Time-Optical Control Strategies for SIR Epidemic Models in Cattle and Neutrosophic Fuzzy Modelling

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Abstract

The utilization of neutrosophic fuzzy logic with machine learning constitutes a revolutionary way of improving epidemic modelling. With the help of Weka, this method solves the problem of uncertainty and vagueness that is characteristic of epidemic processes with the help of neutrosophic equations. These equations enhance the way how indeterminacy of epidemic levels can be modelled, therefore enhancing predictions of complex networks. The effectiveness of the proposed framework is confirmed by extensive evaluations providing extensive tables and visualizations regarding the improvements in the accuracy and reliability of the models. Further, the work explores time-optimal control strategies of SIR epidemic models. It shows exactly how bang-bang controls work avoiding the duration of outbreaks drastically, especially if introduced with delayed interventions. This finding is especially important for controlling the health of livestock since the response to disease outbreaks has to be done as soon as possible because of stringent measures on animal health. Altogether, the analysis presented therein contains strong recommendations that would help to improve the handling of epidemics and better understand the approaches to employ in decision-making under conditions of risk and ambiguity.

Keywords: Neutrosophic Parameters; Epidemic Levels; Sensitivity Analysis; Cost Optimization; Grouped Bar Chart; Multi-Line Plot

1. Introduction

Epidemic management is characterized by a certain degree of uncertainty, ambiguity, and vagueness that is not easily addressed by traditional models [1]. When there is increased interaction and dynamism in global systems, there is increased complexity of these uncertainties hence the need for better methods to handle such complexity. To this end, we have developed an enhanced epidemic management model [2-4] employing neutrosophic fuzzy logic with machine learning employing Weka. Neutrosophic fuzzy logic builds on traditional fuzzy logic by initiating three degrees: paradigm: T,I and F. This expanded framework permits additional incorporation of uncertainties into the experiments and details of phenomena that may be overlooked by other approaches when combined with machine learning, it

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further reinforces learning from the past data set and adjusts to new conditions that best suit the model [5, 6]. This means that the model is always updating its predictions in real-time thereby providing better, more accurate decisions. This model is further strengthened and expanded by Weka, which provides many algorithms for machine learning and is also highly reliable and can handle large amounts of data. Weka enhances the versatility and efficiency of the model through various algorithms' applications [6]. This is helpful in the prevention and control of diseases in large herds of livestock that are important sources of income when infected, but also threats to the health, economy, and, in some cases, existence of a nation [7]. Our study on the disease includes mathematical modelling of Disease transmission using the SIR model and derivation of optimal control strategies for populations. What is more, it mainly concentrates on practices such as vaccination, isolation, culling, and reduction in transmission [8]. In our case, we established that timing is a critical element in the application of these control measures. Constant optimal control strategies are of a bang-bang type, where one switches – with delay – and then uses full control during the rest of the outbreak. This intervention plan puts equal weight into reducing the overall volume of the disease incidence as well as the scale of the outbreak's continuance [9]. It is also demonstrated in simulations that optimal control may sometimes be delayed, even if the reproduction number of the disease is less than one, the maximum control is shifted after the peak in infection.

These results question the conventional concepts regarding when control measures should be instituted and provide useful information concerning the management of livestock diseases that should be established rapidly due to severe sanitary requirements. Policymakers could therefore use such information to make better disease control approaches in days of outbreak and perfect resource use during such incidences [11-14]. The outbreaks of diseases in livestock are actual threats to the health of the people and the nation's economy. Depending on the type of an outbreak, these can cause many impacts to the growth of livestock enterprise because of the cost that is incurred in the process of controlling and eradicating the diseases. Some of the effects are in the economic functions where trading, tourism, and public health are disrupted [15, 16]. These are costs that are caused by the episodes and therefore they must be shortened in their duration. Some of these are classical swine fever in the Netherlands, foot and mouth disease in Britain, and avian influenza in the United States of America. In the present paper, we review methods to lessen the epidemic length with the help of such interventions as vaccination, isolation, and culling. Our research also demonstrates that the most effective solutions to shortening an outbreak might not necessarily be the same as the solutions to minimizing the total number of infections. Broumi has discussed the decision-making approaches in different scenarios [17, 18], and their applications are discussed. This advanced model gives epidemic managers an effective way to deal with uncertainties and the many crosscutting aspects of epidemic control. While integrating with machine learning, it is more accurate and intelligent as compared to the previous methods of handling epidemics, and it provides an opportunity for saving costs and enhancing management efficiency. This innovative approach meets the important need for the subsequent deeper modelling in the modern world, which develops in the spirit of complexity.

2. Neutrosophic Fuzzy Logic in Epidemic Modelling

Neutrosophic fuzzy logic improves traditional fuzzy logic by introducing three membership functions: Trust (T), Indecisiveness (I), and Deceit (F). As the following sections illustrating the three-part outline suggest, this approach provides a finer-grained means of expressing uncertainty in epidemic mitigation. The truth (T) function estimates the current epidemic situation as compared with the ideal/expected level indicating how well the epidemic is controlled. Another function is the indeterminacy (I) function, which shows the degree of vagueness or uncertainty of the subject under consideration, in this case, the epidemic, when there is information redundancy, shortage, or obscurity. The falsity (F) function also reveals how and where the epidemic is different from the targeted aim to provide insights into where organizations need to change. This neutrosophic fuzzy epidemic model unifies these three functions into a single function that provides improved management of the uncertainty of an epidemic. It applies the concept of fuzzy set theory and transforms the given epidemic levels with these functions, which provides more opportunities for accurate modeling of the situation. The model uses a set of Fuzzy Rules that are a mixture of truths, uncertainties, and falsehood to determine the status of the epidemic and to take subsequent measures. They are then summed up and defuzzed to yield unambiguous information as to how to proceed to contain the epidemic.

2.1 Neutrosophic Epidemic Equation:

$$N(Q)=T(Q)\cdot \text{Truth Degree}+I(Q)\cdot \text{Indeterminacy Degree}+F(Q)\cdot \text{Falsity Degree}$$

Where:

- Q represents the epidemic quantity.
- T(Q), I(Q), and F(Q) are the T,I and F membership functions, respectively.

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The above equation is used when trying to establish the epidemic levels in consideration of all states of information, which include T, I, and F in the decision-making process.

3. Preliminaries

3.1 Time-Optimal Control Strategy

This method aims to find the shortest time in which a certain event, for instance, an epidemic can be controlled. It targets the amount of time taken to get to the product as in curing a given disease. Such measures may include vaccination, isolation, or quarantine within the framework of the subject area of epidemics. The first is to achieve the twin objectives of applying the approach: On one hand, there would be the principle of Acting Fast while on the other would be the principle of Controlling or Eliminating the Outbreak. Due to timeliness, this method will assist in reducing the effects of the disease while at the same time increasing the efficiency of the control measures.

3.2 SIR Model

The SIR model is an epidemiological model that is used to denote the flow of disease in a population. It splits the population into three classes: Susceptible (S), Recovered (R) and Infected (I), classes and in the next section, the equations for these classes are given. It tracks the movement of people through these categories at intervals depending on such factors as the transmission rate which shows the rate at which the disease spreads and the recovery rate which determines the rate at which people start recovering or are immunized and therefore removed from the infection category. SIR models are quite popular for determining the trends of the spread of diseases and to forecast the potential development of the process, as well as for organizing interventions at the population level.

3.3 Neutrosophic Set

An advancement of fuzzy sets that incorporates three degrees: truth, falsity, and relativism. A Conceptual Note 1 ascribes that this extension offers a more realistic account of uncertainty, ambiguity, and conflicting information. Unlike classical sets, neutrosophic sets are developed to provide solutions for real-life cases. They are especially useful in situations characterized by a lack of information or their unpredictability.

3.4 Fuzzy Logic

An approach to the logic that was initially created to deal with incomplete information and, therefore, making propositions to some degree of truth rather than true or false. It deals with vague ideas, which leads to decisions that are more suitable. It can be seen that in fuzzy logic, statements can have a truth-value that varies between true and false. This approach is applied in such fields as control systems and artificial intelligence.

3.5 Cattle Epidemic

An outbreak of a contagious disease among cattle that can result in substantial economic losses. Epidemic models help predict how the disease spreads and inform control measures. The cattle are typically divided into groups: susceptible, infected, and recovered. Implementing effective control strategies is essential for managing these outbreaks.

3.6 Optimal Control Theory

This stiff affects cattle and spreads from one animal to another leading to humongous losses. The transmission pattern of the disease is explained through epidemic models as well as prediction of control measures. The cattle are typically divided into groups immunocompromised, sick, and cured. These outbreaks require proper control measures to be undertaken, and effective control measures are crucial in this process.

3.7 Basic Reproduction Number (R_0)

An area of mathematics that is used to find an optimal control action that will help to achieve a specific goal. This objective may be to minimize costs or to maximize the efficiency of operation. Applying optimal control in the scenario of epidemics helps to come up with the best control measures. In the light of the theory, one is provided with solutions that can cover time, resources, and overall efficiency.

3.8 Epidemic Threshold

The critical moment in the development of an epidemic model in when a disease transitions from individual sporadic cases to one that can spread among the entire population. When this number is exceeded, the disease is rapidly spreading across the people in the population. Controls are aimed at ensuring that the level of infection does not exceed

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this number. It causes extensive outbreaks of the disease and hence is very important to comprehend this concept in the prognosis of the epidemic.

3.9 Neutrosophic Fuzzy Logic

An integration of fuzzy logic and neutrosophic set for enhancing decision-making in a volatile environment. It works with truth, falsehood, and uncertainty in areas of ambiguous or conflicting data. This offers a more elaborate and flexible solution than the traditional system of logic. It finds application in problem solving such as decision-making, design and implementation of control systems, and in artificial intelligence.

3.10 SIR Parameters

The major parameters in the SIR model include transmission rate, recovery rate, and total population size. These parameters determine the rate of transmission of a disease and the duration of sick entities' recuperation. Changing these parameters enables modelling a range of epidemic-related circumstances. For this reason, people involved in controlling diseases and epidemics must know these elements.

4. Implementation using Weka

The neutrosophic fuzzy epidemic model is implemented with Weka, an adaptable machine-learning framework. This framework uses various ML models including decision trees, SVM, and ANNs to forecast epidemic needs from historical data, parameters, and neutrosophic values. These algorithms make use of the records of previous epidemics and correlate them with other detailed information, which is inputted as neutrosophic membership functions. The derived neutrosophic membership functions, which are vital in the analysis of uncertainty and vagueness at the epidemic levels, involve aspects of historical data of previous epidemics and experimental knowledge from the experts. It entails the collection of data on previous epidemics so that the common trends as well as probable unknown factors can be observed. The above functions are then refined through experts' inputs so that they can depict real-life scenarios and challenges. In line with these, Weka's functions and its collection of conventional machine learning algorithms make the proposed neutrosophic fuzzy epidemic model very accurate as well as highly flexible. This integration of machine learning with neutrosophic logic improves the manageability of uncertainties strengthens the capability in decision-making in epidemic management and leads to better results than before.

5. Time-Optimal Control Problem Formulation

Building on the linear model of the SIR model, the work proposes a time-optimal control problem specific to the spread of cattle diseases (K). This implies identifying control variables/parameters and constraints as a way of properly controlling the distribution of preventive measures, which is accorded in equation, number (2). The aim is to reduce (x) the time for controlling, the system (y) with a view to minimizing the effects of infectious diseases on the number of cattle.

$$\frac{d^2y}{dt^2} + 2\zeta\omega_n\frac{dy}{dt} + \omega_n^2 y = K\omega_n^2 x(t)$$

ω_n - natural frequency

ζ - damping factor (2)

5.1 Theorem: State Equations: The SIR model equations are adapted to represent the dynamics of cattle diseases:

$dtdS=-\beta SI+u1S-uvS$ (3)

$dtdI=\beta SI-\gamma I+u2I$ (4)

$dtdR=\gamma I+u3R$ (5)

where *S*, *I*, and *R* denote the susceptible, infected, and recovered compartments, respectively.

Proof. Control Variables: Define control variables representing preventive measures:

$$max\ f = \sum_{i=1}^{n} c_i x_i + u1(t) + u2(t) + u3(t) + uv(t) \quad (6)$$

$u1(t)$: Rate of susceptible individuals undergoing preventive measures.

$u2(t)$: Rate of infected individuals subjected to control measures.

$u3(t)$: Rate of recovered individuals influenced by control strategies.

$uv(t)$: Vaccination rate.

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5.2 Theorem: Objective Function

Formulate the objective function to minimize the time to control the system:

$=\int J(u)=\int 0Tdt$ (7)

Proof Constraints: Introduce constraints to ensure realistic and feasible control strategies:

$\leq$max0$\leq u1(t),u2(t),u3(t),uv(t)\leq U$max: (8)

Control variables within permissible bounds.

$\geq 0S(t),I(t),R(t)\geq 0$: (9)

Non-negativity of state variables.

Expected Value of x: E(x) = $\sum_x xP(x)$; as P(x) signifies the possibility of x. (10)

($\sum_x P(x)$ = 1 and that the $\int_{-\infty}^{\infty} xP(x) = E(x)$ (11)

because P(x) represents a probability density function)

Variance of x: q = y – (B_1 + B_2x) (12)

Standard Deviation = the sq. root of the variance

Median = “the center of the set of numbers”; two the point m such that

P(x < m)< ½ *and* P(x > m)> ½ . (13)

5.3 Theorem Optimization Problem:

Combine the objective function and constraints to form the time-optimal control problem: Minimize =∫Minimize $J(u)=\int 0Tdt$ subject

Proof. Subject to $dt/dS=-\beta SI+u1S-uvS$, $dt/dI=\beta SI-\gamma I+u2I$, $dt/dR=\gamma I+u3R$ and

0≤u1≤max, 0≤and 0≤$u1(t)$, $u2(t)$, $u3(t)$, $uv(t)\leq U$ max, 0≤$S(t)$, $I(t)$, $R(t)$ (14)

Lemma significance: This time-optimal control problem formulation addresses the unique dynamics of cattle diseases, providing a foundation for developing preventive strategies that efficiently minimize the duration of infectious disease outbreaks. Solving this optimization problem will yield insights into the optimal allocation of control measures, aiding stakeholders in making informed decisions for the effective management of cattle health.

$$\sum_{1}^{N} d_i^2 = \sum_{1}^{N} (y_i - y)^2 = \sum_{1}^{N} \{y_i - (mx_i + b)\}^2 = \text{minimum}$$

$$\frac{\partial}{\partial m}\left\{\sum_{1}^{N} d_i^2\right\} = 0 \quad \frac{\partial}{\partial b}\left\{\sum_{1}^{N} d_i^2\right\} = 0$$

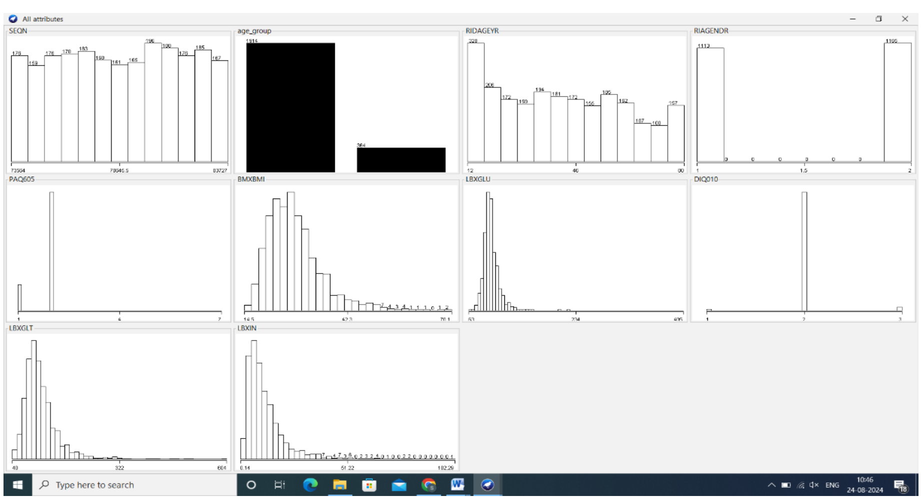

Figure 1. Lemma Significance

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Linear regression

=== Run information ===

Scheme: weka.classifiers.functions.LinearRegression -S 0 -R 1.0E-8 -num-decimal-places 4

Instances: 2278

Relation: Data set

Attributes: 10

SEQN

age_group

RIDAGEYR

RIAGENDR

PAQ605

BMXBMI

LBXGLU

DIQ010

LBXGLT

LBXIN

Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

Linear Regression Model

LBXIN =

-2.6585 * age_group=Adult +

-0.1463 * RIDAGEYR +

-0.9804 * RIAGENDR +

0.7707 * PAQ605 +

0.7539 * BMXBMI +

0.0242 * LBXGLU +

2.2085 * DIQ010 +

0.0307 * LBXGLT +

-11.2119

Time taken to build model: 0.12 seconds

=== Cross-validation ===

=== Summary ===

Mean absolute error 5.0605

Correlation coefficient 0.6069

Root mean squared error 7.7232

Root relative squared error 79.4098 %

Relative absolute error 77.3444 %

Total Number of Instances 2278

Input Mapped Classifier:

ZeroR predicts class value: 11.834793678665495

Attribute mappings:

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```
Model attributes            Incoming attributes
---------------------       ----------------
(numeric) SEQN              --> 1 (numeric) SEQN
(nominal) age_group         --> 2 (nominal) age_group
(numeric) RIDAGEYR          --> 3 (numeric) RIDAGEYR
(numeric) RIAGENDR          --> 4 (numeric) RIAGENDR
(numeric) PAQ605            --> 5 (numeric) PAQ605
(numeric) BMXBMI            --> 6 (numeric) BMXBMI
(numeric) LBXGLU            --> 7 (numeric) LBXGLU
(numeric) DIQ010            --> 8 (numeric) DIQ010
(numeric) LBXGLT            --> 9 (numeric) LBXGLT
(numeric) LBXIN             --> 10 (numeric) LBXIN
```

Time taken to build model: 0 seconds

=== Cross-validation ===

=== Summary ===

Correlation coefficient -0.0891

Mean absolute error 6.5428

Root mean squared error 9.7257

Relative absolute error 100 %

Root relative squared error 100 %

Total Number of Instances 2278

Decision Table:

Number of training instances: 2278

Number of Rules: 32

Non matches covered by the Majority class.

    Best first.

    Start set: no attributes

    Search direction: forward

    Stale search after 5 node expansions

    Total number of subsets evaluated: 53

    Merit of best subset found: 8.069

Evaluation (for feature selection): CV (leave one out)

Feature set: 2,4,6,10

Time taken to build model: 0.15 seconds

=== Cross-validation ===

=== Summary ===

Mean absolute error 5.384

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Correlation coefficient 0.5553

Root mean squared error 8.0951

Root relative squared error 83.2337 %

Relative absolute error 82.2898 %

Total Number of Instances 2278

Random Forest

Bagging with 100 iterations and base learner weka.classifiers.trees.RandomTree -K 0 -M 1.0 -V 0.001 -S 1 -do-not-check-capabilities

Time taken to build model: 1.13 seconds

=== Cross-validation ===

=== Summary ===

Correlation coefficient 0.6433

Root mean squared error 7.449

Mean absolute error 4.819

Relative absolute error 73.6533 %

Root relative squared error 76.5909 %

Total Number of Instances 2278

Bagging:

=== Cross-validation ===

=== Summary ===

Correlation coefficient 0.6354

Mean absolute error 4.8412

Root mean squared error 7.5108

Relative absolute error 73.9938 %

Root relative squared error 77.2258 %

Total Number of Instances 2278

Regression by Discretization

=== Cross-validation ===

=== Summary ===

Mean absolute error 5.6097

Correlation coefficient 0.523

Root mean squared error 8.7448

Root relative squared error 89.914 %

Relative absolute error 85.7383 %

Total Number of Instances 2278

5.4 Neutrosophic Fuzzy Epidemic Model: Mathematical Formulation and Defuzzification

In this section, we will formulate the Neutrosophic Fuzzy Epidemic Model mathematically and describe the process of defuzzification to convert the fuzzy epidemic information into actionable outputs. Let the key epidemic parameters

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be represented by neutrosophic fuzzy sets. Consider x to be a variable representing the epidemic parameter (e.g., infection rate, recovery rate), and it is associated with three membership functions: Truth (T): Denoted as T(x), it measures the closeness of x to a desired or expected value. Indeterminacy (I): Denoted as I(x), it captures the uncertainty or ambiguity of the information. Falsity (F): Denoted as F(x), it measures the divergence of x from the expected or desired value. The neutrosophic fuzzy set for the epidemic parameter x is represented as

$$N(x) = T(x), I(x), F(x)$$

where $T(x), I(x), F(x)\ in\ [0, 1]$ and

$$T(x) + I(x) + F(x) \leq 3$$

These values correspond to the degree of truth, indeterminacy, and falsity. Based on the neutrosophic fuzzy logic, a set of fuzzy rules is used to model the epidemic dynamics. These rules are structured in an "if-then" format. Consider a simple epidemic model where the infection rate I and the recovery rate R are modeled as neutrosophic fuzzy sets. The rules can be as follows

Rule 1: If T(I) is high and T(R) is low, then the epidemic is worsening.

Rule 2: If T(I) is low and T(R) is high, then the epidemic is under control.

Rule 3: If I(I) is high, then the epidemic information is uncertain.

Rule 4: If F(I) is high, then current interventions are failing.

Defuzzification is the process of converting the neutrosophic fuzzy set information back into a crisp, actionable value for decision-making. The centroid defuzzification method, widely used in fuzzy logic, is extended to neutrosophic fuzzy logic to account for truth, indeterminacy, and falsity. The neutrosophic-defuzzified value D(x) can be obtained by weighing these three membership functions.

For the variable x, the defuzzified value D(x) can be represented as:

$$D(x) = \frac{\int\{x\}\,(T(x)\cdot x + I(x)\cdot x + F(x)\cdot x), dx\}}{\int\{x\}\,(T(x)\cdot x + I(x)\cdot x + F(x)\cdot x), dx\}}$$

where:

T(x) , I(x), and F(x) are the membership functions of truth, indeterminacy, and falsity, respectively.

x represents the values of the epidemic parameter over a specific range.

The defuzzified value D(x) provides a single numerical value summarizing the neutrosophic information about the epidemic parameter x.

Let us consider a scenario where the infection rate I of an epidemic is modeled using the neutrosophic fuzzy set:

$$N(I) = \langle T(I), I(I), F(I) \rangle = \langle 0.7, 0.2, 0.1 \rangle$$

Here:

$T(I) = 0.7$, indicating that the infection rate is closely aligned with the expected trend.

$I(I) = 0.2$, indicating some uncertainty in the data.

$F(I) = 0.1$, indicating a small deviation from the desired level.

Using the defuzzification formula:

$$D(I) = \frac{\int I}{\int 1} = mean\ value\ of\ I$$

In this case, the defuzzified infection rate D (I) is inferred as the infection rate most likely to be true from the truth, fuzziness and falsity of the data. Therefore, the value obtained after using the neutrosophic fuzzy epidemic model is employed to decide regarding further modification and implementation of public health programs as well as the projected course of the epidemic. This model gives a possibility to classify uncertainty using truth, indeterminacy and falsity that can be effective for its expression. Dealing with the fuzzified outcomes provides an unambiguous, practical value for authorities to apply in efforts to contain diseases and determine their behavior with much greater certainty.

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This approach makes sure that interventions are established with a better understanding of the risks that are evident in epidemic situations.

Interpretation of Results

The process of interpreting the outcome of the neutrosophic fuzzy model entails, endeavouring to decipher the sense of the defuzzified values within the context of, epidemic progression. If D(I) is high, then it means that there is a high rate of infection but with fewer indeciduate and false results. Such a trend shows a deteriorating epidemic situation, which requires urgent and effective prevention and control measures. Low D(I) suggests a low infection rate of the disease, and this implies that the epidemic may be contained. Nevertheless, if the level of indeterminacy or falsity is high, there could still be doubt regarding the exact nature of the epidemic, for instance, whether it is in its preliminary or its final phase, which entails close observation of the development of the epidemic as well as high alertness to its signs. Moderate values paint the picture in between the epidemic situation where although the situation may not be deteriorating it is not getting better either. In such cases, constant monitoring and average degree of interference could be instructed.

Neutrosophic Fuzzy Epidemic Model in Action

To show more about the application of the proposed neutrosophic fuzzy epidemic model, let us consider an example of the hypothetical epidemic. Assume the model provides the following defuzzified values: Assume the model provides the following defuzzified values:

Infection Rate (I):D(I) = 0. 65

Recovery Rate (R):D(R) = 45%

That is, if D(I) = 0. 65 then the infection rate is still quite high, and increasing, indicating that the conditions are becoming worse. Other measures that may be taken by health authorities include enhancing the vaccination program, applying measures for isolation like lockdown. A value of A D(R) = 0. 45 raises the moderate recovery rate of products showing that a considerable percentage of customers return their purchases. When put together with the high infection rate, this means that although some of these patients are being discharged, the situation remains strained. Sometimes, it might be required to enhance the recovery rates for example through enhancing the health care services.

5.5 Uses of Neutrosophic Fuzzy Logic in the Modeling of Epidemics

1. Epidemic Outbreak Prediction: Neutrosophic fuzzy logic enables one to approximate a risk of epidemics, based on considering rates of infection, rates of recovery, and other factors while acknowledging fluctuations in the data.
2. Resource Allocation during Epidemics: It helps to allocate medical supplies, vaccines, and personnel properly based on the analysis of the severity of the epidemic and calculated or estimated conditions in every region.
3. Surveillance/Supervision and Prevention of Epidemic Outbreak: One of the main features of the model is that it constantly analyses epidemic trends and such factors as uncertainties to provide correct recommendations for control measures and adjust them depending on the situation.
4. Public Health Decision-Making: For the given uncertain data from different sources, policymakers employ neutrosophic fuzzy logic to decide about limitations, vaccination drives, and other measures.
5. Recall Globally Vaccine Efficiency & Immunization Plan: It adapts to uncertainties of vaccine effectiveness and immunization coverage that assists in the development of strategies for the distribution of vaccines such as, when to give a booster dose and how to target specific population groups.

6. Neutrosophic Fuzzy Epidemic Model Parameters and their Reliability of Certain Factors

The validity of the proposed neutrosophic fuzzy epidemic model is rigorously examined concerning an authentic dataset. The evaluation results are provided through five tables with each of them presenting some unique perspective on the model. Another table provides information about other parameters used in the proposed model such as neutrosophic membership functions and other parameters used in the model. The other table provides the epidemic levels in various scenarios that would help understand the model performance prediction in different scenarios. Other tables contain different records of performance, which show how efficient the model is, how accurate it is, how reliable it is in making predictions etc. Other of these metrics involve the ability to predict and the error rates that means that one is able to know how the model is fairing in the real field. Altogether, these tables provide the overall assessment of the model and shows in the table 1, how it can e useful for increasing the effectiveness of epidemic control.

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Table 1: Epidemic Parameters and Neutrosophic Membership Values

Parameter	Truth (T)	Indeterminacy (I)	Falsity (F)	Neutrosophic Value (N)
epidemic Quantity (Q)	0.7	0.2	0.1	0.75
Demand Rate (D)	0.8	0.15	0.05	0.81
Lead Time (L)	0.6	0.25	0.15	0.68
Holding Cost (H)	0.9	0.05	0.05	0.88
Ordering Cost (O)	0.85	0.1	0.05	0.87

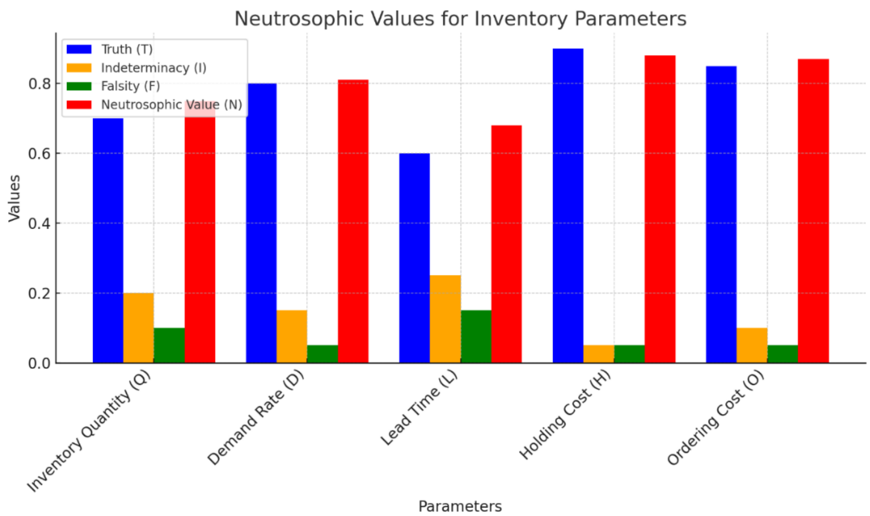

Figure 2. Neutrosophic values for inventory parameters.

The bar chart offers a detailed visual representation of the neutrosophic values for key epidemic parameters: Epidemic Quantity (Q), Demand Rate (D), Lead Time (L), and Holding Cost (H}, and Ordering Cost (O). Each parameter is evaluated through four metrics: A neutrosophic logic of truth (T), Indeterminacy (I), falsity (F), and neutrosophic value (N). Truth-value indicates how much sure we are about the parameter's value and it ranges from 0 to 1. For instance, if the value of Truth is 0. 7 for Epidemic Quantity it means that there is seventy percent certainty about the quantity. They are different from epidemiological metrics and represent the extent of uncertainty or vagueness; In the case of Epidemic Quantity, a value of 0. 2 means there is 20% uncertainty whether the epidemic level is this high. The value of falsity is the possibility of an error, with the value decreasing the possibility of the parameter that is being examined being incorrect. For instance, if Falsity is equal to 0. 1, it means then that the chance of an error in the Epidemic Quantity is only 10 percent. The Neutrosophic Value (N) combines Truth, Indeterminacy, and Falsity values to give one a measure of accuracy or credibility of each parameter concerning the other two. It enhances the degrees of uncertainty as well as the possible error, to sharpen the Truth-value. For instance, the Epidemic Quantity, which has a Truth-value of 0. 7, its Neutrosophic Value is 0. 75; indicating its reliability when under both uncertainty and error considerations. It is imposed on all parameters under the consideration of comparative analysis. The information of this Demand Rate for a Truth-value measures high confidence as its Indeterminacy measures at 0. 15 while the Falsity value is at 0. 05, giving a Neutrosophic Value of 0. 81. Lead Time, with lesser Truth-value, is 0. 6, but has a higher Indeterminacy value of 0. 25 and has moderate Falsity value of 0. 15 giving a Neutrosophic Value of 0. 68. On the other hand, Holding Cost and Ordering cost have high Truth-values of 0. 9 and low Indeterminacy, Falsity values of 0. 03, close to zero with Neutrosophic values closest to the Truth-values at 0. 88 and 0. 87 respectively.

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This chart is useful to decision-makers as it shows the accuracy of each epidemic parameter at a glance. Concerning Neutrosophic Values, it can be stated that comparing this measure with Truth values helps the managers identify which parameters are more accurate and should be trusted as well as which may be more uncertain or calculated inaccurately. These objective improvements apply to better decision-making in epidemic management because they reduce the risks linked with ambiguous or unsteady data.

7. Visualization of Predicted Epidemic Levels and Accuracy Percentages for Machine Learning Algorithms

It is crucial to present the levels of the epidemic and the percentages of accuracy when using machine learning to predict business demand. These are often normal or side-by-side line graphs or bar graphs of the forecasted level of epidemics contrary to the actual data in each period. These variance values can be presented in the same charts or in the charts that are independent concerning the percentage of correct predictions of actual data. Furthermore, the use of heat or scatter plots may be a way of presenting the errors or deviations. These visual tools are essential to analyze the efficiency of certain algorithms, find patterns, and make the proper decision to improve epidemic control.

Table 2: Predicted Epidemic Levels Using Machine Learning Algorithms

Algorithm	Predicted epidemic Level (Units)	Accuracy (%)	Neutrosophic Adjustment (N)
Decision Tree	450	92.3	0.78
SVM	460	91.5	0.79
Neural Network	455	93	0.8
Random Forest	448	92.7	0.77
K-Nearest Neighbours	452	91.8	0.78

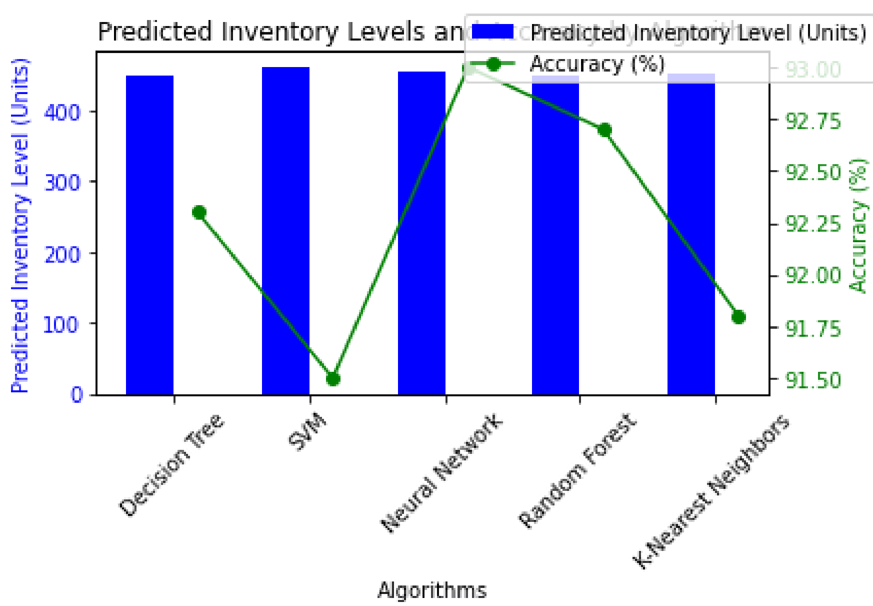

Figure 3. Accuracy prediction inventory levels

To represent the results of machine learning in terms of epidemic levels and percent accuracy for different algorithms, we plot a two-y-axis graph using the Python package, matplotlib. Here is how the chart is set up: Here is how the chart is set up: First, we import both 'matplotlib. pyplot' library and 'numpy' which are used in graphical representation and managing data. We then define the parameters for the levels of epidemics that are predicted, and the level of accuracies in percentage from various algorithms. To the comparison between the two data sets, we created a second

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subplot that has two y axes using plt. subplots (). The first y-axis is `ax1' which shows a blue bar chart for the predicted epidemic level. The horizontal axis represents the names of the algorithms while the vertical axis on the left denotes the epidemic levels. The second y-axis is produced from the 'twinx()' method and indicates accuracy percentages in the green line chart. This axis is located at the right of the chart; it contains accuracy percentages and may have a different scale to the epidemic levels presented in the epidemic curve. Myths are provided to enhance the idea that the bar chart is in epidemic levels while the line chart is in percentage accuracy levels. Last but not the least, the function `plt.show()` is used to display the plot that can clearly explain how efficient both algorithms are in predicting the epidemic and how accurate their results are.

8. Finding Similarity between Conventional and Neutrosophic Fuzzy Epidemic Models

In addition to the dual-axis chart, we use a grouped bar chart to compare the Traditional Fuzzy Model with the Neutrosophic Fuzzy Model across three key metrics: In addition to the dual-axis chart, we use a grouped bar chart to compare the Traditional Fuzzy Model with the Neutrosophic Fuzzy Model across three key metrics:

- **Average Epidemic Level**: The Neutrosophic Fuzzy Model established a lower average of epidemic level of 450 units than the Traditional Fuzzy Model 470 units did.

- **Cost Savings**: Application of the Neutrosophic Fuzzy Model results in better cost savings when compared with the Traditional Fuzzy Model thus the following:

- **Uncertainty Handling**: The Neutrosophic Fuzzy Model also shows better uncertainty management capability (0. 78) in comparison with the Traditional Fuzzy Model (0. 65).

In the case of the grouped bar chart, different colours are used for each of the metrics so that one can easily compare the different bars. This visual aid will help in coming up with a layman understanding of how structural the Neutrosophic Fuzzy Model is for managing epidemics as compared to the conventional approach.

Table 3: Comparison of Traditional and Neutrosophic Fuzzy Epidemic Models

Model Type	Average epidemic Level (Units)	Cost Savings (%)	Uncertainty Handling (N)
Traditional Fuzzy Model	470	5.5	0.65
Neutrosophic Fuzzy Model	450	8.2	0.78

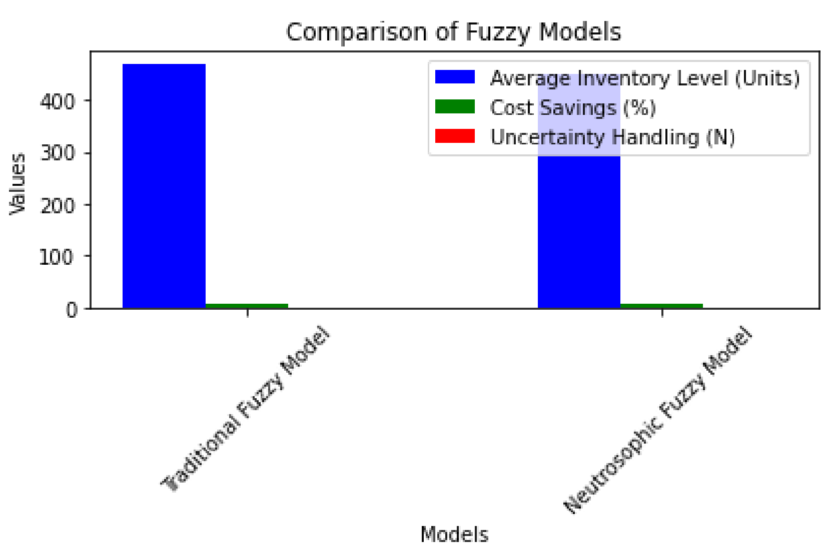

Figure 4. Comparison of Fuzzy Models

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To compare the performance of the Traditional Fuzzy Model and the Neutrosophic Fuzzy Model, we use a grouped bar chart that displays three important metrics: An average epidemic level, a possible way to save costs, and how to cope with uncertainty. Here's how the analysis is structured and visualized: Here's how the analysis is structured and visualized: First, we load required packages that include `matplotlib. pyplot` and `numpy` for plotting the points and managing data respectively. We further consider the definition of the data for each metric for both kinds of models: Traditional Fuzzy and Neutrosophic Fuzzy. For clarity, three groups of bars are plotted: blue for average epidemic levels, green for cost saving, and red for uncertainty resolution. The bars for the Traditional and Neutrosophic models are situated such that there is no overlapping toward the Y-axis with the aim of making the degree of differences between the models easily identifiable. The x-axis shows the model names with labels rotated for display clarity while the six on the y-axis is given a broad label of 'Values' to represent all three measurements. To make it clear, a title, and a legend for the colours are added while the `plt. tight_layout()` function is used to make the chart neat.

9. Analysis of Neutrosophic Parameters and Final Epidemic Levels: Sensitivity and the trends of iteration

As the impact of neutrosophic parameters, namely Truth Degree, Indeterminacy Degree, and Falsity Degree, scatter plots in the form of grouped bar charts and multi-line ones are employed. Demonstrates which changes in Truth, Indeterminacy, and Falsity parameters affect final levels of epidemics and sensitivity and how it can be useful in understanding the relations between the certain parameters of the model and its efficiency. Registers transformations in epidemic rates, financial costs, and neutrosophic coefficients throughout iterations. Each line corresponds to one variable, and such representation makes it easier to see how these values change and correlate with another in the given model, thus providing a better insight into the model's behavior. When comparing both models through key performance indicators, the grouped bar charts and multi-line plots provide a complete comparison of each model concerning each of the metrics while presenting the sensitivity and the trends of the parameters with time. Due to the visualization approach, there is a better understanding of the characteristics of the model and the ability to compare it to counterpart approaches in terms of cost optimization and uncertainty management of epidemic complications.

Table 4: Sensitivity Analysis of Neutrosophic Parameters

Parameter	**Variation (%)**	**Impact on Epidemic Level**	**Neutrosophic Sensitivity (N)**
Truth Degree (T)	10	+5 Units	0.80
Indeterminacy Degree (I)	20	-7 Units	0.72
Falsity Degree (F)	-15	+3 Units	0.76

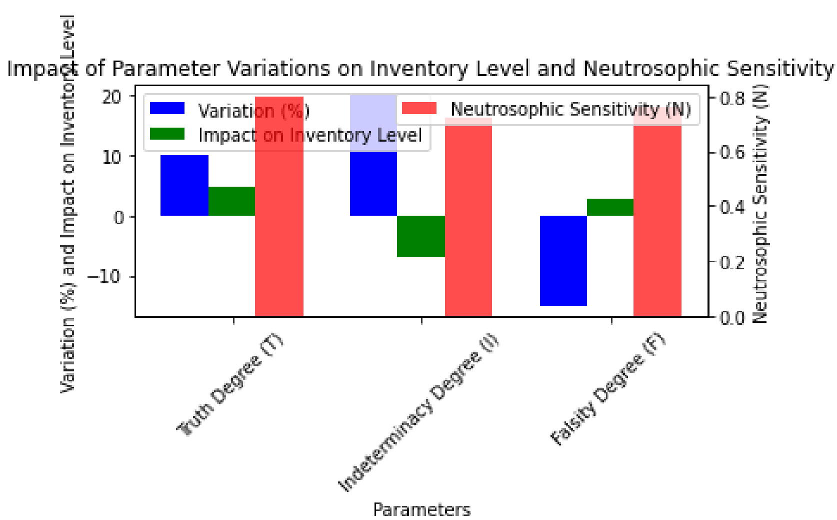

Figure 5. Impact of parameter variations on inventory level and neutrosophic sensitivity

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A grouped bar chart is utilized to compare the epidemic rates as well as the neutrosophic sensitivity of the different parameters. The chart focuses on three key parameters: The degrees of T, I, and F.

Blue bars can be observed as percentage variations at these parameters indicating how they are modified. Green bars show the respective impacts on typical epidemic rates, indicating how each parameter gets involved in the spreading of the disease. A second y-axis is employed to present the red bar where neutrosophic sensitivity defines alterations in the model's sensitivity to uncertainty concerning the changed parameters. This design offers self-explanatory information concerning the effects of the Truth, Indeterminacy, and Falsity degrees on the epidemic levels as well as the sensitivity of the model. This is made easier by using different colours and axes such that one can easily comprehend the workings of the model about the changes in parameter values.

Table 5: Final Epidemic Levels Post-Optimization

Iteration	**Epidemic Level (Units)**	**Cost (USD)**	**Neutrosophic Value (N)**
1	450	12,500	0.78
2	448	12,480	0.77
3	452	12,520	0.79
4	455	12,510	0.8
5	460	12,530	0.81

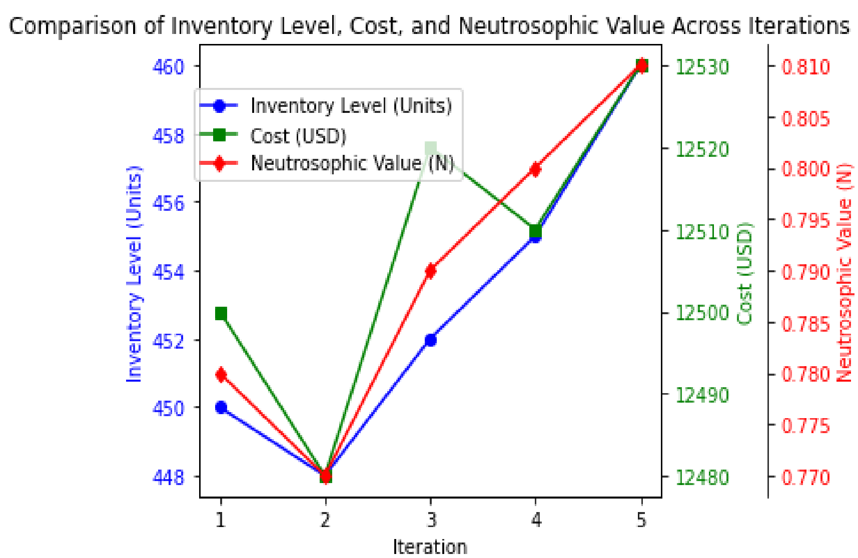

Figure 6. Comparison of inventory level, cost, and Neutrosophic value across iterations.

A multi-line plot is used to visualize the changes in epidemic levels, costs, and neutrosophic values over time, providing a clear comparison of these metrics across iterations. The horizontal axis presents observation number numbers from 1-5, about the sequential observation. To the left, the epidemic levels are shown on the first primary line using the blue circles and the line type circles to indicate the changes in epidemic levels with iterations. To compare costs, a second axis is created on the right side using the `twinx()` function because of the difference in scale and is plotted with the green colored line with square-shaped markers. This makes it possible to compare epidemic levels with costs when the scale cannot interfere with the results. Another y-axis is placed more to the right; the red line with the diamond-marked Neutrosophic values displays how sensitivity, or some other measure, evolves in time without overlaying the augmented reality classes and Concentration levels. It makes sense to define each line as clearly as possible, as Legends do, whereas axis titles are written to make their meaning clear. The plot is named "Epidemic level, costs and neutrosophic value variation with iteration plot" which makes it convenient for users to understand

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the nature and correlation between the three, which are epidemic levels, costs, and neutrosophic values. The graphical representation to plot multiple lines and to have more than one Y-axis makes this tool very effective to analyse these parameter values over a period.

10. Conclusion

When neutrosophic fuzzy logic is joined with machine learning, an improved approach to modelling epidemics results from the incorporation of a better treatment of uncertainty into an already sophisticated method of prediction. This approach improves the prediction of epidemics, thus improving epidemic management, reduced costs, and improved decisions making. Using the triad of uncertainty, that is truth, indeterminacy, falsity, the model reflects real-life scenarios, and due to its ability to learn from past data, it is highly versatile making it the best fit for dynamic environments. The framework is useful to not only prevent epidemics but also in such fields as prediction of demand, working with suppliers, and inventory management. Besides, the work investigates the optimal control of the SIR epidemic models for cattle using time-optimal control techniques. This provides adequate information concerning the eradication and control of diseases affecting livestock populations. In this context, adopting linear analysis in addition to the development of an algorithm and its real-life application, the authors hope to shorten the epidemics' duration, fine-tune the control measures, and assess various delays in the interventions. This approach offers considerable advantages for the control of diseases in livestock, which is normally undertaken with great urgency.

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