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Optimization of Powered Roof Support Selection in Underground Coal Mining: An Enhanced Fuzzy Soft Set-Based Model

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Abstract

Powered roof supports, which are one of the most important pieces of equipment in longwall mining, are required to be selected with the highest level of accuracy, as they play a critical role in terms of cost during the selection process and safety and productivity during the production process. In many cases, these selections are made based on previously experienced field conditions and engineering judgment. However, when the parameters affecting the selection process of powered roof supports are evaluated in detail, it is seen that there are many different parameters influencing this selection, and that each parameter affects the decision in different ways and with different weights. Therefore, it is observed that determining the most suitable powered roof support not only based on experience, but also through a detailed scientific evaluation of these parameters minimizes the probability of error. In this study, the parameters affecting powered roof support selection are evaluated using a mathematically developed model based on fuzzy logic. The parameter with the most significant impact on the selection is identified, and a selection is made among 10 possible powered roof support alternatives. In the developed model, Frequency Fuzzy Soft Set (FFSS) and Recurrent Fuzzy Soft Set (RFSS) methods are applied both separately and jointly. The proposed model is applied to the Ömerler Underground Coal Mine. According to the obtained results, it is found that the threshold value of 0.8 provides a balanced solution between safety and flexibility. Based on these results, it is concluded that the developed mathematical model can be used reliably in multi-criteria decision-making problems.

Keywords:

Powered roof support; Fuzzy soft set; Underground mining

1. Introduction

In underground coal mining, the existence of many different parameters affecting the selection of powered roof supports, which are the most important production equipment, and the fact that these parameters are still not placed within a systematic framework make the selection stage even more complex. In current practices, powered roof support selection is carried out by considering a combination of experience, observation, and operational data. Although this approach is practical for decision-makers, it is not a universally valid selection method in all cases due to variations in the geomechanical parameters of the coal seam, changes in the strength of footwall and hanging wall, and differences in stress conditions. When these limitations are taken into account, the development of systematic, more data-driven, and most importantly, repeatable selection methods for powered roof supports to be used in different geological formations is becoming increasingly important.

Although the subject of powered roof support selection is not addressed in detail in the literature, a limited number of researchers have started to study this topic in recent years. For example, **Yetkin et al. (2016)** developed a fuzzy logic–based multi-criteria selection model for the selection of powered roof supports.

Studies on equipment and method selection in mining are more common in literature. **Yavuz (2014)** applied the Analytic Hierarchy Process (AHP) and the Yager method to the problem of selecting mining methods for underground operations, demonstrating that uncertainties can be effectively managed in multi-criteria decision-making processes. **Jang et al. (2015)** proposed a fuzzy logic–based decision support system to manage unplanned dilution and ore loss in underground production. **Ozfirat (2015)** utilized the fuzzy analytic hierarchy process (F-AHP) for selecting tunnel boring machines operating in soft ground, highlighting the importance of evaluating both geomechanical and economic parameters. **Ozfirat et al. (2017)** used the F-AHP method to select transportation methods in open-pit mines. **Yetkin**

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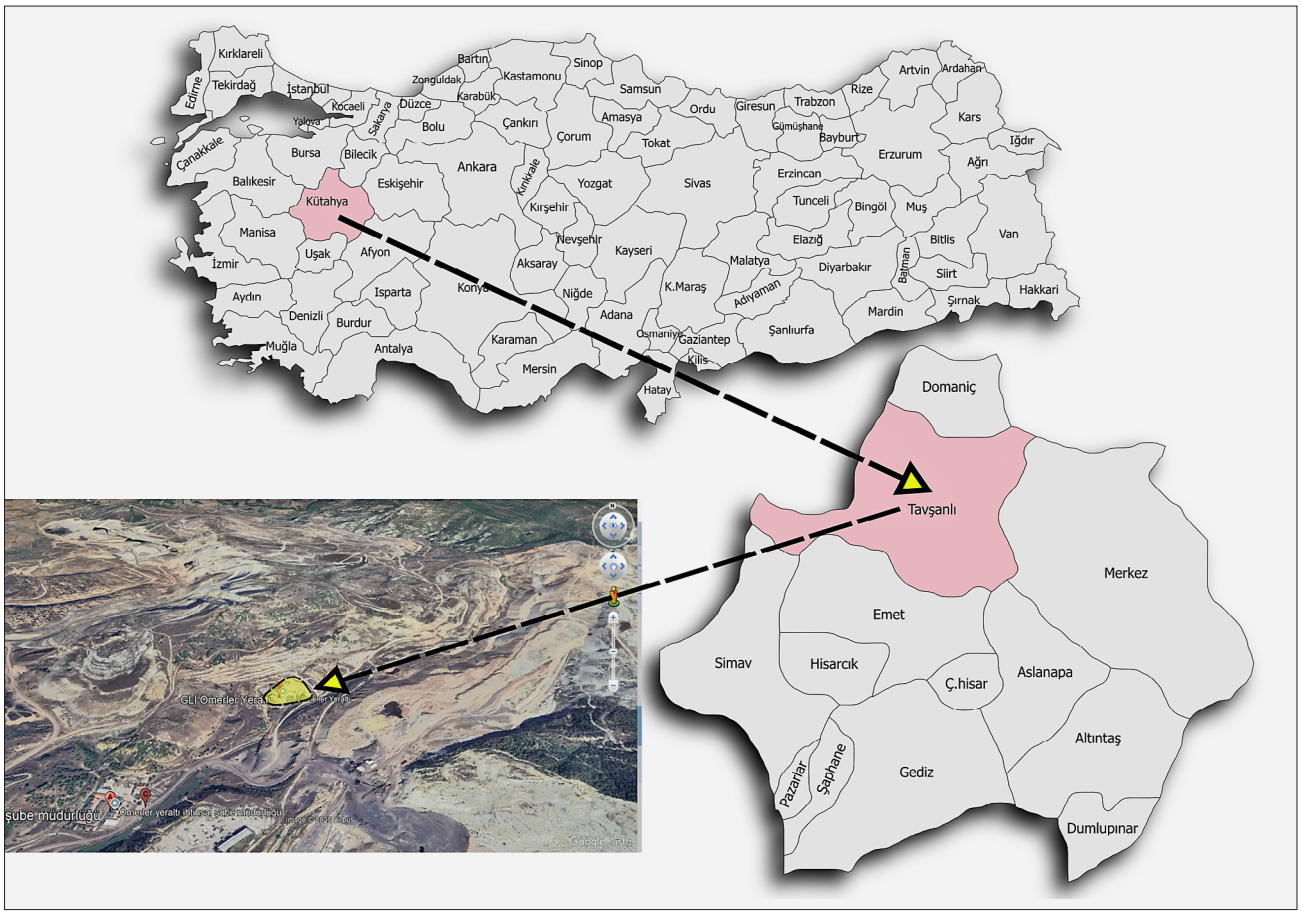


Figure 1: Location map of the study area

& Ozfırat (2019) applied the AHP method to choose the best production method for thick coal seams. **Bajić et al. (2020)** used the F-AHP method to determine the most suitable underground mining method. **Malli et al. (2021)** employed the Fuzzy-WSM method to identify the best transportation method for open-pit mines. **Gligorić et al. (2022)** developed a hybrid decision-making model for selecting support systems in underground mining. **Namin et al. (2023)** proposed a decision-support model combining AHP and fuzzy TOPSIS to optimize haulage system selection in open-pit mining. **Kursunoglu (2024)** integrated FAHP and fuzzy TOPSIS to control methane explosion risks in coal mines. Finally, **Eyuboglu et al. (2025)** used AHP to analyze technical and environmental factors for wind power plant site selection in the Bergama region.

Zadeh (1965) introduces the concept of fuzzy sets in order to eliminate uncertainties in decision-making processes by using membership functions. **Molodtsov (1999)** proposes soft set theory as a general mathematical framework capable of handling incomplete and uncertain information using set valued functions instead of membership functions. **Maji et al. (2001)** and **Maji et al. (2002)** develop fuzzy soft set theory in their studies and apply it to decision-making problems. **Roy et al. (2007)** develop a model that integrates the concepts of uncertainty and fuzziness for decision making problems. The use of soft sets in decision-making processes is further developed by **Çağman et al. (2011); Çağman et al. (2010)**, their study expanded the applicability of soft sets to decision-making problems. As a result of these studies, the use of fuzzy soft set methods in decision-making processes is attracting increasing attention. **Xiao et al. (2009)** obtain successful results compared to classical selection methods by applying this approach. **Yaylalı et al. (2021)** develop an algorithm-supported decision-making method by using soft interval structures. **Hoş et al. (2021)** apply fuzzy soft set–based selection to industrial supplier selection problems. Recent studies demonstrate that the fuzzy soft set method is an applicable approach across different disciplines. **Li et al. (2024)** develop FSS-based models to address uncertainties in travel times. **Hazaymeh (2024)** proposes a time-based FSS method to improve efficiency in decision-making processes. **Alcantud et al. (2024)** examine the interdisciplinary applications of FSS. **Singh et al. (2025)** investigate the use of FSS in medical applications. **Yaylalı Umul (2025)** proposes an intuitive FSS method as a decision-making approach that prioritizes user ratings. **Polat (2025a)**; **Polat (2025b)** develops a group decision-making algorithm demonstrating that this approach is also applicable to complex multi-criteria decision-making problems.

The scope of fuzzy soft set theory has been expanded by various authors in literature. For example, Q-fuzzy soft sets (**Adam & Hassan, 2014**), Possibility Fuzzy Soft Sets (**Alkhazaleh et al., 2011**), (a, b)-Fuzzy soft sets (**Al-shami et al., 2023**), Interval-valued intuitionistic fuzzy soft sets (**Jiang et al., 2010**), and Generalised fuzzy soft sets (**Majumdar & Samanta, 2010**) are some of these structures. The special fuzzy soft sets (RFSS and FFSS) given in this study are fuzzy soft sets derived from the available data, unlike given studies in literature. This study applies fuzzy soft set theory to multi-criteria decision-making processes, using FFSS and RFSS models that reflect the distributional properties of a set of choices. By capturing the frequency with which alternatives meet the criteria and their proximity to reference values, these models produce rankings that reflect the intrinsic structure of the selection set rather than arbitrary collection schemes. Within the scope of this study, a new mathematical model based on the Frequency Fuzzy Soft Set (FFSS) and Recurrence Fuzzy Soft Set (RFSS) approaches is designed in order to overcome the limitations encountered by classical fuzzy decision-making methods in powered roof support selection. The obtained results indicate that both models provide consistent outcomes and that the threshold value of $\alpha = 0.8$ ensures an optimal balance between safety practices and operational flexibility. Overall, the proposed framework offers a repeatable, data-driven, and field-validated decision support approach for safer and more effective design processes in underground mining.

Despite these studies, a systematic, data driven framework for selecting powered roof supports is still lacking one that simultaneously accounts for uncertainty, captures parameter interactions, and ensures repeatability.

2. Study Site

The developed mathematical model is applied at the Ömerler Underground Coal Mine of the Western Lignite Enterprises (GLİ), operating under the Turkish Coal Enterprises (TKİ), located in the Tavşanlı district of Kütahya Province, Türkiye. This site constitutes a significant portion of the country's lignite reserves (**Yetkin & Şimşir, 2019**). The location map of the study area is presented in **Figure 1**.

Coal production in the study area is carried out using the fully mechanized longwall mining method. Coal extraction within the longwall face is performed by shearer loaders, while the roof coal is recovered by caving behind the face. Powered roof supports are used to provide roof control during production, enabling efficient and safe mining operations (**Yetkin & Şimşir, 2019**). Considering the geomechanical properties of the coal and surrounding rock mass, as well as the operational characteristics of the site, the main and sub-parameters affecting powered roof support selection are identified.

3. Selection Criteria and Alternative Powered Roof Supports

At the selection stage of powered roof supports, the primary weighting arises from the physical and mechanical properties of the geological formations of the site. Seam dip, seam thickness, and the strength parameters of the coal as well as the hanging wall and footwall are the main factors that directly affect powered roof support selection. In addition, the in-situ and secondary stress conditions at the site are among the parameters that influence the selection process. Besides these factors, technical and economic parameters related to the mining operation and the powered roof supports themselves are also parameters that need to be considered during the selection stage. In this context, all parameters that may influence the selection process, as mentioned above, are identified in detail, and these parameters are grouped under five main categories and sixteen subcategories. The parameters affecting the selection are presented in **Figure 2**.

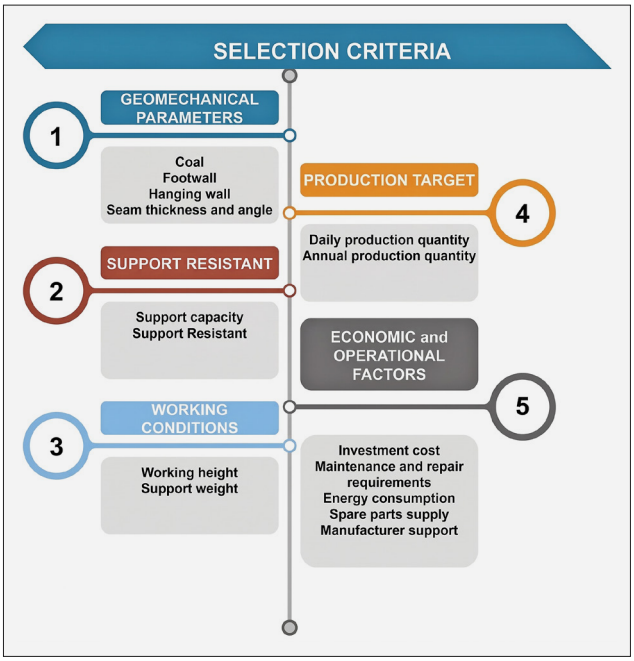


Figure 2: Main and sub-criteria affecting powered roof support selection

One of the most important parameters in the selection stage of powered roof supports is the geomechanical properties of the coal and the strata surrounding it. The strength and load-bearing behaviour of the hanging wall and footwall significantly affect the loads acting on the supports. In addition, the behaviour of the footwall under water contact, together with the high weight of the support, leads to floor heave and penetration of the support into the floor. Under such conditions, not only the load-bearing capacity but also the mass and base area of the powered roof support become critical parameters to be

Table 1: Alternative roof supports selected for the study and some critera

No	Working Height e_{31} (m)	Initial Supporting Force (kN) e_{21}	Support Resistance (MPa) e_{22}	Canopy Width (m) e_{33}
S1	1.7-3.5	3206	0.58-0.65	1.5
S2	1.8-3.8	3958	0.62-0.68	1.5
S3	1.6-3.2	4364	0.65-0.70	1.5
S4	1.8-3.5	3879	0.60-0.65	1.5
S5	1.8-3.3	5234	0.75-0.82	1.5
S6	2.0-3.8	6185	0.80-0.88	1.5
S7	2.0-4.0	6185	0.85-0.92	1.5
S8	1.6-3.2	6185	0.90-0.96	1.5
S9	2.0-4.2	7758	0.94-1.02	1.5
S10*	2.0-3.5	6280	0.81-0.94	1.5

* The powered roof support system currently in use at the work site

Table 2: Priority rankings of parameters

Criteria	Score
Coal - e_{11}	9
Footwall - e_{12}	8
Hanging Wall - e_{13}	10
Seam thickness and angle - e_{14}	7
Support capacity - e_{21}	9
Support resistant - e_{22}	8
Working height - e_{31}	6
Support weight - e_{32}	5
Canopy width - e_{33}	3
Daily production quantity - e_{41}	6
Annual production quantity - e_{42}	5
Investment cost - e_{51}	7
Maintenance and repair requirements - e_{52}	6
Energy consumption - e_{53}	4
Spare parts supply - e_{54}	5
Manufacturer support - e_{55}	5

considered during the selection stage. To reduce the pressure applied to the floor in these situations, powered roof supports with a wider base are required to be preferred.

Furthermore, the strength of the coal is important in terms of the magnitude of the setting loads transferred to the support. Excessive load transfer to the canopy section of the support, which is in contact with the coal seam, disrupts the stability of the support and causes irregularities in face alignment and interruptions in production. The yield and setting pressure values of the hydraulic legs of the powered roof supports are required to be selected in accordance with the stress conditions of the site and to operate within reliable pressure ranges. Powered roof supports are required to operate in harmony with the thickness of the coal seam and to provide the necessary working height for shearer loaders during production. Planned daily, monthly, and annual production rates are required to be compatible with the selected powered roof supports. Powered roof supports with greater operating heights allow higher coal production within the same time period. In addition, the selected powered roof supports are required to operate compatibly with the shearer, armored face conveyor, crusher, and belt conveyor, which also needs to be considered during the selection stage. In powered roof support selection, investment cost, maintenance requirements, energy consumption, spare parts supply, and manufacturer support are critical factors that determine long-term operating costs.

After identifying the parameters influencing powered roof support selection, the selection of alternative support types is carried out. In this study, ten powered roof supports with different operating height ranges (1.6–4.2 m) and different load-bearing capacities are selected. The technical specifications of these supports are presented in **Table 1**. This diversity allows mining operations to evaluate multiple powered roof support alternatives suitable for their specific geological conditions.

The technical characteristics of the selected powered roof supports are shown in **Table 1**. As shown, the difference in the working height and support resistance is due to the different capacities of the supports, which the model is able to account for.

The parameters affecting the selection of powered supports have been scored in **Table 2** according to their degree of influence on a scale from 1 to 10.

After defining the evaluation parameters, the next step involves developing a systematic decision-making framework capable of handling uncertainty and multi-dimensional trade-offs. To this end, the threshold-based fuzzy soft set model is proposed.

4. Proposed Method: Threshold-Based Fuzzy Soft Set Decision Framework

In mining and tunneling operations, equipment selection is a decision-making problem that fundamentally affects the technical and economic success of projects. This process requires managing multiple, often conflicting, criteria, including efficiency, geometric constraints, cost, and operational risk.

Fuzzy set theory (**Zadeh, 1965**) is widely used to address multi-criteria decision-making problems under uncertainty. However, in recent years, soft set theory, introduced by **Molodtsov (1999)** has proven to be a good mathematical tool for problems involving uncertainty due to the flexibility it offers in parameter modelling. Fuzzy soft set theory, which arose from these two set theories, allows assigning not only set-valued approximations to parameters, but also sets of approximation whose elements are graded by membership functions.

Definition 4.1: (Maji et al., 2001): Let U be a universal set, E set of parameters. Γ_F is called a fuzzy soft set over U where $F: E \rightarrow F(U)$ is a mapping from E to the set of all fuzzy subsets of U. For each $e \in E$,

$$\Gamma_F(e) = \left\{ \frac{u}{\mu_{F(e)}(m)} : m \in U, \mu_{F(e)}(m) \in [0,1] \right\}.$$

This study defines the Frequency Fuzzy Soft Set (FFSS) and Recurrence Fuzzy Soft Set (RFSS) methodologies. These approaches, which generate a special type of fuzzy soft set, reflect the frequency and recurrence in the problem content into used membership function.

Let $U=\{u_1, u_2, u_3, \ldots, u_n\}$ denote the universe of discourse (set of alternatives) and $E=\{e_1, e_2, e_3, \ldots, e_m\}$ represent a set of parameters (criteria). Let $F(U)$ denote the set of all fuzzy subsets of U.

This section will present two specific type of fuzzy soft sets with some properties. The primary motivation behind these definitions to allow the decision maker to reflect the available data in the problem. For this purpose, the first definition, Frequency Fuzzy Soft Set (FFSS), reflects the frequency distribution of the options available to the decision maker the choice into fuzzy soft sets. The second definition, Recurrence Fuzzy Soft Set (RFSS), evaluates the alternatives according to their proximity to the average value of each criterion and assigns higher membership degrees to values that approach the central tendency of the data set.

4.1. Frequency Fuzzy Soft Set

Definition 4.1.1: For a criterion $e \in E$ with observed values $\{x_{m,e} : m \in U, e \in E\}$ where the notation $x_{m,e}$ represents the observed value of alternative m with respect to parameter e in a multi-criteria decision-making framework. Frequency Fuzzy Soft Set (FFSS) Γ_F is a fuzzy soft set on U and defined as follows:

$$\Gamma_F(e) = \left\{ \frac{u}{\mu_{F(e)}(m)} : m \in U, \mu_{F(e)}(m) \in [0,1] \right\},$$

$$\mu_{F(e)}(m) = \begin{cases} 1, & f(x_{m,e}) \geq \tau_f \\ \dfrac{f(x_{m,e})}{\tau_f}, & f(x_{m,e}) < \tau_f \end{cases} \quad (1)$$

Where: $f(x_{m,e})$ represents the relative frequency (occurrence ratio) of value m in the dataset, calculated as $f(x_{m,e}) = \frac{n_m}{n}$, where n_m is the number of alternatives with value m and $n=|U|$ is the total number of alternatives. $\tau_f \in (0,1]$ is the frequency threshold, which serves as a discriminating boundary between "frequently occurring" and "rarely occurring" values. The frequency threshold τ_f is computed as **Equation 2**:

Table 3: Frequency Fuzzy Soft Set Membership values of all powered roof support considering each parameter

No	$\mu_{F(e_{31})}(u_i)$	$\mu_{F(e_{21})}(u_i)$	$\mu_{F(e_{22})}(u_i)$	$\mu_{F(e_{33})}(u_i)$
S_1	0.862	0.752	1	1
S_2	0.862	0.752	1	1
S_3	1	0.752	1	1
S_4	0.862	0.752	1	1
S_5	0.862	0.752	1	1
S_6	0.862	1	1	1
S_7	0.862	1	1	1
S_8	1	1	1	1
S_9	0.862	0.752	1	1
S_{10}	0.862	0.752	1	1

Parameter	N	σf	τ_f
$e_{31} = Working\ Height$	9	0.0314	0.116
$e_{21} = Initial\ Supporting\ Force$	8	0.0661	0.133
$e_{22} = Support\ Resistance$	10	0.0000	0.100
$e_{33} = Canopy\ Width$	1	0.0000	0.100

$$\tau_f = \frac{1}{n} + k.\sigma f \quad (2)$$

where the components are defined as follows:

n: The cardinality of the universe U (number of alternatives). The term 1/n represents the minimum expected frequency when each value appears exactly once in the dataset, establishing a baseline for comparison.

σf: Represents the standard deviation, which measures the distribution of frequency values around their averages. It is calculated as **Equation 3**:

$$\sigma f = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(f_i - \overline{f}\right)^2} \quad (3)$$

where N is the number of distinct values observed for alternative u, f_i is the frequency of the i[th] distinct value, and $\overline{f} = \frac{1}{N}\sum_{i=1}^{N} f_i$ is the mean frequency. k: Controls the sensitivity of the threshold (typically $k \in [0.5, 1.0]$). Higher values of k result in more conservative thresholds that requires higher frequencies for full membership. A standard choice is $k = 0.5$.

Proposition 4.1.2: The FFSS membership function $\mu_{F(e)}(m)$ is monotonically non-decreasing and satisfies the condition $0 < \mu_{F(e)}(m) \leq 1$.

Proof: Straightforward from the Definition 4.1.1.

Remark 4.1.3: The FFSS membership function assigns full membership (μ=1) to alternatives whose criterion values occur frequently (at or above the threshold τ_f). Values occurring below the threshold receive pro-

portionally reduced membership scores, reflecting their rarity.

Frequency fuzzy soft sets derived from frequently observed values represent more reliable and stable data.

Example 4.1.4: The frequency fuzzy soft set derived from **Table 1** is given in **Table 3**. In this example $U=\{S_1, S_2, S_3, \dots, S_{10}\}$ is universal set and $E=\{e_{31}=$*Working Height,* $e_{21}=$*Initial Supporting Force,* $e_{22}=$*Support Resistance,* $e_{33}=$*Canopy Width}* is set of parameters.

It is also clear from the results that alternatives with repetitive values of parameters (for example, S6-S8 in initial supporting force) are assigned higher membership degrees. This is in accordance with the FFSS principle, which states that repetitive values of parameters correspond to more reliable and industry-approved configurations.

FFSS calculation steps for the criterion e_{21}: The set of values of powered roof supports for the parameter initial supporting force is $\{3206, 3958, 4364, 3879, 5234, 6185, 6185, 6185, 7758, 6280\}$. According to these values some of relative frequency of Powered Roof Supports, $f(x_{m,e}) = \frac{n_m}{n}$ are evaluated as $f(S_{1,e_{21}}) = \frac{n_m}{n} = \frac{1}{10}$, $f(S_{2,e_{21}}) = \frac{n_m}{n} = \frac{1}{10}$, $f(S_{6,e_{21}}) = \frac{n_m}{n} = \frac{3}{10}$ for the alternatives $S_1, S_2 \wedge S_6$.

In this example σf=0.0661 and τ_f 0.133 (from the formulas given in **Equation 2** and **3**). So the value of membership function for the first, second and sixth alternatives are computed as $\mu_{F(e_{21})}(S_1) = \frac{0.1}{0.133} = 0.752$, $\mu_{F(e_{21})}(S_2) = \frac{0.1}{0.133} = 0.752$ and $\mu_{F(e_{21})}(S_6) = 1$.

4.2. Recurrence Fuzzy Soft Set

Definition 4.2.1: Recurrence Fuzzy Soft Set (RFSS) Γ_R over U, is a fuzzy soft set with the recurrence-based membership function given as in **Equation 4**:

$$\Gamma_R(e) = \left\{\frac{u}{\mu_{R(e)}(u)} : u \in U, \mu_{R(e)}(u) \in [0,1]\right\}, \mu_{R(e)}(u) =$$

$$= \begin{cases} 1, & x_{u,e} \in [\bar{x}_e(1-\delta), \bar{x}_e(1+\delta)] \\ 1 - \dfrac{|x_{u,e} - \bar{x}_e|}{\bar{x}_e}, & otherwise \end{cases} \quad (4)$$

For a given criterion $e \in E$ with observed values $\{x_{u,e} : u \in U, e \in E\}$ where the notation $x_{u,e}$ represents the observed value of alternative u with respect to criterion/parameter e in a multi-criteria decision-making framework. Where the components are defined as follows:

- $\bar{x}_e = \frac{1}{N}\sum_{i=1}^{N} x_{i,e}$ In this formula $x_{u_i,e}$ the value of each alternative for that criterion.
- δ : The tolerance ratio, representing the acceptable proportional deviation from the mean. Typically, $\delta \in [0.10, 0.20]$ is selected based on the desired level of conservatism:
- δ = 0.10: Strict evaluation (±10% tolerance).
- δ = 0.15: Balanced evaluation (±15% tolerance).
- δ = 0.20: Lenient evaluation (±20% tolerance).

Example 4.2.2: The recurrence fuzzy soft set derived from Table 1 is given in **Table 4**. In this example $U=\{S_1, S_2, S_3, \dots, S_{10}\}$ is universal set and $E=\{e_1=Working\ Height, e_2=Initial\ Supporting\ Force, e_3=Support\ Resistance, e_4=Canopy\ Width\}$ is set of parameters. $\delta = 0.10$.

Table 4: Frequency Fuzzy Soft Set Membership values of all powered roof support considering each parameter

No	$\mu_{R(e_1)}(u_i)$	$\mu_{R(e_2)}(u_i)$	$\mu_{R(e_3)}(u_i)$	$\mu_{R(e_4)}(u_i)$
S_1	1	0.602	0.782	1
S_2	1	0.744	0.827	1
S_3	0.884	0.820	0.859	1
S_4	1	0.729	0.795	1
S_5	1	1	1	1
S_6	1	0.838	1	1
S_7	0.895	0.838	0.874	1
S_8	0.884	0.838	0.817	1
S_9	0.858	0.543	0.753	1
S_{10}	1	0.820	0.887	1

Unlike FFSS, RFSS prefers alternatives that are closer to the mean value. This is to ensure that extreme values, although they are considered better, are penalized because of possible operational risks or inefficiencies.

RFSS calculation steps for the criterion e_{21}: The set of values of powered roof supports for the parameter initial supporting force is $x_{S_i,e_2} = \{3206, 3958, 4364, 3879, 5234, 6185, 6185, 6185, 7758, 6280\}$ for $i=\{1,\dots,10\}$. $\bar{x}_e$=5323.4, $[\bar{x}_e(1\text{-}\delta), \bar{x}_e(1+\delta)]$=[4791.06, 5855.74]. As one can observe that $\mu_{R(e_2)}(S_5)$=1 since x_{S_5,e_2} = = 5234 ∈ [4791.06, 5855.74] and $\mu_{R(e_2)}(S_1) = 1 - \frac{|3206 - 5323.4|}{5323.4}$=0.602. Other membership values of the alternatives can be calculated by following the **Equation 4**. Recurrence Fuzzy Soft Set (RFSS) methodology evaluates alternatives based on their proximity to the mean value of each criterion, assigning higher membership degrees to values that converge toward the central tendency of the dataset. This approach is based on the idea of risk mitigation, acknowledging that extreme deviations whether positive or negative can create operational vulnerabilities.

Extremely high performance values may indicate excess capacity, leading to inefficient resource utilization, high operating costs, or reliability issues. Conversely, extremely low performance values indicate insufficient

Table 5: Comparison of FFSS and RFSS

Feature	FFSS	RFSS
Primary criterion	Frequency (prevalence)	Proximity to mean
Preferred values	Frequently observed values	Mean values
Risk approach	Consensus seeking	Avoidance of extremes
Application domain	Reliability-focused	Balance-focused

capacity, which can result in an inability to meet operational requirements and decreased productivity. In contrast, values close to the average represent predictable, sustainable, and stable performance characteristics. Such values statistically better represent the population, are more consistent with industry norms, and facilitate supply chain logistics.

From an engineering standpoint, the selection between FFSS and RFSS carries significant practical implications (see **Table 5**). Operational safety considerations favor average values because excessive features lead to high risk levels. Average features ensure balanced and predictable system behaviour. Components with typical characteristics benefit maintenance planning because they are compatible with standard maintenance protocols and established procedural frameworks.

Proposition 4.2.3: $\Gamma_F(e) = \left\{\frac{u}{1} : u \in U\right\}$ and $\Gamma_R(e) = \left\{\frac{u}{1} : u \in U\right\}$ for all $e \in E$ if the alternative u satisfies all parameters above the threshold level.

Proof: Straightforward from the Definition 4.1.1. and 4.2.1

Following the construction of fuzzy soft sets that capture the attributes of the decision alternatives based on the FFSS and RFSS approaches, the decision-making framework proceeds in two main steps. First, an α-cut penalization mechanism is applied (Subsection 4.3) to refine the membership structure. Then, a weighted multiplicative decision function (Subsection 4.4) is employed to rank the alternatives. These procedures are described in detail in the following subsections.

4.3. α-Cut Penalization

When selecting a powered roof support system, certain criteria require strict safety restrictions. An alternative that underperforms in critical criteria, regardless of its excellence in other parameters, creates operational risks. Critical criteria requiring strict compliance are emphasized through an α-cut penalization mechanism. The penalized membership function is defined as **Equation 5**:

$$\phi_\alpha(\mu) = \begin{cases} \mu, & \mu \geq \alpha \\ e^{-2(\alpha-\mu)}.\mu, & \mu < \alpha \end{cases} \quad (5)$$

Where $\alpha \in [0,1]$ is the satisfaction threshold, representing the minimum acceptable membership degree for critical criteria. μ is the original membership value from FFSS or RFSS evaluation.

This mechanism ensures that alternatives underperforming in critical criteria cannot achieve high overall rankings solely through superior performance in non-critical parameters. The continuously increasing exponential function imposes progressively more severe penalties for increasing deficiencies.

Example 4.3.1: The α-cut penalty mechanism ensures the application of minimum acceptable performance thresholds for safety-critical criteria. To examine the effect of threshold selection, a sensitivity analysis was conducted by varying the satisfaction threshold α across three levels: 0.7 (lenient), 0.8 (moderate), and 0.9 (strict). The application of this method to the FFSS and RFSS sets given in Examples 4.1.1 and 4.2.1, respectively, is shown in the tables below. **Table 6** gives the results of 0.7, 0.8 and 0.9-cut penalizations.

Based on the observed values in the tables above, α = 0.80 appears to provide the most balanced result**.**

4.4. Weighted Multiplicative Decision Function

4.4.1. Criterion Weighting

The powered roof support selection framework includes 16 sub-criteria grouped into 5 main categories, which are given in **Table 2**. Evaluation scores (1-10 scale) were assigned to each sub-criterion. Main criterion weights derived from these scores:

- Geomechanical Parameters: 32.14% (highest priority)
- Economic & Operational Factors: 24.11%
- Working Conditions: 18.75%
- Support Resistant: 15.18%
- Production Target: 9.82%

This study focuses on four quantifiable technical parameters with available numerical data, following to **Table 1**. To evaluate the final weights a two-level weighting approach is used.

Step 1: Calculate main category weight (total score sum).

Step 2: Calculate sub-criterion ratio within category (sub-criterion score).

Step 3: Derive initial weight (main weight × sub-criterion ratio).

Step 4: Normalize to unity (initial weight / sum of four criteria weights).

Final normalized weights are evaluated as $w_1 = 0.26$ (Working Height), $w_2 = 0.29$ (Initial Supporting Force), $w_3 = 0.26$ (Support Resistance) and $w_4 = 0.19$ (Canopy Width).

Although FFSS and RFSS computations utilize only four quantifiable parameters. The remaining 12 criteria

Table 6: The results of 0.7, 0.8 and 0.9-cut penalizations of obtained FFSS and RFSS

FFSS α=0.8

No	e1: Working Height	e2: Initial Force	e3: Support Resistance	e4: Canopy Width
S_1	0.862	0.683	1	1
S_2	0.862	0.683	1	1
S_3	1	0.683	1	1
S_4	0.862	0.683	1	1
S_5	0.862	0.683	1	1
S_6	0.862	1	1	1
S_7	0.862	1	1	1
S_8	1	1	1	1
S_9	0.862	0.683	1	1
S_{10}	0.862	0.683	1	1

FFSS α=0.9

No	e1: Working Height	e2: Initial Force	e3: Support Resistance	e4: Canopy Width
S_1	0.799	0.557	1	1
S_2	0.799	0.557	1	1
S_3	1	0.557	1	1
S_4	0.799	0.557	1	1
S_5	0.799	0.557	1	1
S_6	0.799	1	1	1
S_7	0.799	1	1	1
S_8	1	1	1	1
S_9	0.799	0.557	1	1
S_{10}	0.799	0.557	1	1

RFSS α=0.7

No	e1: Working Height	e2: Initial Force	e3: Support Resistance	e4: Canopy Width
S_1	1	0.494	0.782	1
S_2	1	0.744	0.827	1
S_3	0.884	0.820	0.859	1
S_4	1	0.729	795	1
S_5	1	1	1	1
S_6	1	1	0.838	1
S_7	0.895	0.838	0.874	1
S_8	0.884	0.838	0.817	1
S_9	0.858	0.401	0.753	1
S_{10}	1	0.820	0.887	1

RFSS α=0.8

No	e1: Working Height	e2: Initial Force	e3: Support Resistance	e4: Canopy Width
S_1	1	0.405	0.782	1
S_2	1	0.744	0.827	1
S_3	0.884	0.820	0.859	1
S_4	1	0.729	795	1
S_5	1	1	1	1
S_6	1	1	0.838	1
S_7	0.895	0.838	0.874	1
S_8	0.884	0.838	0.817	1
S_9	0.858	0.325	0.753	1
S_{10}	1	0.820	0.887	1

RFSS α=0.9

No	e1: Working Height	e2: Initial Force	e3: Support Resistance	e4: Canopy Width
S_1	1	0.330	0.672	1
S_2	1	0.540	0.735	1
S_3	0.806	0.715	0.766	1
S_4	1	0.494	0.696	1
S_5	1	1	1	1
S_6	1	1	0.748	1
S_7	0.817	0.748	0.781	1
S_8	0.806	0.748	0.733	1
S_9	0.776	0.270	0.598	1
S_{10}	1	0.715	0.794	1

α Value	FFSS: Penalties Applied	RFSS: Penalties Applied	Severity
0.70	0 penalties	2 penalties (e_{21} only)	**Lenient**
0.80	7 penalties (e_{21} only)	7 penalties (e_{21}, e_{22})	**Balanced**
0.90	16 penalties (e_{31}, e_{21})	22 penalties (all except e_{33})	**Strict**

Table 7: Final Results with Weights for FFSS (w_1=0.26, w_2=0.29, w_3=0.26, w_4=0.19)

Rank	Support	Final Score	$\mu_{F(e_{31})}(u_i)$	$\mu_{F(e_{21})}(u_i)$	$\mu_{F(e_{22})}(u_i)$	$\mu_{F(e_{33})}(u_i)$	Comment
1	S_8	1	1	1	1	1	Perfect across all criteria
2	S_6	0.9623	0.862	1	1	1	High force and resistance
2	S_7	**0.9623**	**0.862**	**1**	**1**	**1**	**Tied with S_6**
4	S_3	0.8873	1	0.683	1	1	Penalized on force
5	S_1	0.8539	0.862	0.683	1	1	Below optimal height and force
5	S_2	0.8539	0.862	0.683	1	1	Tied with S_1
5	S_8	0.8539	0.862	0.683	1	1	Tied with S_1
5	S_8	0.8539	0.862	0.683	1	1	Tied with S_1
5	S_8	0.8539	0.862	0.683	1	1	Tied with S_1
5	S_8	0.8539	0.862	0.683	1	1	Tied with S_1

Table 8: Final Results with Weights for RFSS (w_1=0.26, w_2=0.29, w_3=0.26, w_4=0.19)

Rank	Support	Final Score	$\mu_{R(e_{31})}(u_i)$	$\mu_{R(e_{21})}(u_i)$	$\mu_{R(e_{22})}(u_i)$	$\mu_{R(e_{33})}(u_i)$	Comment
1	**S_5**	**1**	**1**	**1**	**1**	**1**	**Perfect balance - mean values**
2	S_6	**0.9508**	**1**	**0.838**	**1**	**1**	**High resistance**
3	S_{10}	**0.9118**	**1**	**0.820**	**0.887**	**1**	**Good balance**
4	S_7	0.8919	0.895	0.838	0.874	1	Moderate across criteria
5	S_3	0.8758	0.884	0.820	0.859	1	Good but not optimal
6	S_8	0.8735	0.884	0.838	0.817	1	Similar to S_3
7	S_2	0.8199	1	0.665	0.827	1	Low force penalty
8	S_4	0.7951	1	0.633	0.787	1	Multiple penalties
9	S_1	0.6625	1	0.405	0.755	1	Critical force deficiency
10	S_9	0.5565	0.858	0.325	0.685	1	Severe deficiency

indirectly contribute the decision-making algorithm through the hierarchical weighting mechanism. The normalized weights (w_1=0.26, w_2=0.29, w_3=0.26, w_4=0.19) reflect the relative importance of quantifiable criteria within a broader context shaped by evaluations of all 16 sub-criteria.

For instance, the 32.14% weight assigned to geomechanical parameters influences the final weight distribution among the four evaluated criteria, even though these geomechanical properties are not directly computed in the FFSS/RFSS operations.

4.4.2. FFSS and RFSS Fınal Scores and Rankings

Final scores and rankings are calculated for FFSS and RFSS in the following tables **Table 7** and **8** respectively.

Following the application of FFSS/RFSS membership evaluation, α-cut penalization and Criterion Weighting the final overall score for each alternative is computed through a weighted multiplicative aggregation function (**Equation 6**).

$$S(m) = \prod_{e \in E} \left[\phi_\alpha\left(\mu_e(m)\right)\right]^{w_e} \quad (6)$$

where:

- $S(m)$ is the final aggregated score for alternative m.
- $E=\{e_1, e_2, e_3, \ldots, e_m\}$ is the set of evaluation criteria.
- $\phi_\alpha\left(\mu_e(m)\right)$ is the penalized membership value of alternative m for criterion e (obtained from α-cut function).
- w_e is the normalized weight of criterion e, satisfying: $\sum_{e \in E} w_e = 1$, $w_e \in [0,1]$.

4.4.3. Algorithm

The final score for each alternative is computed as follows:

Step 1: Apply FFSS or RFSS to obtain initial membership values $\mu_e(m)$ for each criterion *e*.

Step 2: Apply α-cut penalization to obtain $\phi_\alpha(\mu_e(m))$.

Step 3: Derive criterion weights w_e from scores of parameters.

Step 4: Raise each penalized membership to its corresponding weight (**Equation 7**):

$$\left[\phi_\alpha\left(\mu_e(m)\right)\right]^{w_e} \quad (7)$$

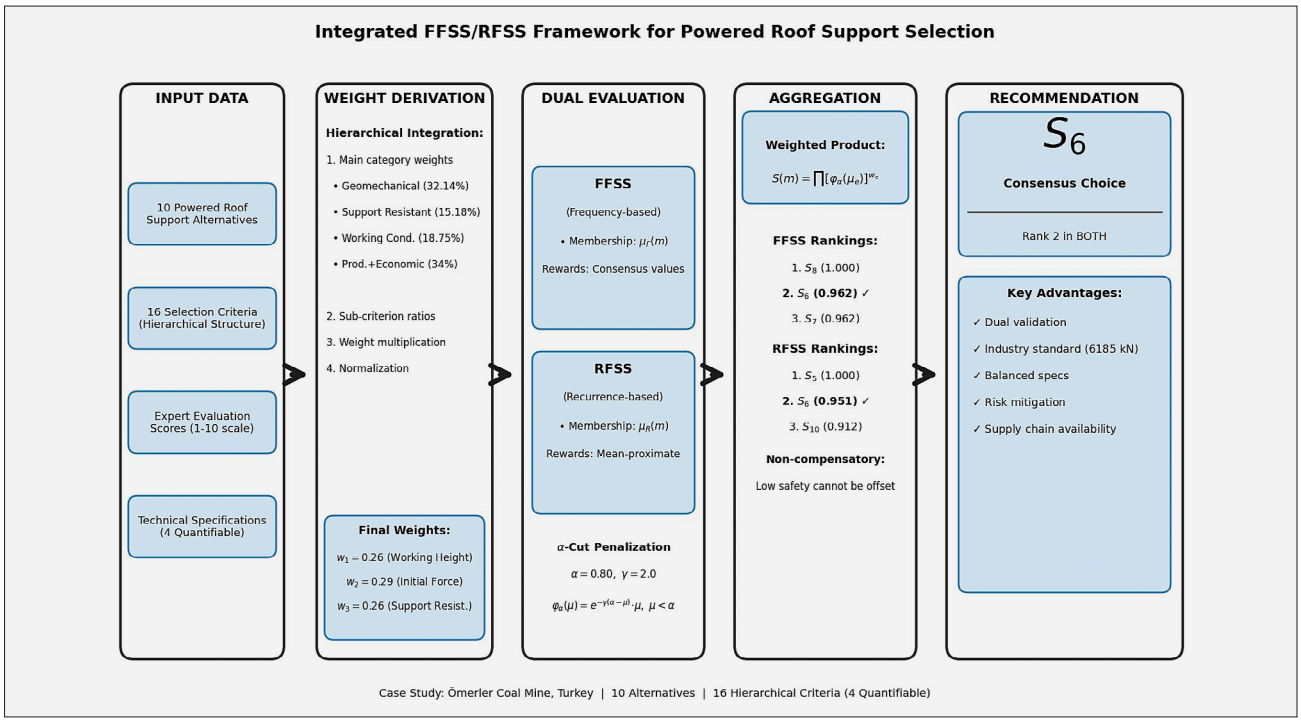


Figure 3: Framework for powered roof support selection

Step 5: Compute the product across all criteria (**Equation 8**):

$$S(m) = \prod_{e \in E} [\phi_\alpha(\mu_e(m))]^{w_e} \quad (8)$$

Step 6: Rank alternatives in descending order of $S(m)$.

The proposed decision framework was applied to the ten alternative roof support systems that are defined in **Table 1** following section reports the computed membership values, aggregated scores, and the resulting rankings based on the FFSS and RFSS methodologies.

5. Results and Discussion

The FFSS/RFSS frameworks with an α-cutoff penalty was implemented to evaluate ten alternatives (S_1 - S_{10}) for the Ömerler Coal Mine. The importance scores assigned to the 16 parameters determined the criteria weights (w_1=0.26, w_2=0.29, w_3=0.26, w_4=0.19), with the highest weight assigned to the initial supporting force due to its critical safety impacts. The analysis shows that the RFSS and FFSS approaches produce complementary results in the decision-making process.

According to FFSS Methodology:

Winner: S_8 (Score: 1.0000)

Runners-up: S_6, S_7 (Score: 0.9623)

Distinguished features: Rewards standardization

According to RFSS Methodology:

Winner: S_5 (Score: 1.0000)

Runner-up: S_6 (0.9508), S_{10} (0.9118)

Despite the methodological differences, alternative S_6 achieved 2nd place in both frameworks (FFSS: 0.9623, RFSS: 0.9508). This dual validation will ultimately yield a good result in the decision-making process, as S_6 meets both the frequency-based consensus criteria and the iteration-based balance principles.

FFSS operates on the principle that frequently occurring specifications reflect industry maturity and operational validation. In this study, the value 6185 kN for Initial Supporting Force appears in three alternatives (S_6, S_7, S_8), resulting in full FFSS membership for these alternatives on criterion e_{21}.

Importantly, the powered roof support (S_{10}) currently in use at the site has been confirmed as one of the best alternatives in the assessment of its suitability for the existing geological and operational conditions of the Ömerler Coal Mine. However, other alternatives such as S_6, S_7, or S_8 may also be evaluated depending on future production targets, economic considerations, and maintenance strategies. Their selection can provide flexibility in balancing cost efficiency, operational safety, and long-term sustainability based on site-specific requirements.

The evaluation of the parameters considered within the scope of the study and the selection process of the powered support are presented as in **Figure 3**.

From the engineering point of view, the results reveal that the alternative S_6 offers a strong balance in terms of load-bearing capability and stability. Unlike S_8, which is an idealized optimal solution, S_6 presents a more realistic and feasible solution under real-world conditions. The consistent ranking of S_6 in the FFSS and RFSS frameworks indicates that the alternative meets the specifications and requirements of the industry and the balance of the performance. Therefore, S_6 can be viewed as

a highly reliable alternative under real-world conditions in the context of underground coal mines.

6. Conclusions

In this study, a Fuzzy Soft Set model is presented, which was developed to enable the fast, effective, and reliable selection of powered roof supports – one of the key pieces of equipment in underground coal mining. In contrast to existing selection approaches in literature and practice, many of which are based on past experiences, this study introduces a mathematical model capable of simultaneously evaluating numerous critical criteria affecting the selection process. The proposed model was applied at the currently operating Ömerler Underground Coal Mine, and the results demonstrated that the model is both theoretically and practically applicable. The primary novelty of this study lies in integrating FFSS and RFSS approaches with an α-cut penalization mechanism, enabling a unified framework that supports both reliability-oriented and balance-oriented decision-making.

Within the scope of the study, the proposed model is shown to be a systematic, objective, and most importantly, repeatable tool capable of managing the selection process for mining engineering applications. In conclusion, this research not only contributes a novel methodological advancement to the academic literature but also provides a practical engineering decision-support tool that enhances safety, efficiency, and sustainability in underground mining operations.

Data Availability: The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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SAŽETAK

Optimizacija odabira hidrauličke samohodne podgrade u podzemnoj eksploataciji ugljena: unaprijeđeni model temeljen na neizrazitim mekim skupovima

Hidraulička samohodna podgrada, kao jedan od najvažnijih elemenata opreme u širokočelnome otkopavanju, mora se pažljivo odabrati jer ima ključnu ulogu u fazi odabira, kao i sigurnosti i produktivnosti tijekom proizvodnoga procesa. U mnogim slučajevima odabir se temelji na prethodnim iskustvima iz prakse i inženjerskoj prosudbi. Međutim, detaljna analiza parametara koji utječu na proces odabira pokazuje da postoji velik broj međusobno različitih čimbenika koji utječu na konačnu odluku, pri čemu svaki od njih ima različit utjecaj i relativnu važnost. Stoga se zaključuje da određivanje najprikladnije samohodne podgrade, osim na iskustvu, treba temeljiti i na sustavnoj znanstvenoj analizi navedenih parametara, čime se smanjuje vjerojatnost pogreške. U ovome radu parametri koji utječu na odabir hidrauličke samohodne podgrade vrednovani su primjenom matematičkoga modela razvijenoga na osnovi neizrazite logike. Utvrđen je parametar s najvećim utjecajem na odabir te je provedena selekcija među deset mogućih varijanti samohodne podgrade. U razvijenome modelu primijenjene su metode frekvencijskoga neizrazitoga mekog skupa (FFSS) i rekurentnoga neizrazitoga mekog skupa (RFSS), zasebno i u kombinaciji. Predloženi model primijenjen je na podzemnome ugljenokopu Ömerler. Dobiveni rezultati pokazuju da granična vrijednost od 0,8 osigurava uravnoteženo rješenje između sigurnosti i fleksibilnosti. Na temelju provedenih analiza zaključuje se da razvijeni matematički model omogućuje pouzdanu primjenu u problemima višekriterijskoga odlučivanja.

Ključne riječi:
hidraulička samohodna podgrada, neizraziti meki skup, podzemna eksploatacija

Author's contribution

Mustafa Emre Yetkin (1) (Assoc. Professor): conceived and designed the study. **Nazan Polat (2)** (Asst. Professor): developed the methodology and performed the analysis. All authors contributed to the study conception, analysis, and manuscript preparation.
All authors have read and agreed to the published version of the manuscript.