Smart ETA Predictions: Leveraging AI and Neutrosophic Fuzzy Soft Sets for Real-Time Accuracy

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Abstract

In this paper we aims to provide a clear definition of Neutrosophic Fuzzy Soft Sets and explain its fundamental operations through relevant examples. This work examines the computation of static Expected Time of Arrival (ETA) utilizing neutrosophic fuzzy soft set values and the fundamental Expected Time of Arrival. Our research also investigates the incorporation of sophisticated artificial intelligence (AI) methods to create reliable and adaptable dynamic Expected Time of Arrival(ETA) prediction models. Through the utilization of many types of data, such as current traffic statistics, weather conditions, road conditions, vehicle status, and driver behavior, we suggest a comprehensive system that adapts to changing circumstances and consistently enhances its ability to make accurate predictions. Our methodology utilizes cutting-edge machine learning algorithms to analyze and interpret vast amounts of diverse data. In addition, we tackle the difficulties of managing uncertainty and indeterminacy in data by utilizing Neutrosophic Fuzzy Soft Sets, which improve the model's resilience and dependability.

Keywords: Neutrosophic Fuzzy Soft Sets; Static Expected Time of Arrival; Dynamic Expected Time of Arrival

1 Introduction

In contemporary transportation systems, anticipating the estimated time of arrival (ETA) is of utmost importance to guarantee effective and reliable logistics, traffic control, and navigation systems. Conventional approaches to ETA prediction typically depend on fixed criteria that do not consider the ever-changing aspects of real-world elements, including traffic circumstances, weather, road quality, car condition, and driver experience. This constraint can result in notable errors in the estimated time of arrival (ETA) estimates,[12] leading to inefficient decision-making and higher operating expenses.

Advancements in artificial intelligence (AI) and machine learning (ML) have recently enabled the development of more advanced methods for predicting estimated time of arrival (ETA). These methods utilize up-to-date information and complex algorithms to adjust to varying circumstances, thereby improving the precision and dependability of estimated time of arrival (ETA) calculations.[13] One of the sophisticated strategies that has gained attention is the utilization of Neutrosophic Fuzzy soft set values. This approach is considered promising, as it can effectively deal with uncertainty, indeterminacy, and incompleteness in data.[2]

Neutrosophic Fuzzy Soft Sets offer a mathematical structure that combines the principles of Neutrosophic and Fuzzy Soft Sets, enabling a more intricate depiction of real-world phenomena. This approach is especially suitable for accurately predicting the estimated time of arrival (ETA) in dynamic situations, as it can incorporate multiple factors of uncertainty and unpredictability that are inherent in transportation systems.[14] Using

fuzzy fuzzy neutrosophic soft set values,[15] it is possible to capture the complex connections among many influencing factors and produce more precise ETA forecasts.
The subsequent sections of this work are structured in the following manner. Section-2 presents an elaborate examination of previous research in ETA prediction and Neutrosophic Fuzzy soft sets. Section -3 presents the initial definitions necessary for our study. Section-4 establishes the notion of neutrosophic fuzzy soft sets and associated arithmetic operations, supported by appropriate examples.Section-5 provides a detailed explanation of the methodology used for ETA prediction utilizing Neutrosophic Fuzzy Soft Set values. Covers the data collection process, feature selection, and model implementation. Section-6 presents the experimental findings and analysis, focusing on the enhancements achieved with the incorporation of artificial intelligence into the prediction of ETA. Section 7 presents a comparative examination of static and dynamic ETA. Section 8 provides an analysis of possible future research and the impact it may have on the area.

2 Related Works

The topic of Estimated Time of Arrival (ETA) prediction has advanced considerably through the utilization of machine learning techniques and the incorporation of complex logical frameworks like Neutrosophic Fuzzy Soft Sets. This section examines many pivotal research and approaches that have played a significant role in the progress of ETA prediction. Vlahogianni et al.[16] examine the application of statistical techniques to identify nonlinearity and nonstationarity in transportation time-series data. The authors specifically concentrate on the implementation of these methods in the context of road traffic flows, establishing a basis for understanding how conventional statistical methodologies might be employed for ETA (Estimated Time of Arrival) prediction. Yang and Yan are investigating the application of data fusion technologies to anticipate travel time on arterial roads in real time. The study integrates data from multiple sources, such as traffic sensors and historical databases, to improve the precision of the predictions.[17] Wang et al.[18] investigate the utilization of Support Vector Machines (SVM) and Random Forest models for the purpose of ETA prediction. The study emphasizes the benefits of machine learning models in terms of their adaptability and precision when compared to conventional methods. Maji et al.[19] utilize soft set theory to address a decision-making issue, demonstrating the adaptability of the framework in managing uncertain data. This study establishes the foundation for incorporating Neutrosophic Fuzzy Soft Sets into ETA prediction algorithms.

3 Preliminaries

Definition 3.1. [4]
Let E be the universal set, Then a **fuzzy set** X over E is defined by $X = \{(x, \mu_X(x))/x \in E$, where $\mu_X : E \to [0, 1]$ is called the membership function of X. The value $\mu_X(x)$ for each $x \in E$, reflects the degree to which x is a member of the fuzzy set X.

Definition 3.2. [5]
Consider the universal set X and $x \in X$. A **Single Valued Neutrosophic Set (SVNS)** A in X is distinguished by function of truth-membership $\mathcal{T}_A$, function of indeterminacy-membership $\mathcal{I}_A$ and function of falsity-membership $\mathcal{F}_A$. For each point x in X, $\mathcal{T}_A(x), \mathcal{I}_A(x), \mathcal{F}_A(x) \in [0, 1]$.Thus, a SVNS N is denoted by, $N = \{(x, \mathcal{T}_A(x), \mathcal{I}_A(x), \mathcal{F}_A(x))|x \in X\}$

Definition 3.3. [3]
Let E be the universal set.Then a **Neutrosophic Fuzzy Set(NFS)** A on E is defined by
$A = \{(x, \mu_A(x), \mathcal{T}_A(x, \mu), \mathcal{I}_A(x, \mu), \mathcal{F}_A(x, \mu))/x \in E\}$ where each membership value is expressed by a truth, indeterminacy and falsity membership function which are respectively denoted as $\mathcal{T}_A(x, \mu), \mathcal{I}_A(x, \mu)$ and $\mathcal{F}_A(x, \mu)$. Moreover $\mathcal{T}_A, \mathcal{I}_A$ and $\mathcal{F}_A$ are real standard or non-standard subsets of $]0^-, 1^+[$, That is,
$\mathcal{T}_A : E \to]0^-, 1^+[$,
$\mathcal{I}_A : E \to]0^-, 1^+[$,
$\mathcal{F}_A : E \to]0^-, 1^+[$.
where,$0^- \leq Sup(\mathcal{T}_A) + Sup(\mathcal{I}_A) + Sup(\mathcal{F}_A) \leq 3^+$.

Definition 3.4. [3]
Let E be the universal set,then **Single-valued Neutrosophic Fuzzy Set(SVNFS)** S on E is defined by $S = \{(x, \mu_S(x), \mathcal{T}_S(x, \mu), \mathcal{I}_S(x, \mu), \mathcal{F}_S(x, \mu))/x \in E\}$, where $\mathcal{T}_S(x, \mu), \mathcal{I}_S(x, \mu), \mathcal{F}_S(x, \mu) \in [0, 1]$,and $0 \leq \mathcal{T}_S(x, \mu) + \mathcal{I}_S(x, \mu) + \mathcal{F}_S(x, \mu) \leq 3$.

4 Neutrosophic Fuzzy Soft Sets: A New Paradigm for Uncertainty Modeling

Definition 4.1. [10] Let $\mathcal{U}$ be a universal set and $\mathcal{P}$ a set of parameters. A pair $(f, \mathcal{A})$ is called a soft set over $\mathcal{U}$ when $\mathcal{A}$ is a subset of $\mathcal{P}$ and f is a mapping from $\mathcal{A}$ to the power set of $\mathcal{U}$.

Definition 4.2. [11] Let $\mathcal{U}$ be a universal set to start with, $\mathcal{P}$ be a set of parameters, and $I^{\mathcal{U}}$ the power set of fuzzy sets of $\mathcal{U}$. A pair $(f, \mathcal{P})$ is called a fuzzy soft set on $\mathcal{U}$ where f is a mapping from $\mathcal{A} \subset \mathcal{P}$ to $I^{\mathcal{U}}$.

Definition 4.3. [3] Let E be a universal set.Then SVNFS S on E is defined by $S = \{(x, \mu_S(x), \mathcal{T}_S(x,\mu), \mathcal{I}_S(x,\mu), \mathcal{F}_S(x,\mu))/x \in E\}$, where $\mathcal{T}_S(x,\mu), \mathcal{I}_S(x,\mu), \mathcal{F}_S(x,\mu) \in [0,1]$,and $0 \leq \mathcal{T}_S(x,\mu)+\mathcal{I}_S(x,\mu)+\mathcal{F}_S(x,\mu) \leq 3$.

We now possess all the necessary elements to establish a precise definition of Neutrosophic Fuzzy Soft Sets(NFSS).

4.1 Neutrosophic Fuzzy Soft Set(NFSS)

To begin, let $\mathcal{U}$ be a universal set, $\mathcal{P}$ a set of parameters, and $\mathcal{N}_{NFS}(U)$ the power set of Neutrosophic Fuzzy sets of $\mathcal{U}$. A pair $(f, \mathcal{P})$ is called a fuzzy fuzzy soft set of neutrophilics on $\mathcal{U}$ when f is a mapping from $\mathcal{A} \subset \mathcal{P}$ to $\mathcal{N}_{NFS}(U)$.
We can improve the definition by using additional precision derived from the definitions of Deli and Broumi.[8]

Definition 4.4. Let $\mathcal{U}$ be an initial universe set and $\mathcal{P}$ be a set of parameters. The set of all NFSs of $\mathcal{U}$ is denoted by $\mathcal{N}_{NFS}(\mathcal{U})$. A neutrosophic fuzzy soft set $\mathcal{N}$ over $\mathcal{U}$ is a set defined by a set valued function $f_{\mathcal{N}}$ that maps $\mathcal{P}$ to $\mathcal{N}_{NFS}(\mathcal{U})$. This set is a parameterized family of some elements of $\mathcal{N}_{NFS}(\mathcal{U})$ and can be expressed as a set of ordered pairs, $\mathcal{N} = (p, < x, \mu_{f_{\mathcal{N}(p)}}(x), \mathcal{T}_{f_{\mathcal{N}(p)}}(x,\mu), \mathcal{I}_{f_{\mathcal{N}(p)}}(x,\mu), \mathcal{F}_{f_{\mathcal{N}(p)}}(x,\mu) >: x \in \mathcal{U}) : p \in \mathcal{P}$. The truth, indeterminacy and falsity of the membership grade are represented by $\mathcal{T}_{f_{\mathcal{N}(p)}}(x,\mu), \mathcal{I}_{f_{\mathcal{N}(p)}}(x,\mu)$, $\mathcal{F}_{f_{\mathcal{N}(p)}}(x,\mu) \in [0,1]$ respectively, with the supremum of each being 1. This implies that the inequality $0 \leq \mathcal{T}_{f_{\mathcal{N}(p)}}(x,\mu) + \mathcal{I}_{f_{\mathcal{N}(p)}}(x,\mu) + \mathcal{F}_{f_{\mathcal{N}(p)}}(x,\mu) \leq 3$ holds.

Example 4.5. The set of movies m_1, m_2, m_3 is evaluated based on four parameters, namely Direction, Script, Casting, and Marketing strategies, denoted by $X = \{p_1, p_2, p_3, p_4\}$. These parameters are used to measure the success or failure of movies.
$f_{\mathcal{N}}(p_1) = \{< m_1, (0.5, 0.7, 0.3, 0.2) >, < m_2, (0.3, 0.2, 0.5, 0.7) >, < m_3, (0.7, 0.9, 0.3, 0.2) >\}$
$f_{\mathcal{N}}(p_2) = \{< m_1, (0.2, 0.3, 0.2, 0.2) >, < m_2, (0.6, 0.7, 0.2, 0.1) >, < m_3, (0.7, 0.9, 0.1, 0.2) >\}$
$f_{\mathcal{N}}(p_3) = \{< m_1, (0.8, 0.7, 0.2, 0.2) >, < m_2, (0.2, 0.3, 0.5, 0.7) >, < m_3, (0.7, 0.8, 0.3, 0.2) >\}$
$f_{\mathcal{N}}(p_4) = \{< m_1, (0.9, 0.7, 0.3, 0.2) >, < m_2, (0.5, 0.2, 0.6, 0.7) >, < m_3, (0.3, 0.4, 0.5, 0.6) >\}$
Then
$\mathcal{N} = \{(p_1, f_{\mathcal{N}}(p_1)), (p_2, f_{\mathcal{N}}(p_2)), (p_3, f_{\mathcal{N}}(p_3)), (p_4, f_{\mathcal{N}}(p_4))\}$ is the Neutrosophic Fuzzy soft set over $(\mathcal{U}, \mathcal{P})$.

4.2 Fundamental Set Operations on Neutrosophic Fuzzy Soft Sets

Definition 4.6. The **complement** of a Neutrosophic Fuzzy Soft Set $\mathcal{N}$ is denoted by $\mathcal{N}^c$ and is defined as
$$\mathcal{N}^c = \{(p, < x, 1-\mu_{f_{\mathcal{N}(p)}}(x), \mathcal{F}_{f_{\mathcal{N}(p)}}(x,\mu), 1-\mathcal{I}_{f_{\mathcal{N}(p)}}(x,\mu), \mathcal{T}_{f_{\mathcal{N}(p)}}(x,\mu) >: x \in \mathcal{U}) : p \in \mathcal{P}\}$$

Example 4.7. Assume $\mathcal{U} = \{u_1, u_2, u_3\}$ represents the collection of gadgets being examined. The set of parameters is denoted by $\mathcal{P} = \{p_1, p_2, p_3, p_4\}$, for instance, the parameters branded (p_1), inexpensive (p_2), uniqueness (p_3) and attractiveness$(p_4)$are represented by these terms. Let
$f_{\mathcal{N}}(Branded) = \{< u_1, (0.6, 0.7, 0.4, 0.2) >, < u_2, (0.4, 0.2, 0.5, 0.7) >, < u_3, (0.7, 0.7, 0.3, 0.2) >\}$
$f_{\mathcal{N}}(Inexpensive) = \{< u_1, (0.3, 0.3, 0.2, 0.2) >, < u_2, (0.6, 0.8, 0.2, 0.1) >, < u_3, (0.7, 0.8, 0.1, 0.2) >\}$
$f_{\mathcal{N}}(Uniqueness) = \{< u_1, (0.8, 0.7, 0.2, 0.2) >, < u_2, (0.2, 0.4, 0.5, 0.7) >, < u_3, (0.7, 0.8, 0.3, 0.1) >\}$
$f_{\mathcal{N}}(Attractiveness) = \{< u_1, (0.9, 0.8, 0.3, 0.2) >, < u_2, (0.5, 0.3, 0.6, 0.7) >, < u_3, (0.4, 0.4, 0.5, 0.6) >\}$
Then
$\mathcal{N} = \{(p_1, f_{\mathcal{N}}(p_1)), (p_2, f_{\mathcal{N}}(p_2)), (p_3, f_{\mathcal{N}}(p_3)), (p_4, f_{\mathcal{N}}(p_4))\}$ is the Neutrosophic Fuzzy soft set over $(\mathcal{U}, \mathcal{P})$.
For describing $\mathcal{N}^c$ we have,
$f_{\mathcal{N}^c}(NotBranded) = \{< u_1, (0.4, 0.2, 0.6, 0.7) >, < u_2, (0.6, 0.7, 0.5, 0.2) >, < u_3, (0.3, 0.2, 0.7, 0.7) >\}$

$f_{\mathcal{N}^c}(expensive) = \{< u_1, (0.7, 0.2, 0.8, 0.3) >, < u_2, (0.4, 0.1, 0.8, 0.8) >, < u_3, (0.3, 0.2, 0.9, 0.8) >\}$
$f_{\mathcal{N}^c}(NotUnique) = \{< u_1, (0.2, 0.2, 0.8, 0.7) >, < u_2, (0.8, 0.7, 0.5, 0.4) >, < u_3, (0.3, 0.1, 0., 0.8) >\}$
$f_{\mathcal{N}^c}(NotAttractive) = \{< u_1, (0.1, 0.2, 0.7, 0.8) >, < u_2, (0.5, 0.7, 0.4, 0.3) >, < u_3, (0.6, 0.6, 0.5, 0.4) >\}$
Then
$\mathcal{N}^c = \{(p_1, f_{\mathcal{N}^c}(NotBranded)), (p_2, f_{\mathcal{N}^c}(expensive)), (p_3, f_{\mathcal{N}^c}(NotUnique)), (p_4, f_{\mathcal{N}^c}(NotAttractive))\}$

Definition 4.8. $\mathcal{N}_1$ and $\mathcal{N}_2$ are two NFSSs over $(\mathcal{U}, \mathcal{P})$ then $\mathcal{N}_1$ is a subset of $\mathcal{N}_2$ if
$\mu_{f_{\mathcal{N}_1}(p)}(x) \leq \mu_{f_{\mathcal{N}_2}(p)}(x)$
$\mathcal{T}_{f_{\mathcal{N}_1}(p)}(x, \mu) \leq \mathcal{T}_{f_{\mathcal{N}_2}(p)}(x, \mu)$
$\mathcal{I}_{f_{\mathcal{N}_1}(p)}(x, \mu) \leq \mathcal{I}_{f_{\mathcal{N}_2}(p)}(x, \mu)$
$\mathcal{F}_{f_{\mathcal{N}_1}(p)}(x, \mu) \geq \mathcal{F}_{f_{\mathcal{N}_2}(p)}(x, \mu)$
We write $\mathcal{N}_1 \subseteq \mathcal{N}_2$

Example 4.9. Let us examine two Neutrosophic Fuzzy Soft Sets (NFSSs) $\mathcal{N}$ and $\mathcal{M}$ over the same universe. The universal set $\mathcal{U} = \{u_1, u_2, u_3\}$ depicts a collection of distinct food products. NFSS $\mathcal{N}$ delimits the outward characteristics of each food item, while NFSS $\mathcal{M}$ delimits its nutritional composition. Each element of the universal set is evaluated in NFSS $\mathcal{N}$ using the following criteria: color, odor, shape, texture, and each element of the universal set is evaluated in NFSS $\mathcal{M}$ using the following criteria: calories, amount of fiber, protein content, and digestibility.
$f_{\mathcal{N}_1}(p_1) = \{< u_1, (0.5, 0.7, 0.3, 0.2) >, < u_2, (0.3, 0.2, 0.5, 0.7) >, < u_3, (0.7, 0.9, 0.3, 0.2) >\}$
$f_{\mathcal{N}_1}(p_2) = \{< u_1, (0.2, 0.3, 0.2, 0.2) >, < u_2, (0.6, 0.7, 0.2, 0.1) >, < u_3, (0.7, 0.9, 0.1, 0.2) >\}$
$f_{\mathcal{N}_1}(p_3) = \{< u_1, (0.8, 0.7, 0.2, 0.2) >, < u_2, (0.2, 0.3, 0.5, 0.7) >, < u_3, (0.7, 0.8, 0.3, 0.2) >\}$
$f_{\mathcal{N}_1}(p_4) = \{< u_1, (0.9, 0.7, 0.3, 0.2) >, < u_2, (0.5, 0.2, 0.6, 0.7) >, < u_3, (0.3, 0.4, 0.5, 0.6) >\}$
Then
$\mathcal{N}_1 = \{(p_1, f_{\mathcal{N}_1}(p_1)), (p_2, f_{\mathcal{N}_1}(p_2)), (p_3, f_{\mathcal{N}_1}(p_3)), (p_4, f_{\mathcal{N}_1}(p_4))\}$
$f_{\mathcal{N}_2}(p_1) = \{< u_1, (0.6, 0.7, 0.4, 0.3) >, < u_2, (0.4, 0.2, 0.6, 0.7) >, < u_3, (0.8, 0.9, 0.4, 0.2) >\}$
$f_{\mathcal{N}_2}(p_2) = \{< u_1, (0.3, 0.4, 0.2, 0.2) >, < u_2, (0.7, 0.8, 0.3, 0.1) >, < u_3, (0.8, 0.9, 0.2, 0.2) >\}$
$f_{\mathcal{N}_2}(p_3) = \{< u_1, (0.9, 0.8, 0.2, 0.2) >, < u_2, (0.3, 0.4, 0.6, 0.7) >, < u_3, (0.7, 0.9, 0.4, 0.2) >\}$
$f_{\mathcal{N}_2}(p_4) = \{< u_1, (0.9, 0.7, 0.4, 0.2) >, < u_2, (0.6, 0.3, 0.6, 0.7) >, < u_3, (0.3, 0.5, 0.6, 0.6) >\}$
Then
$\mathcal{N}_2 = \{(p_1, f_{\mathcal{N}_2}(p_1)), (p_2, f_{\mathcal{N}_2}(p_2)), (p_3, f_{\mathcal{N}_2}(p_3)), (p_4, f_{\mathcal{N}_2}(p_4))\}$
Clearly $\mathcal{N}_1 \subseteq \mathcal{N}_2$

Definition 4.10. Let $\mathcal{N}_1$ and $\mathcal{N}_2$ be two NFSSs on $(\mathcal{U}, \mathcal{P})$ then $\mathcal{N}_1 = \mathcal{N}_2$ if and only if $\mathcal{N}_1 \subseteq \mathcal{N}_2$ and $\mathcal{N}_2 \subseteq \mathcal{N}_1$.

Definition 4.11. Let $\mathcal{P} = \{p_1, p_2, p_3, ..., p_n\}$ be the set of parameters then the NOT set of $\mathcal{P}$ is denoted by $\neg(\mathcal{P})$ and is defined as $\neg(\mathcal{P}) = \{\neg(p_1), \neg(p_2), \neg(p_3), ..., \neg(p_n)\}$, where $\neg(p_i)$ =not $p_i \forall i$

Example 4.12. Assume $\mathcal{U} = \{u_1, u_2, u_3\}$ represents the collection of gadgets being examined. The set of parameters is denoted by $\mathcal{P} = \{p_1, p_2, p_3, p_4\}$, for instance, the parameters branded (p_1), inexpensive (p_2), uniqueness (p_3) and attractiveness$(p_4)$are represented by these terms,then
$\neg(\mathcal{P})$={not branded,expensive,not unique,not attractive}

Definition 4.13. $\mathcal{N}_1$ and $\mathcal{N}_2$ are two NFSSs over $(\mathcal{U}, \mathcal{P})$ then
$\mathcal{N}_1 \cup \mathcal{N}_2 = \{(p, < x, \mu_{f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p)}(x), \mathcal{T}_{f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p)}(x, \mu), \mathcal{I}_{f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p)}(x, \mu), \mathcal{F}_{f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p)}(x, \mu) >: x \in \mathcal{U}) : p \in \mathcal{P}\}$
where, $\mu_{f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p)}(x) = max(\mu_{f_{\mathcal{N}_1}(p)}(x), \mu_{f_{\mathcal{N}_2}(p)}(x))$
$\mathcal{T}_{f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p)}(x, \mu) = max(\mathcal{T}_{f_{\mathcal{N}_1}(p)}(x, \mu), \mathcal{T}_{f_{\mathcal{N}_2}(p)}(x, \mu))$
$\mathcal{I}_{f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p)}(x, \mu) = min(\mathcal{I}_{f_{\mathcal{N}_1}(p)}(x, \mu), \mathcal{I}_{f_{\mathcal{N}_2}(p)}(x, \mu))$
$\mathcal{F}_{f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p)}(x, \mu) = min(\mathcal{F}_{f_{\mathcal{N}_1}(p)}(x, \mu), \mathcal{F}_{f_{\mathcal{N}_2}(p)}(x, \mu))$

Definition 4.14. $\mathcal{N}_1$ and $\mathcal{N}_2$ are two NFSSs over $(\mathcal{U}, \mathcal{P})$ then
$\mathcal{N}_1 \cap \mathcal{N}_2 = \{(p, < x, \mu_{f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p)}(x), \mathcal{T}_{f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p)}(x, \mu), \mathcal{I}_{f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p)}(x, \mu), \mathcal{F}_{f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p)}(x, \mu) >: x \in \mathcal{U}) : p \in \mathcal{P}\}$
where, $\mu_{f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p)}(x) = min(\mu_{f_{\mathcal{N}_1}(p)}(x), \mu_{f_{\mathcal{N}_2}(p)}(x))$
$\mathcal{T}_{f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p)}(x, \mu) = min(\mathcal{T}_{f_{\mathcal{N}_1}(p)}(x, \mu), \mathcal{T}_{f_{\mathcal{N}_2}(p)}(x, \mu))$
$\mathcal{I}_{f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p)}(x, \mu) = max(\mathcal{I}_{f_{\mathcal{N}_1}(p)}(x, \mu), \mathcal{I}_{f_{\mathcal{N}_2}(p)}(x, \mu))$
$\mathcal{F}_{f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p)}(x, \mu) = max(\mathcal{F}_{f_{\mathcal{N}_1}(p)}(x, \mu), \mathcal{F}_{f_{\mathcal{N}_2}(p)}(x, \mu))$

Example 4.15. In this context, we will examine the Neutrosophic Fuzzy sets $\mathcal{N}$ and $\mathcal{M}$, which are discussed in the example section of the definition of inclusion.
$f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p_1) = \{< u_1, (0.5, 0.7, 0.3, 0.2) >, < u_2, (0.3, 0.2, 0.5, 0.7) >, < u_3, (0.7, 0.9, 0.3, 0.2) >\}$

$f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p_2) = \{< u_1, (0.2, 0.3, 0.2, 0.2) >, < u_2, (0.6, 0.7, 0.2, 0.1) >, < u_3, (0.7, 0.9, 0.1, 0.2) >\}$
$f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p_3) = \{< u_1, (0.8, 0.7, 0.2, 0.2) >, < u_2, (0.2, 0.3, 0.5, 0.7) >, < u_3, (0.7, 0.8, 0.3, 0.2) >\}$
$f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p_4) = \{< u_1, (0.9, 0.7, 0.3, 0.2) >, < u_2, (0.5, 0.2, 0.6, 0.7) >, < u_3, (0.3, 0.4, 0.5, 0.6) >\}$
Then, $\mathcal{N}_1 \cup \mathcal{N}_2 = \{(p_1, f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p_1)), (p_2, f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p_2)), (p_3, f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p_3)), (p_4, f_{\mathcal{N}_1 \cup \mathcal{N}_2}(p_4))\}$
$f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p_1) = \{< u_1, (0.5, 0.7, 0.4, 0.3) >, < u_2, (0.3, 0.2, 0.6, 0.7) >, < u_3, (0.7, 0.9, 0.4, 0.2) >\}$
$f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p_2) = \{< u_1, (0.2, 0.3, 0.2, 0.2) >, < u_2, (0.6, 0.7, 0.3, 0.1) >, < u_3, (0.7, 0.9, 0.2, 0.2) >\}$
$f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p_3) = \{< u_1, (0.8, 0.7, 0.2, 0.2) >, < u_2, (0.2, 0.3, 0.6, 0.7) >, < u_3, (0.7, 0.8, 0.4, 0.2) >\}$
$f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p_4) = \{< u_1, (0.9, 0.7, 0.4, 0.2) >, < u_2, (0.5, 0.2, 0.6, 0.7) >, < u_3, (0.3, 0.4, 0.6, 0.6) >\}$
Then, $\mathcal{N}_1 \cap \mathcal{N}_2 = \{(p_1, f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p_1)), (p_2, f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p_2)), (p_3, f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p_3)), (p_4, f_{\mathcal{N}_1 \cap \mathcal{N}_2}(p_4))\}$

5 Enhancing Expected Time of Arrival(ETA) Calculations with Neutrosophic Fuzzy Soft Sets

Calculating the Estimated Time of Arrival (ETA) is essential in many fields, including emergency response services, logistics, and transportation. Precise estimates of arrival times are essential for effective organization, distribution of resources, and judgment. However, conventional approaches often fail to take into account the different uncertainties present in real-world situations. In order to handle these uncertainties, Neutrosophic Fuzzy Soft Sets (NFSS) offer an intricate and dependable mathematical framework for ETA estimations.
The uncertainties in ETA calculations arise from multiple causes. Traffic conditions, such as accidents, road construction, or peak hour congestion, can vary in an unpredictable manner. Weather conditions, another crucial aspect, have the ability to quickly change and affect both road safety and travel speeds. In addition, the condition of the roads can differ as a result of maintenance operations or unforeseen obstructions, making the prediction of travel times more challenging. Human variables, such as driver behavior and decision making, introduce an additional level of variability. The presence of these uncertainties poses significant difficulty in accurately estimating ETAs using traditional approaches, which frequently depend on deterministic or overly simplistic models.
The importance of fuzzy neutrosophic soft sets in computing ETA rests in their ability to fully manage these uncertainties. NFSS expands on conventional fuzzy sets by integrating three membership functions: veracity, ambiguity, and falsehood. The inclusion of this trio enables NFSS to more accurately simulate the inherent ambiguity and unpredictability of real-world variables. NFSS, by attributing degrees of truth, indeterminacy, and falsehood to each parameter affecting the ETA, offers a more intricate and adaptable depiction of uncertainty. This feature is especially advantageous in dynamic settings, where circumstances might quickly and unpredictably alter.

5.1 Algorithm for Expected Time of Arrival(ETA) Calculation using Neutrosophic Fuzzy Soft Sets

An algorithm is proposed for calculating the estimated time of arrival (ETA) using neutrosophic fuzzy soft sets. This is a comprehensive algorithm that outlines the process of calculating the estimated time of arrival (ETA) using neutrosophic fuzzy soft sets. It covers various time intervals and aims to determine the optimal time for travel.

5.1.1 Formula for Expected Time of Arrival(ETA)

Based on the definition of a neutrosophic fuzzy soft set $\mathcal{N}$, the formula for Estimated Time of Arrival (ETA) should integrate the concepts of membership grade,truth, indeterminacy, and falsity of membership grades. In this context, the ETA calculation will consider the aggregated effects of these membership functions on the parameters. Let

- $\mathcal{U}$ represents the universal set of possibilities..
- Let $\mathcal{P}$ represent the set of parameters that influence ETA.
- $\mathcal{N}$ be the neutrosophic fuzzy soft set over $\mathcal{U}$

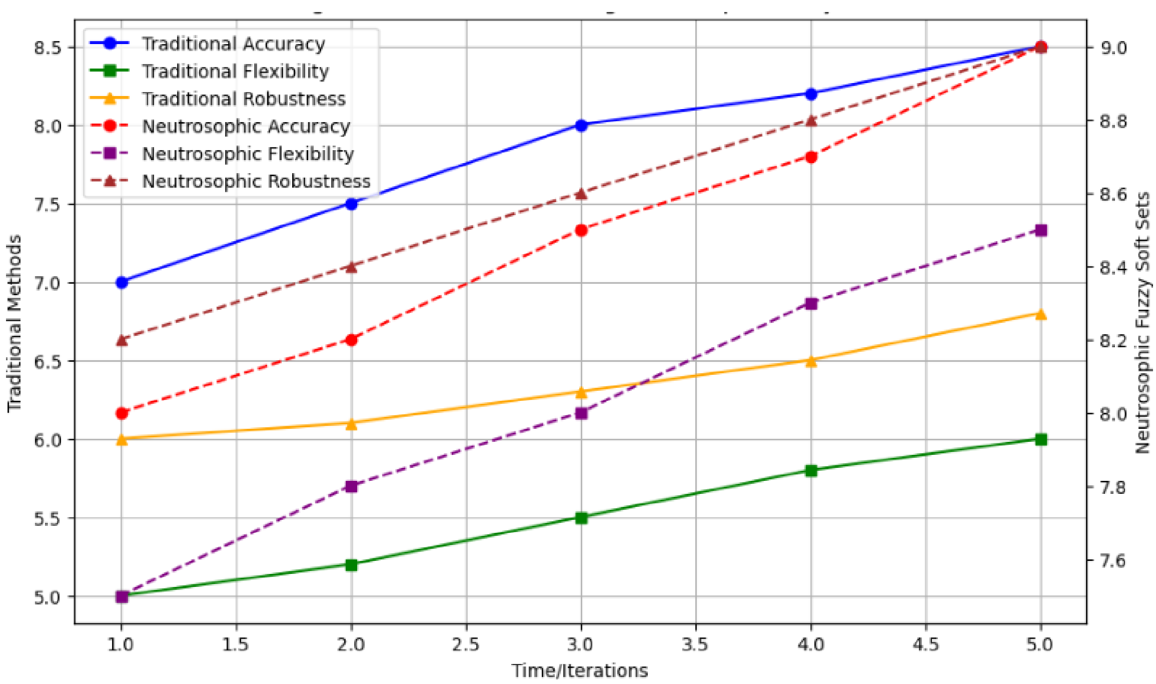

Figure 1: Dual Axis Line Chart Showing the Advantages of Neutrosophic Fuzzy Soft Set ETA Calculations

- $f_{\mathcal{N}}$ be the set-valued function mapping parameters to neutrosophic fuzzy soft sets.
- $\mu_{f_{\mathcal{N}}(p)}(x)$ be the membership grade of x under the parameter p.
- $\mathcal{T}_{f_{\mathcal{N}}(p)}(x,\mu), \mathcal{I}_{f_{\mathcal{N}}(p)}(x,\mu), \mathcal{F}_{f_{\mathcal{N}}(p)}(x,\mu)$ be the truth, indeterminacy, and falsity membership functions, respectively.

The estimated time of arrival (ETA) can be determined by summing the impacts of various membership functions, taking into account their significance in establishing the ETA.
The formula for ETA:
ETA=$\frac{1}{n}\sum_{p\in\mathcal{P}} w_p(\mu_{f_{\mathcal{N}}(p)}(x).\mathcal{T}_{f_{\mathcal{N}}(p)}(x,\mu).B_T + \mathcal{I}_{f_{\mathcal{N}}(p)}(x,\mu).U_T + \mathcal{F}_{f_{\mathcal{N}}(p)}(x,\mu).E_T)$
where

- w_p is the weight of the parameter p.
- B_T is the base travel time of the parameter p.
- U_T is the uncertainty time contribution from parameter p.
- $E_T$is the error time of the parameter p.
- n is the normalization factor,typically $n = \sum_{p\in\mathcal{P}} w_p$.

5.1.2 Algorithm for Static Expected Time of Arrival(ETA) Calculation

- **Commencement**:
  - Define the universal set $\mathcal{U}$ and the parameter set $\mathcal{P}$.
  - Define the neutrosophic fuzzy soft set function $f_{\mathcal{N}}$.
- **Define the Functions of Membership:**
  - Membership Function ($\mu_{f_{\mathcal{N}}(p)}(x)$).
  - Truthfulness of membership function.

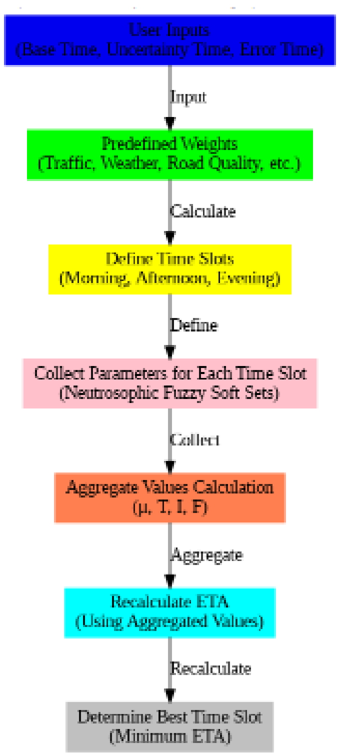

Figure 2: Algorithm for Expected Time of Arrival(ETA) Calculation

- Indeterminacy of the membership function.
- Falsity of the membership function.

- **Total Values:**
  - Aggregate membership values using criteria weights.
- **Calculate Expected Time of Arrival(ETA)**
  - Using the ETA formula to determine the ETA by aggregating the base time, uncertainty time, and error time.
- **Discover the Optimal Time Slot**
  - Iterate through various time periods.
  - Determine the ETA for each slot and identify the slot with the lowest ETA.

5.2 Modeling Problem: Determining the Optimal Time Slot for Traveling by Utilizing ETA Calculations(Static ETA) with Neutrosophic Fuzzy Soft Set Values

The aim of this problem is to create a prognostic model for estimating the Estimated Time of Arrival (ETA) for several time periods (morning, afternoon, and evening) and to identify the most efficient travel time that reduces the duration of the journey. The model will utilize past travel data, including origin and destination points, travel durations, and dates, in addition to contextual details such as time of day, day of the week, past traffic conditions, weather data, and road conditions. To account for the inherent uncertainties and ambiguity in these parameters, we employ neutrosophic fuzzy soft sets (NFSS) as a means to represent and manage this imprecision. The ultimate objective is to offer precise estimated time of arrival (ETA) forecasts and determine the most favorable time period for travel to assist travelers in avoiding heavy traffic and delays. This will ultimately improve travel efficiency and planning.
We are personally reviewing the estimated time of arrival (ETA) during the morning time slot, while the ETA for other time slots is determined using a Python program. The entire Python code is included in the **Appendix-1**.

Parameters	Morning	Afternoon	Evening
Traffic	(0.4, 0.3, 0.1,0.1)	(0.7, 0.5, 0.1,0.2)	(0.6, 0.6, 0.1,0.2)
Weather	(0.6, 0.22, 0.1,0.2)	(0.4, 0.1, 0.1,0.3)	(0.4, 0.3, 0.1,0.2)
Road Quality	(0.6, 0.43, 0.1,0.3)	(0.7, 0.4, 0.1,0.2)	(0.7, 0.5, 0.1,0.1)
Vehicle Condition	(0.9, 0.45, 0.05,0.04)	(0.8, 0.1, 0.1,0.2)	(0.85, 0.1, 0.05,0.04)
Driver Experience	(0.85, 0.6, 0.05,0.05)	(0.95, 0.15, 0.05,0.03)	(0.865, 0.2, 0.05,0.03)
Time of day	(0.5, 0.2, 0.1,0.1)	(0.6, 0.3, 0.1,0.2)	(0.4, 0.5, 0.1,0.3)
Historical Data	(0.7, 0.3, 0.1,0.2)	(0.6, 0.3, 0.1,0.3)	(0.8, 0.1, 0.1,0.2)

Table 1: Neutrosophic Fuzzy Soft Set values for each parameter in three different time slots

Parameters	Aggregated value for Morning
Traffic	(0.08, 0.06, 0.02,0.02)
Weather	(0.12, 0.044, 0.02,0.04)
Road Quality	(0.09, 0.065, 0.015,0.045)
Vehicle Condition	(0.09, 0.045, 0.005,0.004)
Driver Experience	(0.085, 0.06, 0.005,0.005)
Time Of Day	(0.075, 0.03, 0.015,0.015)
Historical Data	(0.07, 0.03, 0.01,0.02)

Table 2: Aggregated Values for Morning Slot

5.2.1 Implementation of the Algorithm

- **User Inputs**: Gather user input for the base travel time, uncertainty time, and error time. For example, the base time is 20 minutes, the Uncertainty Time is 15 minutes, and the Error Time is 10 minutes.
- **Define the parameters influencing travel time**: Traffic, Weather, Road Quality, Vehicle Condition, Driver Experience, Time of Day, and Historical Data. Allocate weights to each criterion according to their perceived significance. Sample weights: Traffic = 0.20, weather = 0.20, road quality = 0.15, vehicle condition = 0.10, driver experience = 0.10, day time = 0.15, historical data = 0.10.
- **Define Time Slots** Segment the day into distinct time intervals: Morning, Afternoon, and Evening.
- **Gather values for Neutrosophic Fuzzy Soft Sets:** The **Table 1** provides neutrosophic fuzzy soft set values for each parameter in each time slot, including the membership grade (μ), truth $\mathcal{T}$, indeterminacy($\mathcal{I}$), and falsity ($\mathcal{F}$) of the membership grade (μ).
- **Aggregate Values Calculation:** Create a function that combines the membership values according to the weights assigned to each criterion and determines the combined values of truth, indeterminacy, and falsity. The aggregated values for morning slot is given in **Table 2**.
- **Recalculate ETA:** Utilize the fundamental time, the time of uncertainty, and the time of error to compute the Estimated Time of Arrival (ETA) using consolidated values. Applying the ETA calculation, we calculate that the expected arrival time for the morning slot is 6.91 minutes.
- **Determine Best Time Slot:** Based on the Python ETA calculator provided in the Appendix, the estimated time of arrival (ETA) for the evening time slot is 7.58 minutes,while for the afternoon time slot it is 7.20 minutes. Hence, the most favorable period to travel is the morning slot.

6 AI-Enhanced System for Estimating Time of Arrival (Dynamic ETA) utilizing Neutrosophic Fuzzy Soft Sets

The integration of artificial intelligence (AI) with neutrosophic fuzzy soft sets (NFSS) to calculate estimated arrival time (ETA) is a new approach that combines AI with sophisticated mathematical frameworks to improve

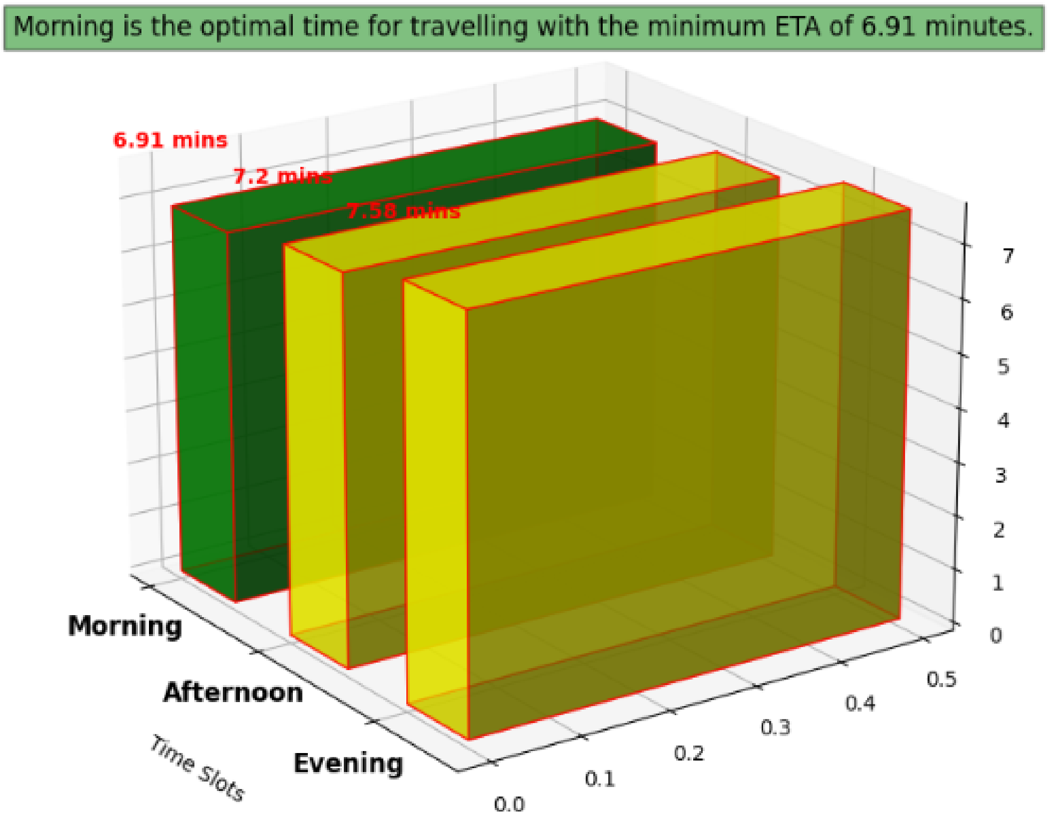

Figure 3: 3D Diagram Showing the Conclusion of the Executed Algorithm

the precision and dependability of ETA predictions. The process of integrating ETA calculations (Estimated Time of Arrival) with AI involves the use of machine learning models to improve the accuracy of travel time predictions through the analysis of historical and real-time data. By integrating dynamic and intricate interactions among many elements that affect journey time, this can improve the estimation of ETA.
Here, we are addressing the identical modeling issue that we previously mentioned in the section on calculating static ETA. We are utilizing Neutrosophic Fuzzy Soft Set values in the machine learning model to compute the Estimated Time of Arrival (ETA) and identify the most favorable time interval for travel.

6.1 Distinct Phases in the AI-integrated ETA Computation Process using Python

- **Accumulation of Information and Preparation**
  Collect historical data on travel durations, including details on various elements that can impact them, such as traffic conditions, driver expertise, climate conditions, and other relevant variables.Pre process the data by addressing missing values, standardizing features, and splitting them into separate training and testing sets. In this analysis, we are taking into account many factors such as Traffic, Weather, Road Quality, Vehicle Condition, Driver Experience, Time Of Day, and Historical Data for three distinct time periods: ”Morning”, ”Afternoon”, and ”Evening”.

- **Neutrosophic Fuzzy Soft Set Values** Neutrosophic Fuzzy soft sets are a mathematical framework utilized to efficiently handle and quantify the uncertainty inherent in data.Assign values to each parameter to represent the degree of membership, the truth value of the membership, the indeterminacy of the membership, and the falsity of the membership.

- **Data Preparation** Neutrosophic fuzzy soft set values are gathered for each parameter over three distinct time intervals: morning, afternoon, and evening.We can acquire these data from several sources. To determine the values for each parameter, we will rely on multiple sources. GPS data from automobiles, traffic cameras, road sensors, or mobile applications can be utilized to gather traffic data. Weather data can be acquired from meteorological stations, weather APIs, or local weather monitoring systems.

Parameters	Feature Importance
Traffic	(0.038462,0.057692,0.000000, 0.000000)
Weather	(0.076923,0.019231,0.000000, 0.000000)
Road Quality	(0.038462, 0.076923,0.000000, 0.000000)
Vehicle Condition	(0.076723, 0.057692,0.057692,0.000000)
Driver Experience	(0.076923,0.096154,0.000000, 0.000000)
Time Of Day	(0.038462,0.057692, 0.076923,0.000000)
Historical Data	(0.057692, 0.076923,0.019231,0.000000)

Table 3: Table Showing the importance of each parameter in ”Random-Regression Model”

Government reports, road maintenance records, and crowd-sourced platforms are sources of road quality data. The condition of a vehicle can be monitored through onboard diagnostics (OBD) systems, maintenance logs, or vehicle health monitoring systems. The driver experience can be evaluated by reviewing driving records, considering the number of years of driving experience, and analyzing feedback from driving performance monitoring systems. The time of day is a simple characteristic that can be acquired. Historical data can be acquired from previous travel records, historical traffic and weather data, and current time voyage logs. **Table 1** provides the neutrosophic fuzzy soft set values for each parameter.

- **Handling Data and Training Models**The purpose of standardizing these characteristics is to ensure that each feature has an equal impact on the training process of the model. The machine learning technique ”Random Forest Regression” is taught using the preprocessed data. This model has numerous decision trees that are aggregated to enhance the precision and resilience of predictions. During the training process, the model acquires knowledge of patterns in the data by dividing it into subsets based on the features that minimize the prediction error the most at each iteration. The Python program implementing the machine learning technique ”Random Forest Regression” is provided in the **Appendix-2**, along with a full explanation.
- **Significance of each parameter**The parameter weights of the ”Random Forest Regression Model” are not explicitly defined. The Random Forest model autonomously assesses the significance of each parameter by evaluating their contribution to minimizing the prediction error. The importance can be accessed by utilizing the ”feature importance attribute” of the trained model. We are entering the nuetrosophic fuzzy soft set values provided in **Table 1**, Once the python program provided in the Appendix is executed successfully, we will obtain the significance of each parameter indicated in **Table 3**.
- **ETA Prediction** The program utilizes learned patterns to provide predictions about trip times for new data pieces. The example utilizes real-time data to forecast estimated time of arrivals (ETAs) for the morning, afternoon, and evening time intervals.
- **Determining the Optimal Time Slot** The time interval with the lowest estimated arrival time (ETA) is considered to be the optimal time for travel. The input travel times for three distinct slots are 45 minutes, 50 minutes, and 40 minutes, respectively. In this particular example, the estimated arrival time (ETA) for the morning is 45.00 minutes. The estimated arrival time (ETA) for the afternoon is 47.40 minutes. The estimated arrival time (ETA) for the evening is 43.10 minutes. The optimal time to travel is in the evening, with an estimated arrival time (ETA) of 43.10 minutes.

7 Comparative Analysis of Static and Dynamic ETA Calculations using Neutrosophic Fuzzy Soft Sets

We have already computed the ideal trip time using the ETA method in two distinct manners: static ETA calculation and ETA calculation employing a machine learning technique. In this section, we desire to explore the contrast between these two.
The static ETA calculations for a particular day yield the following results: - The ETA for the morning slot is 10.17 minutes; - The ETA for the afternoon slot is 9.10 minutes; - The ETA for the evening slot is 11.41 minutes. The actual recorded travel times for these slots are as follows: - Morning slot: 10.15 minutes - Afternoon

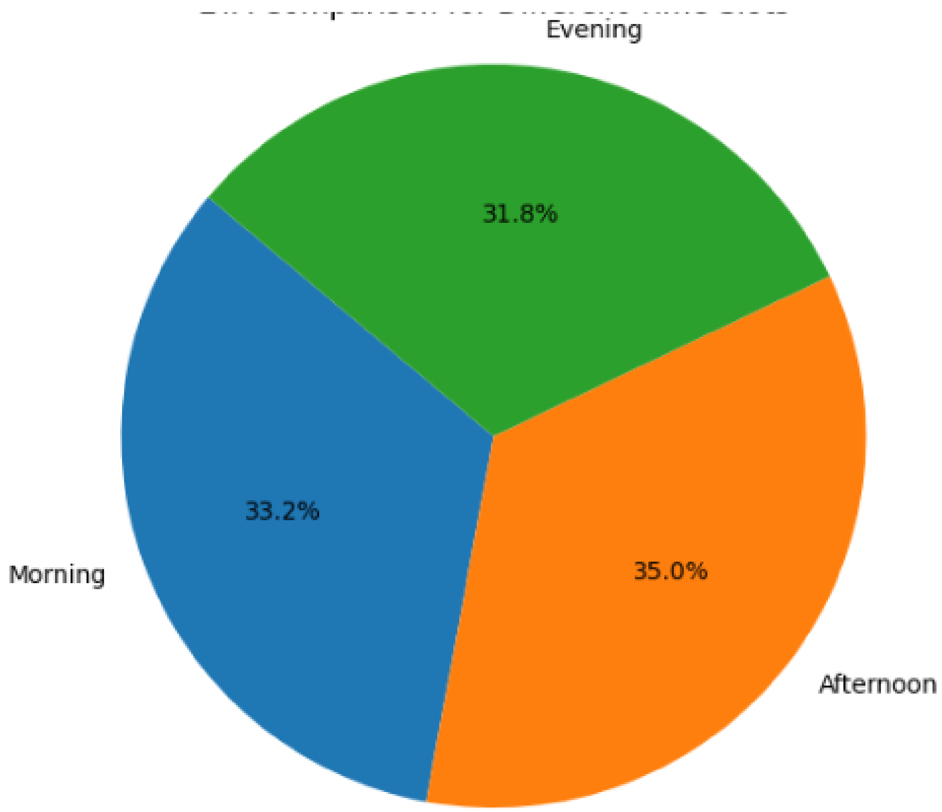

Figure 4: ETA Comparison for Different Timeslot

Time Slot	Static ETA(Min)	Dynamic ETA(Min)	Difference
Morning	10.17	11.390	-1.220
Afternoon	9.10	10.193	-1.093
Evening	11.41	11.642	-0.232

Table 4: Comparison Table for Static and Dynamic ETA

slot: 9.50 minutes- Evening slot: 12.65 minutes, this is derived from the historical data that were utilized for training the model. The Dynamic ETA is determined using the Python program provided in the **Appendix-3** and the results are summarized in **Table 4**. The Dynamic ETA demonstrates enhanced performance as a result of utilizing real-time data and adaptive learning. The ”Random Forest Regression” model incorporates both real-time and historical data to calculate the ETA, resulting in more precise results compared to static ETA. **Figure 5** visually illustrates a comparison.

8 Conclusion

Integrating machine learning and neutrosophic fuzzy soft sets, we can create a robust system that can accurately predict the expected time of arrival (ETA). This approach possesses the capability to efficiently handle uncertainties and dynamic changes in travel conditions, leading to more accurate and dependable predictions. This method has the potential to be enhanced and refined by including more complex data and advanced machine-learning algorithms.The ETA prediction utilizing neutrosophic fuzzy soft sets can enhance delivery time estimates in several industries such as transportation and logistics, urban planning, traffic management, ride-sharing, and public transportation. Integrating dynamic ETA prediction models with navigation systems and mobile applications to offer customers up-to-date, flexible route assistance.In the future conducting research on the influence of several external circumstances, such as road closures, public events, and accidents, on estimated time of arrival (ETA) estimates, and devising solutions to minimize their impact.

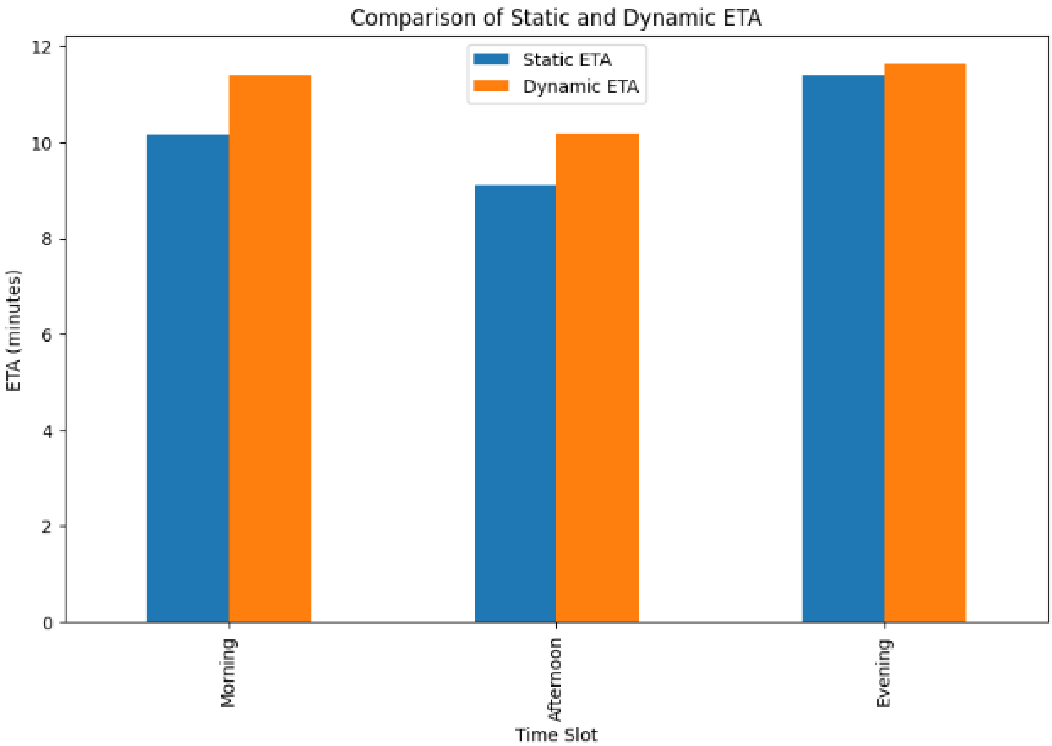

Figure 5: Comparison Diagram for Static and Dynamic ETA

Appendix

1. Python Program for Static ETA Calculation:https://github.com/priya91ian/ETA-Calculator-Thesis.git
2. Python Program for AI Integrated ETA Calculation:https://github.com/priya91ian/ETA-with-ML-Algorithm.git
3. Python Program for Comparison of Static and Dynamic ETA: https://github.com/priya91ian/Static-and-Dynamic-ETA-Comparison.git

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