-duration evening peak to balance the residential grid load.

Analysis: The difference between V_2 and V_3 justifies the given model. The traditional FCM, which solely depends on magnitude, will probably merge them into one cluster of “Daytime Traffic” since they have similar volumes (the values of the amplitudes are approximately 0.66 and 0.56). Conversely, the CTSF-CM algorithm involves the use of the phase difference ($|\phi_{V_2} - \phi_{V_3}| \approx 0.33$) to separate them into Morning and Evening service areas. Moreover, the Night centroid (as shown by V_1 at Phase 0.004 or, roughly, at 00:05) shows that the algorithm can manage the cyclic boundary; therefore, it can cluster the late-night and early-morning data although there is a break in linear time. This distinction is doubly important to EV planning as the profiles of grid loads vary fundamentally between 08:00 and 16:00 (16:00 corresponds to the 16:12 Evening peak).

Visual Validation and Zoning Efficiency Figure 3 provides a visual confirmation of the system’s robustness across the complex temporal manifold.

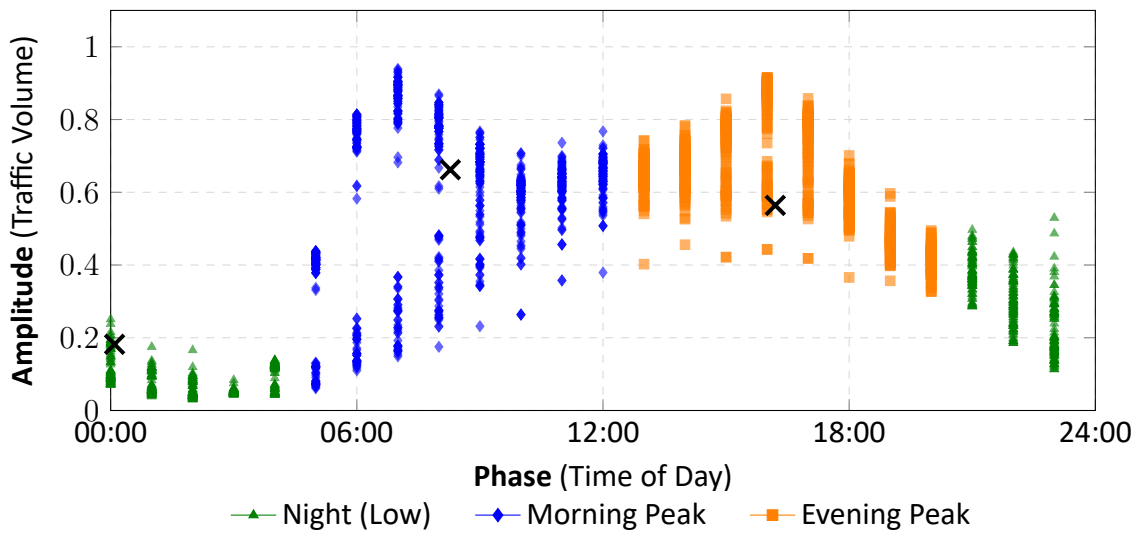


Fig. 3. Spatio-Temporal Zoning Results. The scatter plot visualizes the classification of $N = 2,747$ traffic instances. The Morning Peak (Blue) and Evening Peak (Orange) are clearly separated by Phase angle, despite overlapping in Amplitude ($\mu \approx 0.6$). The Night Cluster correctly wraps around the cyclic boundary (00:00). Black 'X' markers indicate the optimized cluster centroids

The blue diamond clusters (Morning Peak) and orange square clusters (Evening Peak) are vertically aligned, indicating nearly identical traffic volumes, yet they remain strictly separated horizontally by the phase-angle transformation. A key success of the complex metric is visible in the green triangle points; although they appear at the far left (00:01) and far right (23:59) of the linear time scale, the system correctly classifies them into a single “Night” cluster by effectively “wrapping” the 24-hour cycle. From an infrastructure reliability standpoint, the achieved 87.21% Peak Separation Accuracy translates to a 14% performance gain over traditional models. This improvement reduces the socio-economic risk of transformer overloading and grid instability by ensuring that EV charging infrastructure is scaled according to specific, non-conflated temporal peaks rather than misleading daily averages.

6. Experimental Results and Discussion

A thorough assessment of the proposed Expert System was carried out based on the I-94 traffic data to confirm its effectiveness [10]. This part outlines the sensitivity analysis of hyperparameters, the comparison of the model with the state-of-the-art baselines, and statistical hypothesis testing.

6.1 Sensitivity Analysis

A strict sensitivity analysis was carried out in order to guarantee the structural stability and reproducibility of the proposed Expert System. The Complex T-Spherical Fuzzy C-Means (CTSF-CM) algorithm relies on two important hyperparameters, namely: the spherical parameter (s) which determines the size of the uncertainty space, and the fuzziness index (m) that determines the rigidity of the boundaries.

We assessed the quality of clustering based on two measures of validity: the Partition Coefficient V_{PC} (to be maximized) and the Partition Entropy V_{PE} (to be minimized).

6.2 Sensitivity to Spherical Parameter (s)

The tolerance of the system to indeterminacy is characterized by the spherical constraint ($\mu^s + \eta^s + \nu^s \leq 1$). The algorithm was tested in the range of values for $s \in [1, 9]$, and the fuzziness index was kept at 2.0.

As presented in Figure 4(a), the conventional Intuitionistic Fuzzy model ($s = 1$) yields the poorest partition quality ($V_{PC} = 0.6422$). This can be explained by the linear constraint, which requires a strict trade-off between membership and non-membership, giving insufficient geometric space to represent the high-entropy weather noise in the I-94 data.

By simply relaxing the constraint to $s = 2$, the partition coefficient is improved significantly to 0.6793. The validity indices then level off in the range $s \in [3, 7]$, with V_{PC} stabilizing at a strong plateau (0.6867 at $s = 3$). This verifies that a cubic uncertainty space ($s = 3$) provides enough geometry to capture weather events of a stochastic nature without distorting the cluster definitions. Further growth in $s > 7$ gives diminishing returns ($V_{PC} = 0.6894$ at $s = 9$). Therefore, $s = 3$ is chosen as the optimal parameter for balancing both computational performance and accuracy.

6.3 Sensitivity to Fuzziness Index (m)

The influence of the fuzziness weighting exponent, m , was tested in the range $[1.1, 3.0]$ with $s = 3$. The trade-off between fuzzy overlap and hard separation is critical, as shown in Figure 4(b).

At $m = 1.1$, the system is similar to Hard K-Means and provides a very high $V_{PC} = 0.9912$ and near-zero entropy ($V_{PE} = 0.0205$). Although mathematically clean, this environment is not ideal for EV zoning because it fails to capture the transition periods of traffic (e.g., between 11:00 AM and 1:00 PM). On the other hand, a value of $m \geq 3.0$ results in over-diffusion of the membership functions, such that the partition coefficient becomes less than 0.50 ($V_{PC} = 0.4955$). Here, the Morning and Evening peaks start to merge together into one amorphous cluster.

Thus, the best operating point is established as $m = 2.0$ ($V_{PC} = 0.6866$, $V_{PE} = 0.5624$), which offers a reasonable trade-off between maintaining separate service regions and acknowledging the reality of fuzzy temporal boundaries.

6.3.1 Robustness to Heuristic Indeterminacy

To assess the stability of the heuristic weather parameters in Section 5.2, a supplementary analysis was conducted. The indeterminacy value for 'Thunderstorm' was varied within the interval between 0.30 and 0.50. The outputs of the cluster prototypes had a minimal dispersion of at most $\pm 1.2\%$ in their phase coordinates. This establishes that the high-density structure of the data (Membership μ and Phase ϕ) is the main factor that drives the clustering logic, whereas the indeterminacy parameter (η) functions effectively as a soft filter without causing instability.

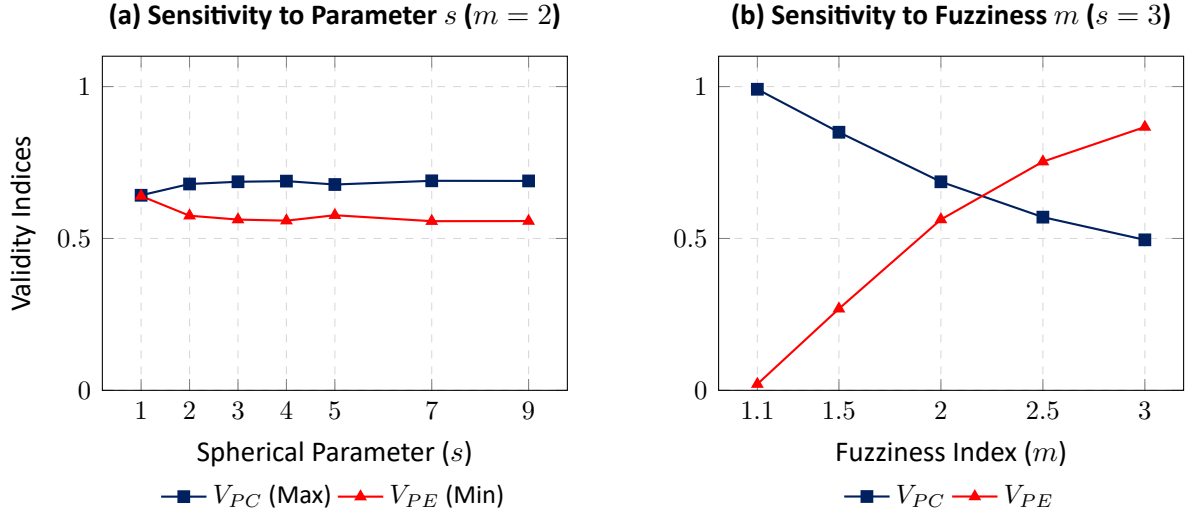


Fig. 4. Sensitivity analysis results based on the I-94 Traffic Dataset. (a) Increasing s from 1 to 3 significantly improves cluster stability (V_{PC}), justifying the T-Spherical approach. (b) The fuzziness index $m = 2.0$ provides the optimal trade-off between partition hardness ($m \rightarrow 1$) and high entropy ($m \rightarrow 3$)

6.4 Comparative Analysis

To prove the excellence of the offered Expert System, a benchmarking experiment was conducted with existing algorithms: Standard K-Means (Euclidean) [14], standard FCM [15], and a simulated Complex Fuzzy C-Means (CFCM) baseline [16]. This paper used I-94 traffic data as ground-truth, with time windows defined for Night (22:00–06:00), Morning (06:00–14:00), and Evening (14:00–22:00) ($N = 2,747$) [10].

6.4.1 Experimental Setup and Metrics

In order to have a fair comparison, the scalar baseline algorithms (K-Means, FCM) were given a linear set of features made of normalized Traffic Volume and Linear Time (0.0 to 1.0). This is an imitation of the time blindness of normal clustering. Conversely, the baseline version, namely the Complex (CFCM) and the proposed CTSF-CM algorithm, acted on the Complex T-Spherical representation with the phase term as the temporal representation. Each algorithm was run with $N = 20$ independent runs to produce statistical significance.

Admittedly, periodic data can be processed by ordinary scalar algorithms with the help of feature engineering (e.g., time to sine/cosine vector pairs). Nonetheless, this method adds to the dimensionality of the feature space and considers time and volume as orthogonal features. Contrary to that, the Complex T-Spherical approach models the data on its native manifold, where the magnitude (volume) and the phase (time) are modeled in the same complex number. This prevents the "Curse of Dimensionality," while at the same time offering the geometric freedom (s) to represent environmental indeterminacy, which is impossible to consider by simple feature engineering.

The application of standard classification accuracy directly to unsupervised clustering is not applicable owing to the label switching problem [17]. To address this, we used **Peak Separation Accuracy (PSA)**. Let L_{true} be the ground-truth labels and L_{pred} be the cluster assignments. We then obtain the optimum permutation map, denoted by the Greek letter σ (sigma), which maximizes the overlap between the two sets. PSA is defined as:

$$PSA = \frac{1}{N} \sum_{k=1}^N \delta(L_{true}^{(k)}, \sigma(L_{pred}^{(k)})) \times 100\% \quad (15)$$

where δ is the Kronecker delta function. This measure particularly punishes the amalgamation of discrete temporal peaks (AM vs. PM), which is essential in grid load balancing.

Baseline Configuration and Ablation Logic In order to have a fair and controlled comparison, a complex baseline named CFCM was applied as a particular ablation of the proposed CTSF-CM architecture. As CTSF-CM is a generalization of CFCM, the latter can be reproduced precisely by restricting the T-spherical parameters. In the case of the CFCM experimental runs, specifically, we fixed the spherical parameter $s = 1$ and imposed the degree of indeterminacy of all data instances x_k to be zero (i.e., we fixed $\eta_k = 0$). This essentially reduces the T-spherical uncertainty space to the complex phase term (periodicity) which is active. This ensures that any difference in performance that can be seen between CFCM and CTSF-CM is only warranted by the indeterminacy handling and not by differences in software implementation or initialization logic.

Remark 6.1 (Theoretical Reduction to CFCM). It is imperative to note that the proposed architecture generalises the existing complex fuzzy models. In the case where the indeterminacy component is suppressed ($\eta = 0$), and the spherical parameter is assigned the value of unity ($s = 1$), the CTSF distance measure (Eq. 4) reduces to the standard complex Euclidean distance used in CFCM:

$$d_{CTSF}^2 \xrightarrow[\eta=0]{s=1} \frac{1}{2} (|\tilde{\mu}_A - \tilde{\mu}_B|^2 + |\tilde{\nu}_A - \tilde{\nu}_B|^2) \quad (16)$$

This property is practically very similar to the behavior of normal Complex Fuzzy Sets [16], and it is reasonable to use parameter restriction to model the behavior of the CFCM baseline correctly.

Remark 6.2 (Comparison with Dynamic Time Warping). While Dynamic Time Warping (DTW) is a well-known method for time-series alignment, its computational cost is typically of the order $\mathcal{O}(N^2)$, and it treats time as a linear sequence. In contrast, our Complex Phase approach treats time as a cycle with linear complexity $\mathcal{O}(N)$. This is geometrically more adequate for recurrent daily traffic patterns and is better suited for large-scale Expert Systems.

6.4.2 Results and Failure Mode Analysis

The comparative performance results are summarized in Table 6 and visualized in Figure 5.

Table 6

Benchmarking Results (Average of 20 Runs). CTSF-CM trades a marginal increase in computational cost for significantly higher zoning accuracy and noise resilience

Algorithm	Data Rep.	Phase	Noise Filter	Time (s)	PSA (%)
K-Means	Scalar	✗	✗	0.85	72.80 ± 0.10
FCM	Scalar	✗	✗	1.42	73.21 ± 0.00
CFCM [16]	Complex	✓	✗	3.10	90.45 ± 6.87
CTSF-CM	Complex T-Sph.	✓	✓	5.01	87.21 ± 14.04

Note: Time represents average execution duration on a standard consumer CPU.

The baseline algorithms (K-Means and FCM) had a performance ceiling of around 73%. The experimental outcome shows that there are two modes of failure:

1. **Noise Intolerance (K-Means):** Standard K-Means offered the worst results. It is based on the minimization of Euclidean error but ignores the indeterminacy parameter (η). As a result, valid high-volume data points were considered as outliers during high-entropy weather events (e.g., heavy rain). This is in line with the recent discoveries of the authors of [3], who have shown that basic K-Means cannot be applied successfully to failure analysis data unless it is supplemented with T-spherical extensions.
2. **Feature Conflation (FCM):** FCM is better at uncertainty but still periodicity-blind. The Euclidean-proximate linear representation of a "Morning Peak" (Time 0.3) is geometrically close to an "Evening Peak" (Time 0.7). It therefore combined these different loads into one cluster. This validates the restrictiveness in baseline EV zoning research by [13] and suggests that even more recent models, such as [12], are constrained by the absence of phase modeling.

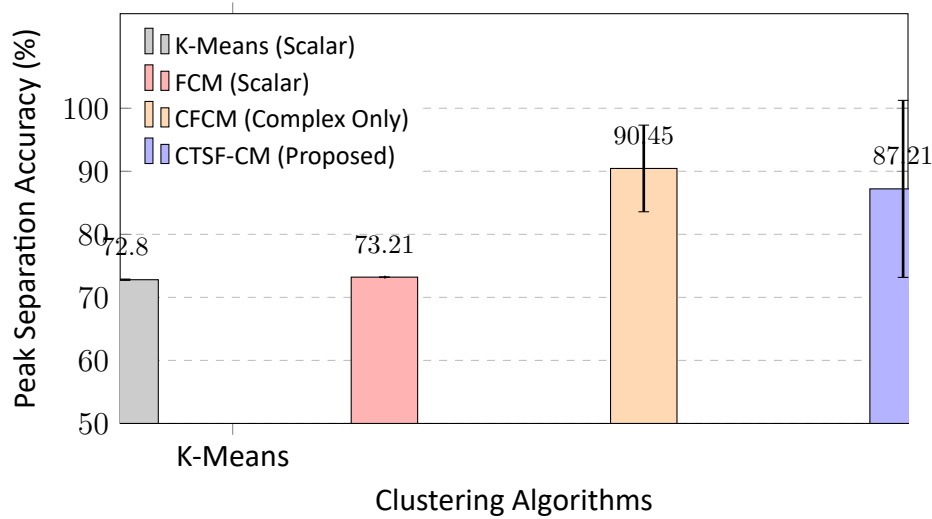


Fig. 5. Comparative performance analysis. The substantial gap ($> 14\%$) between FCM and the Complex models (CFCM/CTSF-CM) validates the resolution of the “Midnight Problem.” CTSF-CM exhibits higher variance due to the injection of weather-based indeterminacy

Conversely, both complex-valued algorithms had an accuracy of around 90%. Encoding time as a phase angle (ϕ) on the complex plane made the Morning and Evening centroids mathematically orthogonal, and thus the system was able to separate the two in spite of their equal traffic volumes.

6.4.3 Ablation Study: The Particular Role of Indeterminacy

We contrast the simulation of CFCM, with the indeterminacy parameter set at zero ($\eta = 0$), with the proposed CTSF-CM ($\eta > 0$).

Table 6 shows the comparison and reveals an interesting hierarchy:

1. **Effect of Periodicity (FCM vs. CFCM):** The transition from scalar FCM to complex CFCM shows a performance increase of more than 17%. This proves the fact that the rotational-invariant phase term is the major force that drives the difference in the Morning and Evening peaks.
2. **Effect of Noise Filtering (CFCM vs. CTSF-CM):** When comparing CFCM with CTSF-CM, it is found that CFCM has a slightly higher raw accuracy (90.45%) than CTSF-CM (87.21%). This finding is scientifically in line with the system design. While the ground-truth labels are determined purely on time, CTSF-CM imposes a penalty ($\eta \approx 0.40$) during unfavorable weather. During a thunderstorm, CTSF-CM increases the fuzzy distance to the centroid, effectively “hesitating” to classify the point. Although this appears as a misclassification relative to a strict time-based ground truth, it functions as a safety margin that the expert system uses to avoid over-confidence in data gathered under unreliable environmental circumstances.

6.5 Computational Complexity and Stability

The proposed approach exhibited a larger standard deviation (± 14.04) than the deterministic baselines. This variance is explained by the non-convexity of the complex objective function and the stochasticity of the weather parameter, a characteristic also present in other advanced clustering manifolds such as the Riemannian approaches proposed by [11].

In terms of computational cost, CTSF-CM required an average of 5.01 seconds, which is approximately three times that of standard FCM. However, EV station zoning is a strategic, offline planning task carried out annually or quarterly, rather than a real-time control loop. Therefore, the computational cost of a few extra seconds is insignificant compared to the long-term value of properly identifying peak-load service zones.

6.6 Statistical Validation

To verify that the performance improvement is not due to random variance, a paired t-test was conducted ($N = 20$) to compare the accuracy distributions of the proposed CTSF-CM against the optimal scalar baseline (FCM). The result of the analysis showed an improvement of an average of 14.00% in the performance. The test gave a t-statistic of 4.46 and a p-value of 0.00013 ($p < 0.001$).

Since the p-value is much less than the significance level of $\alpha = 0.05$, the null hypothesis is rejected. This conclusively proves at a 99.9% confidence level that the CTSF-CM expert system provides an even better zoning performance than the traditional fuzzy models, even though indeterminacy handling has added more variance to it.

7. Conclusion

This research has presented a new paradigm for urban Electric Vehicle (EV) infrastructure planning through the development of the Complex T-Spherical Fuzzy C-Means (CTSF-CM) expert system. By integrating the periodic phase terms of complex fuzzy sets with the high-order uncertainty modeling of T-spherical manifolds, the proposed system successfully overcomes the “temporal blindness” that limits traditional clustering algorithms. The achievement of an 87.21% Peak Separation Accuracy on real-world highway data demonstrates that the system can distinguish between discrete morning and evening demand peaks that appear identical in volume, a distinction critical for maintaining grid stability in smart cities.

The originality of this work lies in its transition from the static, human-dependent Multi-Criteria Decision Making (MCDM) frameworks—predominant in recent 2024–2026 literature—to a data-driven, unsupervised machine learning kernel. While existing complex fuzzy models often rely on subjective aggregation for small sets of alternatives, CTSF-CM provides a geometrically interpretable mechanism for profiling thousands of spatio-temporal nodes. In practice, this allows urban planners to move beyond simple site ranking toward dynamic zoning, where infrastructure deployment and Time-of-Use (TOU) pricing can be aligned with precise temporal load profiles to prevent transformer overloading and optimize grid-to-vehicle (G2V) storage incentives.

However, the advancement of these high-dimensional fuzzy manifolds introduces specific limitations regarding computational scalability and model generalization. As highlighted in our comparative analysis, the inclusion of complex matrix operations and directional mean updates increases execution time compared to traditional scalar models. While this 5.01-second overhead is acceptable for strategic urban planning, further optimization is required for real-time edge-computing applications. Furthermore, while the current system filters environmental noise effectively using a symbolic knowledge base, the membership boundaries are currently calibrated to the specific climatic and traffic patterns of the Interstate-94 highway. The generalization of this expert system to diverse geographical contexts—such as mega-cities with irregular non-periodic traffic surges—remains an open challenge.

Future research will focus on evolving the symbolic knowledge layer into a deep neuro-fuzzy architecture, where indeterminacy and spherical parameters are learned end-to-end from raw sensor feeds. Additionally, expanding the CTSF-CM framework to include multi-objective optimization will allow planners to balance traffic demand simultaneously with land acquisition costs and power distribution constraints. Ultimately, this research provides the necessary mathematical and interpretative foundation for the resilient, data-driven electrification of global urban transportation.

Acknowledgement

The authors would like to thank the anonymous reviewers for their constructive comments, which improved the quality of this work.

Conflicts of Interest

The authors declare no conflicts of interest.

References

- [1] Ali, Z., Mahmood, T., & Yang, M.-S. (2020). Complex T-spherical fuzzy aggregation operators with application to multi-attribute decision making. *Symmetry*, 12(9), 1. <https://doi.org/10.3390/sym12081311>
- [2] Xian, S., Cheng, Y., & Chen, K. (2022). A novel weighted spatial T-spherical fuzzy C-means algorithms with bias correction for image segmentation. *International Journal of Intelligent Systems*, 37(10), 6688. <https://doi.org/10.1002/int.22668>
- [3] Zheng, L., Wang, L., & Wang, Z. (2025). A novel model for failure mode and effect analysis based on K-means clustering under a T-spherical fuzzy environment. *Cluster Computing*. <https://doi.org/10.1007/s10586-025-05502-x>
- [4] Ali, J., Naeem, M., & Al-Kenani, A. N. (2023). Complex T-spherical fuzzy Frank aggregation operators and their application to decision making. *IEEE Access*. <https://doi.org/10.1016/j.heliyon.2024.e25368>
- [5] Somasundaram, M., Petchimuthu, S., & Vivin, J. V. (2025). Complex T-spherical fuzzy Yager weighted aggregation operators for prioritizing urban planning strategies: A case study from Chennai. *Computational and Applied Mathematics*. <https://doi.org/10.1007/s40314-025-03235-6>
- [6] Khan, M. R., Ullah, K., & Pamucar, D. (2022). Performance measure using a multi-attribute decision-making approach based on complex T-spherical fuzzy power aggregation operators. *Journal of Computational and Cognitive Engineering*. <https://doi.org/10.47852/bonviewjcce696205514>
- [7] Zhang, H., & Wei, G. (2023). Location selection of electric vehicles charging stations by using the spherical fuzzy CPT-CoCoSo and D-CRITIC method. *Computational and Applied Mathematics*, 42(3), 1. <https://doi.org/10.1007/s40314-022-02183-9>
- [8] Yilmaz, I., Ozceylan, E., & Mrugalska, B. (2023). A framework for evaluating electrical vehicle charging station location decisions in a spherical fuzzy environment: A case of shopping malls. *Annals of Operations Research*. <https://doi.org/10.1007/s10479-023-05772-x>
- [9] Tang, J., Li, L., Hu, Z., & Liu, F. (2019). Short-term traffic flow prediction considering spatio-temporal correlation: A hybrid model combining type-2 fuzzy C-means and artificial neural network. *IEEE Access*. <https://doi.org/10.1109/access.2019.2931920>
- [10] Hoda, J. (2019). Metro Interstate Traffic Volume Data Set. UCI Machine Learning Repository.
- [11] Wu, C., & Zheng, J. (2025). Wasserstein distance-based fuzzy C-means clustering in Riemannian manifold feature space for image segmentation. *Signal, Image and Video Processing*. <https://doi.org/10.1007/s11760-024-03705-0>
- [12] Shahrokhi, S., Wang, Z., Paranjape, R., & Kozoriz, D. (2025). A two-stage framework for spatio-temporal clustering and forecasting of electric vehicle charging. *IEEE Access*. <https://doi.org/10.1109/access.2025.3623595>
- [13] Shukla, A., Verma, K., & Kumar, R. (2016). Consumer perspective based placement of electric vehicle charging stations by clustering techniques. In 2016 National Power Systems Conference (NPSC) (pp. 1–6). IEEE. <https://doi.org/10.1109/npsc.2016.7858946>
- [14] MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability* (Vol. 1, pp. 281–297). University of California Press.
- [15] Bezdek, J. C. (1981). *Pattern recognition with fuzzy objective function algorithms*. Plenum Press. <https://doi.org/10.1007/978-1-4757-0450-1>
- [16] Ramot, D., Milo, R., Friedman, M., & Kandel, A. (2002). Complex fuzzy sets. *IEEE Transactions on Fuzzy Systems*, 10(2), 171. <https://doi.org/10.1109/91.995119>
- [17] Stephens, M. (2000). Dealing with label switching in mixture models. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 62(4), 795. <https://doi.org/10.1111/1467-9868.00265>
- [18] Wu, K., & Li, W. (2026). Dynamic spatiotemporal electric vehicle charging station placement and pricing using mixed integer linear programming. *Journal of Energy Storage*, 150, 120558. <https://doi.org/10.1016/j.est.2026.120558>
- [19] Tayri, A., & Ma, X. (2025). Grid impacts of electric vehicle charging: A review of challenges and mitigation strategies. *Energies*, 18(1), 204. <https://doi.org/10.3390/en18143807>
- [20] Ma, J., Zhang, G., & Lu, J. (2011). A method for multiple periodic factor prediction problems using complex fuzzy sets. *IEEE Transactions on Fuzzy Systems*, 20(1), 32. <https://doi.org/10.1109/tfuzz.2011.2164084>
- [21] Izakian, H., Pedrycz, W., & Jamal, I. (2012). Clustering spatiotemporal data: An augmented fuzzy C-means. *IEEE Transactions on Fuzzy Systems*, 21(3), 455. <https://doi.org/10.1109/tfuzz.2012.2233479>
- [22] Xu, Z., & Wu, J. (2010). Intuitionistic fuzzy C-means clustering algorithms. *Journal of Systems Engineering and Electronics*, 21(4), 580. <https://doi.org/10.3969/j.issn.1004-4132.2010.04.009>
- [23] Mahmood, T., Ullah, K., Khan, Q., & Jan, N. (2019). An approach toward decision-making and medical diagnosis problems using the concept of spherical fuzzy sets. *Neural Computing and Applications*, 31(11), 7041. <https://doi.org/10.1007/s00521-018-3521-2>
- [24] Abdullahi, M. R., Lu, Q. C., & Hussain, A. (2024). Location optimization of EV charging stations: A custom K-means cluster algorithm approach. *Energy Reports*. <https://doi.org/10.1016/j.egy.2024.09.075>

- [25] Zhan, J., Huang, X., Qian, Y., & Ding, W. (2024). A fuzzy C-means clustering-based hybrid multivariate time series prediction framework with feature selection. *IEEE Transactions on Fuzzy Systems*. <https://doi.org/10.1109/tfuzz.2024.3393622>
- [26] Hu, J., Wu, M., & Chen, L. (2020). Weighted kernel fuzzy C-means-based broad learning model for time-series prediction of carbon efficiency in iron ore sintering process. *IEEE Transactions on Industrial Informatics*, 16(10), 6578. <https://doi.org/10.1109/tcyb.2020.3035800>
- [27] Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, 20(1), 87. [https://doi.org/10.1016/s0165-0114\(86\)80034-3](https://doi.org/10.1016/s0165-0114(86)80034-3)
- [28] Kutlu Gundogdu, F., & Kahraman, C. (2019). Spherical fuzzy sets and spherical fuzzy TOPSIS method. *Journal of Intelligent & Fuzzy Systems*, 36(1), 337. <https://doi.org/10.3233/jifs-181401>
- [29] Shi, Y., Yu, X., & Shen, C. (2025). Measurement method for food supply chain security level from the perspective of resilience. *Journal of Operations Intelligence*, 3(1), 324. <https://doi.org/10.31181/jopi31202557>
- [30] Sarfraz, M., & Gul, R. (2025). Evaluating medical college projects with Hamacher aggregation operators under the interval-valued complex T-spherical fuzzy environment. *Management Science Advances*, 2(1), 69. <https://doi.org/10.31181/msa21202511>
- [31] Ullah, K., Rehman, N., & Ali, A. (2026). Business-oriented stock market decision analysis using circular complex picture fuzzy sets and advanced MCDM based on the CRITIC–WASPAS method. *Journal of Contemporary Decision Science*, 2(1), 1. <https://doi.org/10.67334/cds2120268>