

Square soft-rough matrices

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Abstract

One key aspect of soft set theory is abstraction. The main idea in soft set theory revolves around making decisions with the guidance of experts. The combination of soft sets and rough sets led to the creation of soft-rough sets. This study expands the concept of soft-rough matrices to square soft-rough matrices (ss-r m). Various noteworthy properties of ss-r m are examined in this paper.

Keywords: *Soft sets, rough sets, soft-rough sets, soft-rough matrices, square soft-rough matrices.*

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1 Introduction

Various old theories, like Probability theory, Theory of evidence, and the Heisenberg uncertainty principle, are in books to deal with uncertainty well. Alongside these, recent tools such as fuzzy sets, rough sets, soft sets, neural networks, and genetic algorithms offer better ways to handle uncertainty. Many researchers actively contribute to improving these recent uncertainty theories. Present studies focus on mixes of these theories, like soft-rough sets, rough soft-sets, soft-rough fuzzy sets, rough soft fuzzy sets, modified soft-rough sets, and more. This book aims to explore the theory of uncertainty in fuzzy sets, rough sets, and soft sets. The main goal is to study mixes from the three theories, particularly soft-rough sets, soft-rough fuzzy sets, and soft-rough interval-valued fuzzy sets. As an extension of soft-rough matrices, the

idea of square soft-rough matrices is introduced, and some of their features are looked into.

There are different tools to deal with uncertainty, including old theories like Probability theory and newer ones like fuzzy sets, interval-valued fuzzy sets, intuitionistic fuzzy sets, rough sets, and soft sets. In Pawlak's rough set theory [8], uncertainty is shown by the edge of a set instead of a membership function. Vijayabalaji and Balaji [12] made rough matrices using rough membership functions and suggested a decision theory. Molodstov [6] talked about problems in existing theories, like rough sets, and said they lack good tools. He introduced a new mathematical tool, soft sets, to fix these problems and make dealing with uncertainties better. Soft sets let us roughly describe things, and we can use different things like real numbers, functions, and words. Maji and Roy [5] used soft sets in decision-making, and Wille [14] showed property systems in a binary way. Several researchers [3, 7, 9, 10, 15] studied property systems and exhibited how they relate to data analysis. Cagman [1, 2] suggested a decision-making way and said soft matrices represent soft sets. They are good because we can easily store and work with them on computers. Vijayabalaji and Ramesh [11] showed product soft matrices and talked about a decision theory. Feng Feng [4] talked about mix models from soft sets and rough sets, like soft-rough sets. Soft-rough sets are new because they make a new structure using soft guesses instead of Pawlak's rough ideas. Maji and Roy [5] used AHP in group decisions with soft matrices. Vijayabalaji [13] introduced the concept of soft-rough matrices by building upon soft-rough sets. He structured these matrices by assigning three values to the positive region, negative region, and boundary region of a soft-rough set. Section 2 explains why there is a requirement for square soft-rough matrices, while Section 3 presents these matrices, introducing compelling concepts and rules.

2 Need of square soft-rough matrices

Soft set theory involves abstraction, focusing on decisions guided by experts. The collaboration of soft sets and rough sets gave rise to soft-rough sets. In this research, the idea of soft-rough matrices is broadened to square soft-rough matrices (ss-r m). This paper explores several important characteristics of ss-r m. A square soft-rough matrix is an n by n matrix, where n is the number of rows and columns. The advantage of using a square soft-rough matrix lies in its symmetry and uniformity. Because it has an equal number of rows and columns, it simplifies certain computations and analyses. This symmetry can lead to more efficient mathematical operations and a clearer representation of relationships within the data. Additionally, the square format can enhance the applicability of square soft-rough matrices in various mathematical and computational models, making them versatile and easier to work with in certain

contexts.

3 Square soft-rough matrices

This part introduces our new idea, square soft-rough matrices, with clear explanations and includes interesting definitions and theorems for better understanding.

Definition 3.1. A special function $I_{SR} : U \rightarrow \{0, 0.5, 1\}$ defined on soft-rough set is termed as square soft-rough matrix (s-s-r m).

That is a soft-rough matrix is defined by

$$\varpi_{SR} = \begin{cases} 1, & \text{if } u \in Pos_p(X) \\ 0, & \text{if } u \in Neg_p(X) \\ a, & \text{if } u \in Bnd_p(X), \text{ where } a = 0.5 \end{cases}$$

$$\text{So, } \varpi_{SR} = \begin{pmatrix} \varrho_{11} & \varrho_{12} & \cdots & \varrho_{1n} \\ \varrho_{21} & \varrho_{22} & \cdots & \varrho_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \varrho_{m1} & \varrho_{m2} & \cdots & \varrho_{nn} \end{pmatrix} = (\varrho_{xy})_{nn}.$$

Definition 3.2. A s-s-r m is said to be zero s-s-r m if $\varrho_{xy} = 0$ for all $\varrho_{xy} \in \varpi_{SR}$.

Definition 3.3. The complement of a s-s-r m is defined as $\varrho_{xy} = 1 - \varrho_{xy}$ for all $\varrho_{xy} \in \varpi_{SR}$.

Definition 3.4. Let $[a_{xy}]$ and $[b_{xy}] \in \varpi_{SR}$. Then the intersection of $[\varrho_{xy}]$ and $[\varsigma_{xy}]$ is defined by $[\varrho_{xy}] \cap [\varsigma_{xy}] = \min\{\varrho_{xy}, \varsigma_{xy}\}$.

Definition 3.5. Let $[\varrho_{xy}]$ and $[\varsigma_{xy}] \in \varpi_{SR}$. Then the union of $[\varrho_{xy}]$ and $[\varsigma_{xy}]$ is defined by $[\varrho_{xy}] \cup [\varsigma_{xy}] = \max\{\varrho_{xy}, \varsigma_{xy}\}$.

Theorem 3.6. Let $[\varrho_{xy}]$ and $[\varsigma_{xy}] \in \varpi_{SR}$. Then

- (i) $([\varrho_{xy}] \cup [\varsigma_{xy}])^c = [\varrho_{xy}]^c \cap [\varsigma_{xy}]^c$.
- (ii) $([\varrho_{xy}] \cap [\varsigma_{xy}])^c = [\varrho_{xy}]^c \cup [\varsigma_{xy}]^c$.

Proof.

(i) For all x and y ,

$$\begin{aligned} & ([\varrho_{xy}] \cup [\varsigma_{xy}])^c \\ &= (\max\{\varrho_{xy}, \varsigma_{xy}\})^c \\ &= 1 - \max\{\varrho_{xy}, \varsigma_{xy}\} \\ &= \min\{1 - \varrho_{xy}, 1 - \varsigma_{xy}\} \\ &= [\varrho_{xy}]^c \cap [\varsigma_{xy}]^c. \end{aligned}$$

(ii) For all x and y ,

$$\begin{aligned} & ([\varrho_{xy}] \cap [\varsigma_{xy}])^c \\ &= (\min\{\varrho_{xy}, \varsigma_{xy}\})^c \end{aligned}$$

$$\begin{aligned}
 &= 1 - \min \{ \varrho_{xy}, \varsigma_{xy} \} \\
 &= \max \{ 1 - \varrho_{xy}, 1 - \varsigma_{xy} \} \\
 &= [\varrho_{xy}]^c \cup [\varsigma_{xy}]^c.
 \end{aligned}$$

Theorem 3.7. Let $[\varrho_{xy}], [\varsigma_{xy}] \in \varpi_{SR}$. Then

- (i) $\varrho_{xy} \cup a_{xy} = \varrho_{xy}$
- (ii) $\varrho_{xy} \cap a_{xy} = \varrho_{xy}$
- (iii) $\varrho_{xy} \cup \varsigma_{xy} = \varsigma_{xy} \cup \varrho_{xy}$
- (iv) $\varrho_{xy} \cap \varsigma_{xy} = \varsigma_{xy} \cap \varrho_{xy}$

Proof.

Let $\varrho_{xy} \in I_{SR}$

(i) $\varrho_{xy} \cup \varrho_{xy} = a_{xy}$

$$\begin{aligned}
 \varrho_{xy} \cup \varrho_{xy} &= [\varrho_{xy}] \cup [\varrho_{xy}] \text{ for all } x, y \\
 &= \{ \max \{ \varrho_{xy}, \varrho_{xy} \} \} \text{ for all } x, y \\
 &= \{ \varrho_{xy} \} \\
 &= \varrho_{xy}.
 \end{aligned}$$

(ii) $\varrho_{xy} \cap \varrho_{xy} = \varrho_{xy}$

$$\begin{aligned}
 \varrho_{xy} \cap \varrho_{xy} &= [\varrho_{xy}] \cap [\varrho_{xy}] \text{ for all } x, y \\
 &= \min \{ \varrho_{xy}, \varrho_{xy} \} \text{ for all } x, y \\
 &= \{ \varrho_{xy} \} \\
 &= \varrho_{xy}.
 \end{aligned}$$

(iii) $\varrho_{xy} \cap \varsigma_{xy} = \varsigma_{xy} \cap \varrho_{xy}$

$$\begin{aligned}
 \varrho_{xy} \cap \varsigma_{xy} &= \{ \varrho_{xy} \} \cap \{ \varsigma_{xy} \} \text{ for all } x, y \\
 \varrho_{xy} \cap \varsigma_{xy} &= \min \{ \varrho_{xy}, \varsigma_{xy} \} \text{ for all } x, y \\
 &= \min \{ \varsigma_{xy}, \varrho_{xy} \} \text{ for all } x, y \\
 &= \varsigma_{xy} \cap \varrho_{xy}.
 \end{aligned}$$

(iv) $\varrho_{xy} \cup \varsigma_{xy} = \varsigma_{xy} \cup \varrho_{xy}$

$$\begin{aligned}
 \varrho_{xy} \cup \varsigma_{xy} &= \{ \varrho_{xy} \} \cup \{ \varsigma_{xy} \} \text{ for all } x, y \\
 \varrho_{xy} \cup \varsigma_{xy} &= \max \{ \varrho_{xy}, \varsigma_{xy} \} \text{ for all } x, y \\
 &= \max \{ \varsigma_{xy}, \varrho_{xy} \} \text{ for all } x, y \\
 &= \varsigma_{xy} \cup \varrho_{xy}.
 \end{aligned}$$

Theorem 3.8. Let $[\varrho_{xy}], [\varsigma_{xy}]$ and $[\xi_{xy}] \in \varpi_{SR}$. Then

(i) $(\varrho_{xy} \cup \varsigma_{xy}) \cup \xi_{xy} = \varrho_{xy} \cup (\varsigma_{xy} \cup \xi_{xy})$

$$(ii)(\varrho_{xy} \cap \varsigma_{xy}) \cap \xi_{xy} = \varrho_{xy} \cap (\varsigma_{xy} \cap \xi_{xy}).$$

Proof.

Let ϱ_{xy} , ς_{xy} and $\xi_{xy} \in I_{SR}$

$$(i)(\varrho_{xy} \cup \varsigma_{xy}) \cup \xi_{xy} = \varrho_{xy} \cup (\varsigma_{xy} \cup \xi_{xy})$$

$$\begin{aligned} (\varrho_{xy} \cup \varsigma_{xy}) \cup \xi_{xy} &= (\varrho_{xy} \cup \varsigma_{xy}) \cup \xi_{xy} \\ &= \max\{\varrho_{xy}, \varsigma_{xy}\} \cup \xi_{xy} \text{ for all } x, y \\ &= \max\left\{\max\{\varrho_{xy}, \varsigma_{xy}\}, \xi_{xy}\right\} \\ &= \max\left\{\varrho_{xy}, \max\{\varsigma_{xy}, \xi_{xy}\}\right\} \\ &= \varrho_{xy} \cup \max\{\varsigma_{xy}, \xi_{xy}\} \\ &= \varrho_{xy} \cup (\varsigma_{xy} \cup \xi_{xy}) \end{aligned}$$

$$(ii)(\varrho_{xy} \cap \varsigma_{xy}) \cap \xi_{xy} = \varrho_{xy} \cap (\varsigma_{xy} \cap \xi_{xy})$$

$$\begin{aligned} (\varrho_{xy} \cap \varsigma_{xy}) \cap \xi_{xy} &= (\varrho_{xy} \cap \varsigma_{xy}) \cap \xi_{xy} \\ &= \min\{\varrho_{xy}, \varsigma_{xy}\} \cap \xi_{xy} \text{ for all } x, y \\ &= \min\left\{\min\{\varrho_{xy}, \varsigma_{xy}\}, \xi_{xy}\right\} \\ &= \min\left\{\varrho_{xy}, \min\{\varsigma_{xy}, \xi_{xy}\}\right\} \\ &= \varrho_{xy} \cap \min\{\varsigma_{xy}, \xi_{xy}\} \\ &= \varrho_{xy} \cap (\varsigma_{xy} \cap \xi_{xy}) \end{aligned}$$

Theorem 3.9. Let $[\varrho_{xy}], [\varsigma_{xy}] \in \varpi_{SR}$. Then

$$(i)(\varrho_{xy} \cup \varsigma_{xy})^C = \varrho_{xy}^C \cap \varsigma_{xy}^C$$

$$(ii)(\varrho_{xy} \cap \varsigma_{xy})^C = \varrho_{xy}^C \cup \varsigma_{xy}^C$$

Proof.

Let $\varrho_{xy}, \varsigma_{xy} \in I_{SR}$

$$(i)(\varrho_{xy} \cup \varsigma_{xy})^C = (\varrho_{xy} \cup \varsigma_{xy})^C \text{ for all } x, y$$

$$\begin{aligned} (\varrho_{xy} \cup \varsigma_{xy})^C &= 1 - (\varrho_{xy} \cup \varsigma_{xy}) \\ &= 1 - \left\{\max(\varrho_{xy}, \varsigma_{xy})\right\} \text{ for all } x, y \\ &= \min\left\{(1 - \varrho_{xy}), (1 - \varsigma_{xy})\right\} \\ &= \min\left\{\varrho_{xy}^C, \varsigma_{xy}^C\right\} \\ &= \varrho_{xy}^C \cap \varsigma_{xy}^C. \end{aligned}$$

$$(ii)(\varrho_{xy} \cap \varsigma_{xy})^C = (\varrho_{xy} \cap \varsigma_{xy})^C \text{ for all } x, y$$

$$\begin{aligned} (\varrho_{xy} \cap \varsigma_{xy})^C &= 1 - (\varrho_{xy} \cap \varsigma_{xy}) \\ &= 1 - \left\{ \min(\varrho_{xy}, \varsigma_{xy}) \right\} \text{ for all } x, y \\ &= \max\left\{ (1 - \varrho_{xy}), (1 - \varsigma_{xy}) \right\} \\ &= \max\left\{ \varrho_{xy}^C, \varsigma_{xy}^C \right\} \\ &= \varrho_{xy}^C \cup \varsigma_{xy}^C. \end{aligned}$$

Theorem 3.10. Let $[\varrho_{xy}]$, $[\varsigma_{xy}]$ and $[\xi_{xy}] \in \varpi_{SR}$. Then

$$(i)(\varrho_{xy} \cup \varsigma_{xy}) \cap \xi_{xy} = (\varrho_{xy} \cap \xi_{xy}) \cup (\varsigma_{xy} \cap \xi_{xy})$$

$$(ii)(\varrho_{xy} \cap \varsigma_{xy}) \cup \xi_{xy} = (\varrho_{xy} \cup \xi_{xy}) \cap (\varsigma_{xy} \cup \xi_{xy}).$$

Proof.

Let $\varrho_{xy}, \varsigma_{xy}$ and $\xi_{xy} \in I_{SR}$.

$$(i)(\varrho_{xy} \cup \varsigma_{xy}) \cap \xi_{xy} = (\varrho_{xy} \cap \xi_{xy}) \cup (\varsigma_{xy} \cap \xi_{xy})$$

$$\begin{aligned} (\varrho_{xy} \cup \varsigma_{xy}) \cap \xi_{xy} &= \max\left\{ \varrho_{xy}, \varsigma_{xy} \right\} \cap \xi_{xy} \\ &= \min\left\{ \max(\varrho_{xy}, \varsigma_{xy}), \xi_{xy} \right\} \\ &= \max\left\{ \min(\varrho_{xy}, \xi_{xy}), \min(\varsigma_{xy}, \xi_{xy}) \right\} \\ &= \min\left\{ \varrho_{xy} \cap \xi_{xy}, \varsigma_{xy} \cap \xi_{xy} \right\} \\ &= (\varrho_{xy} \cap \xi_{xy}) \cup (\varsigma_{xy} \cap \xi_{xy}). \end{aligned}$$

$$(ii)(\varrho_{xy} \cap \varsigma_{xy}) \cup \xi_{xy} = (\varrho_{xy} \cup \xi_{xy}) \cap (\varsigma_{xy} \cup \xi_{xy})$$

$$\begin{aligned} (\varrho_{xy} \cap \varsigma_{xy}) \cup \xi_{xy} &= \min\left\{ \varrho_{xy}, \varsigma_{xy} \right\} \cup \xi_{xy} \\ &= \max\left\{ \min(\varrho_{xy}, \varsigma_{xy}), \xi_{xy} \right\} \\ &= \min\left\{ \max(\varrho_{xy}, \xi_{xy}), \max(\varsigma_{xy}, \xi_{xy}) \right\} \\ &= \max\left\{ \varrho_{xy} \cup \xi_{xy}, \varsigma_{xy} \cup \xi_{xy} \right\} \\ &= (\varrho_{xy} \cup \xi_{xy}) \cap (\varsigma_{xy} \cup \xi_{xy}). \end{aligned}$$

Theorem 3.11. Let $[\varrho_{xy}] \in \varpi_{SR}$. Then

$$\varrho_{xy} \cup \varrho_{xy} = \varrho_{xy} \cap \varrho_{xy} = \varrho_{xy}.$$

Proof.

Follows from Theorem 3.7.

Theorem 3.12. Let $[\varrho_{xy}]$ and $[\varsigma_{xy}] \in \varpi_{SR}$. Then

$$(i) \varrho_{xy} \cup (\varrho_{xy} \cap \varsigma_{xy}) = \varrho_{xy}$$

$$(ii) \varrho_{xy} \cap (\varrho_{xy} \cup \varsigma_{xy}) = \varrho_{xy}.$$

Proof.

Let ϱ_{xy} and $\varsigma_{xy} \in \varpi_{SR}$

$$(i) \varrho_{xy} \cup (\varrho_{xy} \cap \varsigma_{xy}) = \varrho_{xy} \cup (\varrho_{xy} \cap \varsigma_{xy}) \text{ for all } x,y$$

$$\begin{aligned} &= \max\left\{\varrho_{xy}, (\varrho_{xy} \cap \varsigma_{xy})\right\} \\ &= \max\left\{\varrho_{xy}, \min(\varrho_{xy}, \varsigma_{xy})\right\} \\ &= \varrho_{xy}. \end{aligned}$$

$$(ii) \varrho_{xy} \cap (\varrho_{xy} \cup \varsigma_{xy}) = \varrho_{xy_{xy}} \cap (\varrho_{xy_{xy}} \cup \varsigma_{xy_{xy}}) \text{ for all } x,y$$

$$\begin{aligned} &= \min\left\{\varrho_{xy}, (\varrho_{xy} \cup \varsigma_{xy})\right\} \\ &= \min\left\{\varrho_{xy}, \max(\varrho_{xy}, \varsigma_{xy})\right\} \\ &= \varrho_{xy}. \end{aligned}$$

Theorem 3.13. Let $[\varrho_{xy}]$ and $[\varsigma_{xy}] \in \varpi_{SR}$. Then

$$(i) \varrho_{xy} \cup \varsigma_{xy} = \varsigma_{xy} \cup \varrho_{xy}$$

$$(ii) \varrho_{xy} \cap \varsigma_{xy} = \varsigma_{xy} \cap \varrho_{xy}.$$

Proof.

Follows from Theorem 3.7.

Definition 3.14. Let $\varrho_{xy} \in \varpi_{SR}$. Then the transpose of ϱ_{xy} is defined as

$$\varrho_{xy}^T = \varrho_{xy}.$$

Theorem 3.15. Let $[\varrho_{xy}] \in \varpi_{SR}$. Then

$$(i) (\varrho_{xy} \cup \overline{\varrho_{xy}})^T = \overline{\varrho_{xy}}^T$$

$$(ii) (\varrho_{xy} \cap \overline{\varrho_{xy}})^T = \overline{\varrho_{xy}}^T$$

$$(iii) (\varrho_{xy}^T)^T = \overline{\varrho_{xy}}.$$

Proof.

Let $\varrho_{xy} \in I_{SR}$ and $\varrho_{yx}^T = \varrho_{xy}$

(i)

$$\begin{aligned} (\varrho_{xy} \cup \varrho_{xy})^T &= \left(\max(\varrho_{xy}, \varrho_{xy}) \right)^T \\ &= (\varrho_{xy})^T. \end{aligned}$$

(ii)

$$\begin{aligned} (\varrho_{xy} \cap \varrho_{xy})^T &= \left(\min(\varrho_{xy}, \varrho_{xy}) \right)^T \\ &= (\varrho_{xy})^T \\ &= \varrho_{yx} \\ &= \varrho_{xy}^T. \end{aligned}$$

(iii) $(\varrho_{xy}^T)^T = \varrho_{xy}$ for all x, y

$$\begin{aligned} (\varrho_{xy}^T)^T &= (\varrho_{xy}^T)^T \\ &= \varrho_{yx} \\ &= \varrho_{xy}. \end{aligned}$$

Theorem 3.16. Let $[\varrho_{xy}]$ and $[\varsigma_{xy}] \in \varpi_{SR}$. Then

$$\begin{aligned} (i) (\varrho_{xy} \cup \varsigma_{xy})^T &= \varrho_{xy}^T \cup \varsigma_{xy}^T \\ (ii) (\varrho_{xy} \cap \varsigma_{xy})^T &= \varrho_{xy}^T \cap \varsigma_{xy}^T. \end{aligned}$$

Proof.

Let $\varrho_{xy}, b_{xy} \in I_{SR}$ and

$\varrho_{yx}^T = \varrho_{xy}$ and $\varsigma_{yx}^T = \varrho_{xy} \in \varpi_{SR}$

$$\begin{aligned} (\varrho_{xy} \cup b_{xy})^T &= \left(\max\{\varrho_{xy}, \varsigma_{xy}\} \right)^T \text{ for all } x, y \\ &= \max\{\varrho_{yx}, \varsigma_{yx}\} \text{ for all } x, y \\ &= \varrho_{yx} \cup \varsigma_{yx} \\ &= \varrho_{xy}^T \cup \varsigma_{xy}^T. \end{aligned}$$

$$\begin{aligned} (\varrho_{xy} \cap \varsigma_{xy})^T &= \left(\max\{\varrho_{xy}, b_{xy}\} \right)^T \text{ for all } x, y \\ &= \min\{\varrho_{yx}, \varsigma_{yx}\} \text{ for all } x, y \\ &= \varrho_{yx} \cap \varsigma_{yx} \\ &= \varrho_{xy}^T \cap \varsigma_{xy}^T. \end{aligned}$$

Theorem 3.17. Let $[\varrho_{xy}]$, $[\varsigma_{xy}]$ and $[\xi_{xy}] \in \varpi_{SR}$. Then

$$(i) [\varrho_{xy}] \cup ([\varsigma_{xy}] \cap [\xi_{xy}]) = ([\varrho_{xy}] \cup [\varsigma_{xy}]) \cap ([\varsigma_{xy}] \cup [\xi_{xy}]).$$

$$(ii) [\varrho_{xy}] \cap ([\varsigma_{xy}] \cup [\xi_{xy}]) = ([\varrho_{xy}] \cap [\varsigma_{xy}]) \cup ([\varrho_{xy}] \cap [\xi_{xy}]).$$

Proof.

(i) For all x and y ,

$$\begin{aligned} & ([\varrho_{xy}] \cup ([\varsigma_{xy}] \cap [\xi_{xy}])) \\ &= \max\{[\varrho_{xy}], [\varsigma_{xy}] \cap [\xi_{xy}]\} \\ &= \max\{[\varrho_{xy}], \min\{[\varsigma_{xy}], [\xi_{xy}]\}\} \\ &= \min\{\max\{[\varrho_{xy}], [\varsigma_{xy}]\}, \max\{[\varrho_{xy}], [\xi_{xy}]\}\} \\ &= ([\varrho_{xy}] \cup [d_{xy}]) \cap ([\varrho_{xy}] \cup [\xi_{xy}]). \end{aligned}$$

(ii) For all x and y ,

$$\begin{aligned} & ([\varrho_{xy}] \cap ([\varsigma_{xy}] \cup [\xi_{xy}])) \\ &= \min\{[\varrho_{xy}], [\varsigma_{xy}] \cup [\xi_{xy}]\} \\ &= \min\{[\varrho_{xy}], \max\{[\varsigma_{xy}], [\xi_{xy}]\}\} \\ &= \max\{\min\{[\varrho_{xy}], [\varsigma_{xy}]\}, \min\{[\varrho_{xy}], [\xi_{xy}]\}\} \\ &= ([\varrho_{xy}] \cap [\varsigma_{xy}]) \cup ([\varrho_{xy}] \cap [e_{xy}]). \end{aligned}$$

Definition 3.18. Let $[\varrho_{xy}]$ and $[\varsigma_{xy}] \in \varpi_{SR}$. Then the not intersection of $[\varrho_{xy}]$ and $[\varsigma_{xy}]$ is defined by $[\varrho_{xy}] \wedge [\varsigma_{xy}] = \min\{1 - \varrho_{xy}, 1 - \varsigma_{xy}\}$.

Definition 3.19. Let $[\varrho_{xy}]$ and $[\varsigma_{xy}] \in \varpi_{SR}$. Then the not union of $[\varrho_{xy}]$ and $[\varsigma_{xy}]$ is defined by $[\varrho_{xy}] \vee [\varsigma_{xy}] = \min\{1 - \varrho_{xy}, 1 - \varsigma_{xy}\}$.

Theorem 3.20. Let $[\varrho_{xy}]$ and $[d_{xy}] \in \varpi_{SR}$. Then

$$(i) ([\varrho_{xy}] \wedge [\varsigma_{xy}])^c = [\varrho_{xy}]^c \vee [\varsigma_{xy}]^c.$$

$$(ii) ([\varrho_{xy}] \vee [\varsigma_{xy}])^c = [\varrho_{xy}]^c \wedge [d_{xy}]^c.$$

Proof.

(i) For all x and y ,

$$\begin{aligned} & ([\varrho_{xy}] \wedge [\varsigma_{xy}])^c \\ &= (\max\{1 - \varrho_{xy}, 1 - \varsigma_{xy}\})^c \\ &= 1 - \max\{1 - \varrho_{xy}, 1 - \varsigma_{xy}\} \\ &= \min\{1 - (1 - \varrho_{xy}), 1 - (1 - \varsigma_{xy})\} \\ &= \min\{1 - [\varrho_{xy}]^c, 1 - [\varsigma_{xy}]^c\} \\ &= [\varrho_{xy}]^c \vee [\varsigma_{xy}]^c. \end{aligned}$$

(ii) For all x and y ,

$$\begin{aligned} & ([\varrho_{xy}] \vee [\varsigma_{xy}])^c \\ &= (\min\{1 - \varrho_{xy}, 1 - \varsigma_{xy}\})^c \\ &= 1 - \min\{1 - \varrho_{xy}, 1 - \varsigma_{xy}\} \\ &= \max\{1 - (1 - \varrho_{xy}), 1 - (1 - \varsigma_{xy})\} \\ &= \max\{1 - [\varrho_{xy}]^c, 1 - [\varsigma_{xy}]^c\} \\ &= [\varrho_{xy}]^c \vee [\varsigma_{xy}]^c. \end{aligned}$$

4 Conclusion

This paper talks about square soft-rough matrices (ssr m) and presents some interesting theorems and results related to them. This theory expands the concept of soft-rough matrices to ssr m.

5 Open Problem

Our research suggests that the following open problems could potentially be resolved.

- (1) Is it feasible to determine the inverse of ssr m.
- (2) Can we explore the concept of determinant and adjoint of SSRM in an intriguing manner.

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