

FUZZY SOFT SETS ASSESSMENT OF PLANT GROWTH-PROMOTING BACTERIA FOR THE RECOVERY OF POTASSIUM CHLORATE-STRESSED LONGAN TREES

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ABSTRACT. *This study introduces a novel algorithm based on fuzzy soft sets to enhance the efficiency assessment of plant growth-promoting bacteria (PGPB) in the recovery of longan plants stressed by potassium chlorate ($KClO_3$). The research was driven by the objective to critically examine and enhance the applications of fuzzy soft sets in intricate decision-making contexts within agricultural biotechnology. We constructed a new algorithmic framework for evaluating PGPB efficacy on $KClO_3$ -stressed longan plants. We propose a novel algorithm that addresses prior restrictions by enabling precise assessments in scenarios with varying choice and score values. Moreover, the proposed method is explicitly tailored for fuzzy set data or conventional basic data and inherently incorporates a consistency ratio check to ensure reliability. Our findings demonstrate that this novel approach successfully identifies Phosphate Solubilizing Bacteria (PSB) as the superior treatment for mitigating the decline of longan plants. A detailed practical example further illustrates the method's applicability and effectiveness in addressing such complex bio-decision-making challenges.*

Keywords: Fuzzy soft sets, Plant growth-promoting bacteria, Potassium chlorate stress, Longan, Algorithm evaluation

1. Introduction. Longan (*Dimocarpus longan* L.), commonly known as longan, represents a cornerstone of Thailand's principal fruit exports. Its exceptional nutritional profile and well-documented medicinal properties have collectively elevated longan to a distinguished status among cultivated fruits. The widespread adoption of potassium chlorate ($KClO_3$) as a floral induction agent in longan cultivation followed the initial documentation of its efficacy, thereby enabling both conventional and off-season fruit production protocols [1]. However, despite $KClO_3$'s substantial contribution to the advancement of commercial longan production, its application concurrently induces a range of physiological stress responses within the foliar tissues. These detrimental responses manifest as reductions in leaf water potential, net CO_2 assimilation, transpiration, stomatal conductance rates, and photochemical efficiency (F_v/F_m). Furthermore, $KClO_3$ treatment has

been observed to accelerate the destruction of the photosynthetic apparatus, alongside elevating levels of malondialdehyde (MDA) and reactive oxygen species (ROS). The escalating damage to the photosynthetic machinery, synergistically with heightened MDA and ROS accumulation, and altered activities of key antioxidant enzymes such as superoxide dismutase (SOD) and peroxidase (POD), collectively contributes to the progressive deterioration of longan trees [2]. Consequently, strategies involving the application of plant growth-promoting bacteria (PGPB) have been investigated as a potential solution to mitigate these adverse effects and facilitate the recovery of KClO_3 -stressed longan plants. Nevertheless, optimizing the selection of appropriate conditions from numerous interacting factors necessitates the integration of robust mathematical tools for informed decision-making.

The inherent complexity and variability of biological responses often result in data characterized by significant uncertainties. To effectively manage such stochastic elements and facilitate robust decision-making in diverse scientific and engineering fields, researchers have formulated various theoretical frameworks. These include established methodologies such as probability theory and fuzzy set theory [3], rough sets [4], and other advanced mathematical tools. Building upon these foundations, Molodtsov introduced soft set theory in 1999 [5] as a novel and versatile mathematical tool specifically designed to model vagueness and uncertainty without the inherent limitations often associated with other approaches. This theory has demonstrated broad applicability across a variety of domains, prompting extensive investigation and development by numerous authors since its inception [6, 7, 8, 9, 10]. Further enhancing the capacity to model nuanced uncertainties, Maji et al. [11] proposed an extension of soft set theory into fuzzy soft set theory, meticulously defining fuzzy soft sets, fuzzy soft subsets, their union, and intersection, alongside investigating their properties. This advancement significantly broadened the scope for handling intricate decision-making problems. Roy and Maji [12] subsequently explored the practical application of fuzzy soft set algorithms for decision-making, proposing an approach that involved calculating score values within fuzzy soft sets and utilizing a comparison table as a key component of their algorithmic process in 2007. However, recognizing potential efficiencies, Kong et al. [13] in 2009 introduced a revised algorithm that streamlined the computation of score values for fuzzy soft sets in decision-making contexts by eliminating the reliance on a comparison table. More recently, the field has continued to evolve with contributions such as Rotjanasom et al.'s definition and investigation of fuzzy parameterized relative soft sets in 2021 [14]. Building upon this foundation, Phaengtana et al. [15] advanced decision-making methodologies by introducing the concept of partial averages for fuzzy soft sets and developing a corresponding problem-solving model. Illustrating the practical utility of these theoretical developments, Waraha et al. [16] successfully applied fuzzy soft sets, in conjunction with the analytic hierarchy process (AHP) technique, to develop a predictive flood alarm model for Northern Thailand. In further refinement, Thammajitr et al. [17] in 2022 proposed fuzzy parameterized relative fuzzy soft sets, investigating their properties and subsequently outlining a robust framework for addressing complex decision-making problems based on this innovative paradigm. In 2024, Tuncel and Gunturk [18] proposed a fuzzy multi-criteria decision support system that provides a structured framework to address the complexities of agricultural land selection. They presented a decision support system that integrates game theory with fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) to solve the land selection problem when establishing an orchard. They defined the factors for agricultural land selection based on expert interviews, brainstorming, and cross-functional teams, and performed the necessary tests and analysis. Later, Jin et al. [19] in 2025 proposed a hesitant fuzzy β -covering rough set, investigating the properties and relationships

among approximation operations, and further provided an axiomatic characterization of the approximation operators. They presented a VIKOR-based multi-criteria group decision-making method using hesitant fuzzy β -covering rough set. Xu et al. [20] in 2026 presented the spherical fuzzy analytic hierarchy process (SF-AHP) is employed to develop a robust emission reduction efficiency model. The model is validated through application to a real-world prefabricated building project. Results demonstrate that the proposed approach enhances the objectivity and accuracy of carbon emission assessments in prefabricated construction, thereby supporting informed decision-making toward sustainable development goals.

Despite these significant advancements, the current body of research concerning the application of fuzzy soft sets to decision-making problems is not without its challenges. A notable limitation arises with the established algorithms by Roy and Maji [12] and Kong et al. [13], which can struggle to provide unambiguous evaluations when alternatives vary considerably in their factor and score values. Inspired by prior efforts and acknowledging persistent challenges in existing methods, the primary objective of this research is to advance the application of fuzzy soft sets in complex decision-making. We propose a novel algorithm that overcomes previous limitations by facilitating accurate evaluations in cases involving differing choice and score values. Moreover, the proposed method is specifically designed for fuzzy set data or conventional basic data and inherently incorporates a consistency ratio check to ensure reliability. Furthermore, this algorithm is explicitly tailored to evaluate complex biological parameters, demonstrating a highly effective assessment of PGPB efficiency in the revitalization of KClO_3 -stressed longan plants.

The remainder of this paper is structured as follows. Section 2 provides a comprehensive review of essential preliminaries concerning soft sets and fuzzy soft sets, along with a concise summary of decision-making techniques previously introduced by Roy and Maji [12] and Kong et al. [13]. Section 3 meticulously details the methodology for constructing the proposed fuzzy soft set algorithm tailored for decision-making applications. In Section 4, the efficacy of the proposed method is robustly illustrated through a numerical example, followed by a rigorous comparative analysis demonstrating its validity and superiority. Finally, Section 5 concludes the paper by summarizing the key findings and discussing potential avenues for future research.

2. Preliminaries. In this section, we summarize the preliminary definitions and results that are required later in this paper.

Molodtsov [5] first initiated a mathematical tool which is the soft set theory for modeling uncertainty.

Definition 2.1. [5] *Let U be an initial universe set and let E be a set of parameters. Let $P(U)$ denote the power set of U and let $\emptyset \neq A \subseteq E$. A pair $(\hat{F}, A)$ is called a soft set over U , where $\hat{F}$ is a mapping given by $\hat{F} : A \rightarrow P(U)$.*

Definition 2.2. [3] *Let X be a nonempty set. A function f from X to the unit interval $[0, 1]$ is called a fuzzy set on X .*

Maji et al. [11] presented the definition of a fuzzy soft set.

Definition 2.3. [11] *Let U be an initial universe set, E be a set of parameters and let $\emptyset \neq A \subseteq E$. A pair (F, A) is called a fuzzy soft set over U , where F is a mapping given by $F : A \rightarrow \text{Fuz}(U)$ and $\text{Fuz}(U)$ is the set of all fuzzy sets on U .*

Example 2.1. *Assume that $U = \{u_1, u_2, u_3, u_4, u_5\}$ is a universal set and $E = \{e_1, e_2, e_3, e_4\}$ is a set of all parameters. If $A = \{e_1, e_2, e_4\}$ and*

$$\begin{aligned}
F(e_1) &= \{u_1/0.3, u_2/0.7, u_3/0.6, u_4/0.9, u_5/0.5\}, \\
F(e_2) &= \{u_1/0.7, u_2/0.8, u_3/0.4, u_4/0.5, u_5/0.6\}, \\
F(e_4) &= \{u_1/0.8, u_2/0.3, u_3/0.6, u_4/0.8, u_5/0.3\},
\end{aligned}$$

then the fuzzy soft set (F, A) is written by

$$\begin{aligned}
(F, A) &= \{(e_1, \{u_1/0.3, u_2/0.7, u_3/0.6, u_4/0.9, u_5/0.5\}), \\
&\quad (e_2, \{u_1/0.7, u_2/0.8, u_3/0.4, u_4/0.5, u_5/0.6\}), \\
&\quad (e_4, \{u_1/0.8, u_2/0.3, u_3/0.6, u_4/0.8, u_5/0.3\})\}.
\end{aligned}$$

We can represent this fuzzy soft set (F, A) in a tabular form as Table 1.

TABLE 1. The fuzzy soft set (F, A)

U	e_1	e_2	e_4
u_1	0.3	0.7	0.8
u_2	0.7	0.8	0.3
u_3	0.6	0.4	0.6
u_4	0.9	0.5	0.8
u_5	0.5	0.6	0.3

Now, we briefly review the algorithms in decision-making problems.

Roy and Maji [12] defined the comparison table approach in decision-making problems.

Let $U = \{o_1, o_2, \dots, o_n\}$ be an object set and let $E = \{e_1, e_2, \dots, e_k\}$ be a set of parameters.

The comparison table is a square table in which the numbers of rows and columns are equal, rows and columns both are labeled by the object names $o_1, o_2, \dots, o_n$ of U , and the entries are c_{ij} , $i, j \in \{1, 2, \dots, n\}$ given by c_{ij} = the number of parameters for which the membership value of o_i exceeds or equals the membership value of o_j . Obviously, $0 \leq c_{ij} \leq k$, and $c_{ii} = k$, for all i, j , where k is the number of all parameters in a fuzzy soft set. Thus, c_{ij} indicates a numerical measure, which is an integer number and o_i dominates o_j in c_{ij} number of parameters out of k parameters.

Roy and Maji [12] used the comparison table in the algorithm as follows:

Algorithm in [12]:

Step 1. Input the fuzzy soft sets (F, A) , (G, B) and (H, C) .

Step 2. Input the parameter set P .

Step 3. Compute the resultant fuzzy soft set (S, P) from (F, A) , (G, B) and (H, C) .

Step 4. Compute the comparison table of (S, P) and compute t_i and r_i for o_i for all i .

Step 5. Compute the score value $(S_i = r_i - c_i)$ of o_i for all i .

Step 6. The decision is S_k if $S_k = \max_i S_i$.

Step 7. We choose only o_k if k has more than one value.

Kong et al. [13] revised the algorithm of Roy and Maji [12] by computing the score value of fuzzy soft sets without the comparison table.

Algorithm in [13].

From Step 4, the algorithm [12] is revised as below: c_{ij} and r_i should be redesigned as

$$c_{ij} = \sum_{k=1}^m (f_{ik} - f_{jk}), \quad r_i = \sum_{j=1}^m c_{ij},$$

where f_{ik} is the membership value of object o_i for the k th parameter, and m is the number of parameters.

Step 5. The decision is k if $r_k = \max_i r_i$.

In [13], the decision depends on choice value c_i , where c_i signifies the sum of the membership values of all parameters of object o_i .

In 2015, Wu et al. [21] presented the multi-attribute fuzzy soft sets.

With the assumption that $U = \{o_1, o_2, \dots, o_i\}$, $i \in \{1, 2, \dots, m\}$ is the universal set and $E = \{P_1, P_2, \dots, P_j\}$, $j \in \{1, 2, \dots, n\}$ is the parameter set, the general multiple attribute decision-making method of the basic fuzzy soft set was built, and the specific content is as follows.

First of all, the decision attribute usually has different dimensions, orders of magnitude, and attribute categories (efficiency attribute and cost type attribute). There are, unfortunately, no unified metrics between different decision attributes, to eliminate the influence on the result of decisions of dimension, orders of magnitude, and category, one must standardize the decision attribute values. The efficiency type attribute refers to the attribute of the attribute value, the larger the better, and cost attribute refers to the attribute of the attribute value, the smaller the better.

Using different formulas for the standardization of the two types of attributes: cost type attribute index according to the following formula:

$$f_{ij} = \frac{\max\{a_{ij}\} - \{a_{ij}\}}{\max\{a_{ij}\} - \min\{a_{ij}\}},$$

The efficiency attribute index was calculated by the following formula:

$$f_{ij} = \frac{\{a_{ij}\} - \min\{a_{ij}\}}{\max\{a_{ij}\} - \min\{a_{ij}\}},$$

$i = 1, 2, \dots, m$; $j = 1, 2, \dots, n$.

The decision-making information matrix $V = [a_{ij}]_{m \times n}$ from original data was converted into standardized matrix $D = [f_{ij}]_{m \times n}$; further according to the decision matrix $D = [f_{ij}]_{m \times n}$ build basic fuzzy soft set (F, E) . Based on domain objects, the mapping F of basic fuzzy soft set (F, E) is presented in Table 2 as follows.

TABLE 2. The basic fuzzy soft set (F, E)

U	P_1	P_2	P_3	$\dots$	P_j
o_1	f_{11}	f_{12}	f_{13}	$\dots$	f_{1j}
o_2	f_{21}	f_{22}	f_{23}	$\dots$	f_{2j}
o_3	f_{31}	f_{32}	f_{33}	$\dots$	f_{3j}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
o_i	f_{i1}	f_{i2}	f_{i3}	$\dots$	f_{ij}

The algorithms of Roy and Maji [12] and Kong et al. [13] are not easy to judge in cases that have different factors of the choice value and score value. Moreover, the proposed methods are designed for fuzzy set data which are not designed for basic data and there are no checks on the correctness of the algorithm. To deal with the proposed problems, we present a new algorithm for decision-making problems based on fuzzy soft sets in the next section.

3. Algorithm. In this section, we present an algorithm to identify a better approach to evaluate the efficiency of plant growth-promoting bacteria on the recovery performance of KClO_3 -stressed longan plants using fuzzy soft sets.

Longan Tree Samples: Twenty-four longan trees, *Dimocarpus longan* L., 10 years old (bush size 57.7 m) in Lamphun Province, Thailand, were used in this experiment (Figure 1).



FIGURE 1. Characteristics of the longan bush

Experimental Procedures: Six groups of longan trees ($n = 4$ trees) were treated as follows: Group 1 = Negative control group (NC): $KClO_3$ -stressed longan trees untreated with 2 percent (v/v) molasses solution and growth-promoting bacteria.

Group 2 = Control group (C): $KClO_3$ -stressed longan trees treated with 2 percent (v/v) molasses solution.

Group 3 = KSB group (KSB): $KClO_3$ -stressed longan trees treated with 2 percent (v/v) molasses solution containing 2 percent (v/v) potassium-solubilizing bacteria.

Group 4 = PSB group (PSB): $KClO_3$ -stressed longan trees treated with 2 percent (v/v) molasses solution containing 2 percent (v/v) phosphate-solubilizing bacteria.

Group 5 = Mix group (M): $KClO_3$ -stressed longan trees treated with 2 percent (v/v) molasses solution containing 2 percent (v/v) potassium-solubilizing bacteria and phosphate-solubilizing bacteria.

Group 6 = Healthy control group (H): healthy longan trees untreated with 2 percent (v/v) molasses solution and growth-promoting bacteria.

Longan trees in Groups 2-5 received monthly treatments of either 2 percent (v/v) molasses solution or a $PGPB$ – containing 2 percent (v/v) molasses solution, for three applications. Subsequently, their growth performance was observed, and the collected data were used for algorithm development.

Now, we will adapt the algorithm proposed by Kong et al. [13] to a new algorithm as follows.

Algorithm

Step 1. Selection of a desired number of rhizosphere bacteria (m).

Step 2. Selection of a desired number of parameters (n).

Step 3. Input the basic data.

Step 4. The efficiency attribute index was calculated by the following formula:

$$f_{ij} = \frac{\{a_{ij}\} - \min\{a_{ij}\}}{\max\{a_{ij}\} - \min\{a_{ij}\}},$$

$i = 1, 2, \dots, m; j = 1, 2, \dots, n$.

Step 5. Construction of a fuzzy soft set (F, E) and tabulation.

Step 6. Compute the choice value c_i and the score value s_i of object o_i where

$$c_i = \sum_{j=1}^n f_{ij}, \quad s_i = \sum_{j=1}^n (c_i - c_j), \quad i = 1, 2, \dots, m,$$

where f_{ij} is the membership value of object o_i , and n is the number of parameters.

Step 7. The decision making is s_k if $s_k = \max_i s_i$.

Step 8. Computation of the consistency test (CI) and the consistency ratio (CR). The consistency test $CI = \frac{s_i - m}{m - 1}$, where m is the number of the universes and the consistency

TABLE 3. The random indices RI

m	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

ratio $CR = \frac{CI}{RI}$, where RI is the random indices corresponding to the number of the universes.

The consistency ratio (CR) is acceptable if it does not exceed 0.10 [22].

Step 9. We choose only o_k if k has more than one value corresponding to the choice value c_i .

We present the flowchart of the algorithm as follows.

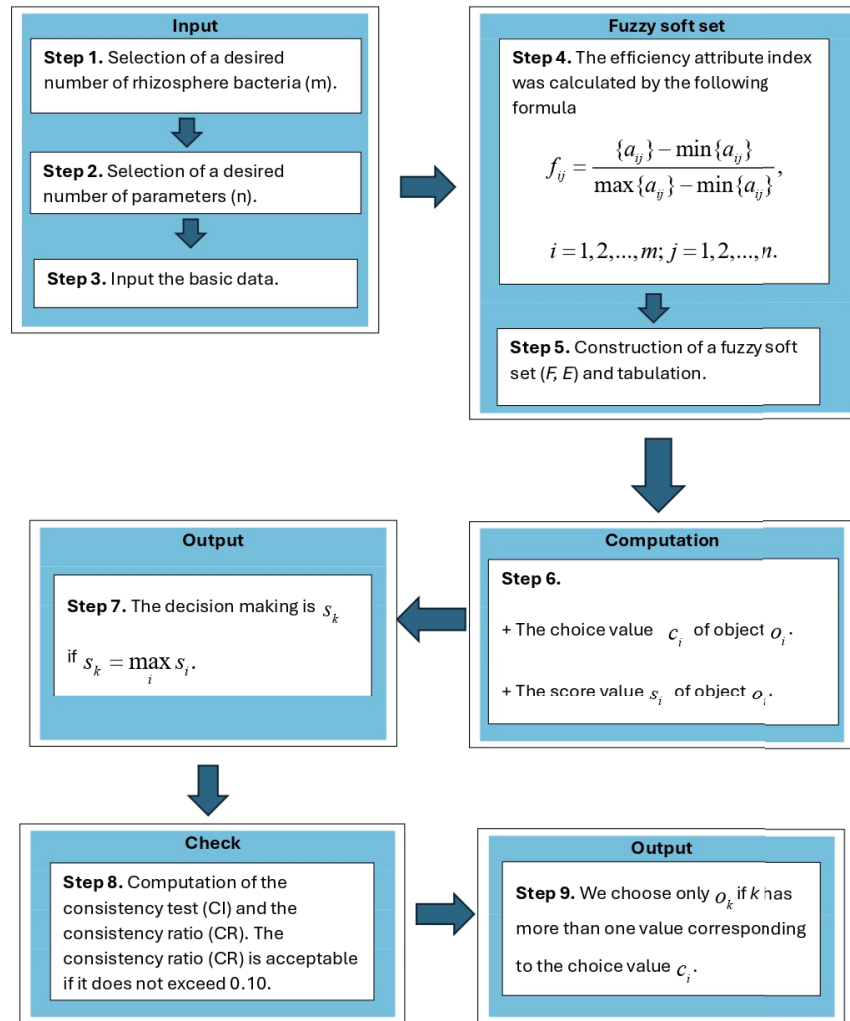


FIGURE 2. Flowchart of the algorithm

4. Numerical Example. In this section, we present an example using the new algorithm in a decision-making problem.

Example 4.1. We identify a better approach to evaluate the efficiency of plant growth-promoting bacteria on the recovery performance of decadent longan plants. We consider the longan plants at 24 trees on growth performance at 90 days for any rhizosphere bacteria.

Step 1. When it comes to the selection of the desired number of rhizosphere bacteria (m). Let $U = \{NC, C, KSB, PSB, M, H\}$ represent six selected rhizosphere bacteria in Negative control, Control, Potassium, Phosphate, Mix, and Healthy, respectively.

Step 2. Next, the selection of the desired number of parameters (n).

Let $P = \{P_1, P_2, P_3\}$ be the parameters where P_1 is the rate of increase in leaf area of the longan plants, P_2 is the chlorophyll content (SPAD), and P_3 is the ratio of leaf area to unit leaf weight.

Step 3. Input the basic data (see Table 4).

TABLE 4. The basic data

U	P_1	P_2	P_3
NC	0.04	60.15	26.54
C	0.53	371.73	33.49
KSB	1.23	413.85	34.96
PSB	1.48	390.11	36.95
M	1.21	424.92	36.29
H	0.76	388.92	33.97

Step 4. Since all three parameters are “the larger, the better”, we calculated it by the following formula:

$$f_{ij} = \frac{\{a_{ij}\} - \min\{a_{ij}\}}{\max\{a_{ij}\} - \min\{a_{ij}\}},$$

$i = 1, 2, \dots, m; j = 1, 2, \dots, n$ (see Table 5).

Step 5. The construction of a fuzzy soft set (F, P) and tabulation (see Table 5).

TABLE 5. The fuzzy soft set (F, P)

U	P_1	P_2	P_3	$c_i = \sum_{j=1}^n f_{ij}$
NC	0.00	0.00	0.00	0.00
C	0.34	0.85	0.67	1.86
KSB	0.83	0.97	0.81	2.61
PSB	1.00	0.90	1.00	2.90
M	0.81	1.00	0.94	2.75
H	0.50	0.90	0.71	2.11

Step 6. We compute the choice value c_i (see Table 5) and the score value $s_i = \sum_{j=1}^n (c_i - c_j)$ of o_i for all i (see Table 6).

Step 7. From Table 6, it is clear that the maximum score is 5.17, which was scored by s_4 of PSB .

Step 8. We compute the consistency test (CI) and the consistency ratio (CR). Thus, $CI = \frac{5.17-6}{6-1} = \frac{-0.83}{5} = -0.166$ and $CR = \frac{CI}{RI} = \frac{-0.166}{1.24} = -0.133$. It is clear that the consistency ratio (CR) is acceptable because it does not exceed 0.10.

Step 9. Plant growth characteristics were analyzed using three key parameters: the rate of increase in leaf area, chlorophyll content, and the leaf area to unit leaf weight ratio. The findings demonstrated that the Phosphate Solubilizing Bacteria (PSB) treatment provided a superior method for evaluating the efficacy of plant growth-promoting bacteria ($PGPB$) in improving the recovery performance of potassium chlorate ($KClO_3$)-stressed longan

TABLE 6. The score value

U	$s_i = \sum_{j=1}^n (c_i - c_j)$
NC	-12.23
C	-1.07
KSB	3.43
PSB	5.17
M	4.27
H	0.43

plants. Phosphate Solubilizing Bacteria (PSB) are essential in the soil phosphorus cycle, as they transform insoluble phosphorus into forms accessible to plants, hence enhancing phosphorus uptake in crops. Additionally, PSB can produce many plant hormones that modulate root morphology; nutrient absorption; plant growth, including cell division and differentiation; chlorophyll concentration; and enhanced leaf shape.

Remark 4.1. This novel algorithm is specifically designed to handle fundamental data, representing a generalization of Kong et al.'s method. Furthermore, its efficacy is underscored by its superior performance, as quantified by the consistency ratio (CR), which serves to validate the algorithm's reliability.

5. Conclusions. This study develops an algorithm incorporating fuzzy soft sets to optimize the evaluation of plant growth-promoting bacteria (PGPB) efficacy in revitalizing declining longan plants. A detailed practical example illustrates the method's applicability and effectiveness in addressing complex decision-making challenges. Despite its advantages, the suggested algorithm has a notable limitation regarding scalability. When the number of alternatives in the decision-making process is significantly large, the computational time required may increase substantially. Addressing this challenge through algorithmic optimization remains an important avenue for future research.

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