

A NEUTROSOPHIC VAGUE FLOYD–WARSHALL ALGORITHM FOR MULTI-CRITERIA SHORTEST-PATH PROBLEMS

Siti Nurul Fitriah Mohamad^{1*}

Mashitah Mohd Yasin²

Norarida Abd Rhani³

Firdawati Mohamed⁴

¹Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Kelantan, (UiTM), Malaysia
(Email: fitriah@uitm.edu.my)

²Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Kelantan, (UiTM), Malaysia
(Email: 2024772317@student.uitm.edu.my)

³Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Kelantan, (UiTM), Malaysia
(Email: norarida@uitm.edu.my)

⁴Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Kelantan, (UiTM), Malaysia
(Email: firdawati02@uitm.edu.my)

Article history

Received date : 10-9-2026

Revised date : 10-9-2026

Accepted date : 17-10-2026

Published date : 25-10-2026

To cite this document:

Mohamad, S. N. F., Mohd Yasin, M., Abd Rhani, N., & Mohamed, F. (2026). A neutrosophic vague Floyd–Warshall algorithm for multi-criteria shortest-path problems. *Journal of Islamic, Social, Economics and Development (JISED)*, 11 (87), 927-936.

Abstract: Routing decisions in computer networks frequently involve imprecise, incomplete, and uncertain information arising from variations in bandwidth, delay, throughput, load, and link reliability. The classical Floyd–Warshall algorithm requires scalar and consistently ordered edge weights; therefore, it cannot directly evaluate multiple routing criteria with conflicting optimisation directions. This study develops a direction-aware Neutrosophic Vague Floyd–Warshall framework for multi-criteria routing under uncertainty. An illustrative directed network comprising five nodes, 11 edges, and nine routing criteria was analysed. The linguistic assessments were represented using a corrected seven-level neutrosophic vague scale and converted into numerical scores through a neutrosophic vague score function. Length, delay, cost, hop count, and load were treated as cost criteria, whereas bandwidth, maximum transmission unit, throughput, and reliability were treated as benefit criteria. The criterion scores were directionally normalised and aggregated using equal weights to produce a nonnegative composite penalty for each edge. These penalties were subsequently processed using the Floyd–Warshall recurrence, while a next-node matrix was employed to reconstruct the globally optimal routes. The results identified 1→3→5 as the optimal route from node 1 to node 5, with a total composite penalty of 0.6852. Independent enumeration of all feasible simple paths confirmed this result. The proposed framework resolves inconsistencies associated with direct vector comparisons and greedy Boolean edge selection while providing a transparent approach for uncertain multi-criteria routing. Future research should validate the framework using large-scale, dynamic, and real-time network data and expert-derived criterion weights.

Keywords: Floyd–Warshall algorithm; neutrosophic vague set; network optimisation; shortest-path problem.

Introduction

The shortest-path problem is a fundamental problem in graph theory and network optimisation. Given a weighted graph, the objective is to identify a path between two vertices that minimises the total cost associated with the traversed edges. Shortest-path algorithms have been applied in transportation planning, logistics, telecommunication systems, computer networks, and navigation systems. The Floyd–Warshall algorithm is particularly suitable for the all-pairs shortest-path problem because it determines the shortest paths between every pair of vertices through a dynamic-programming recurrence (Floyd, 1962). Its mathematical structure is also closely related to Warshall’s (1962) algorithm for determining the transitive closure of a graph. Classical shortest-path algorithms normally assume that every edge weight is known precisely. This assumption is difficult to justify in many routing applications because network conditions may be affected by variable bandwidth, fluctuating traffic loads, uncertain transmission delays, changing throughput, and incomplete reliability information. Fuzzy set theory was introduced to represent gradual membership and imprecise information (Zadeh, 1965). Subsequent extensions, including intuitionistic fuzzy sets and vague sets, incorporated additional information concerning non-membership and intervals of possible membership (Atanassov, 1986; Gau & Buehrer, 1993). Nevertheless, these representations may not fully distinguish truth, indeterminacy, and falsity when network information is incomplete or conflicting.

Neutrosophic sets address this limitation by representing information through truth-membership, indeterminacy-membership, and falsity-membership components. The single-valued neutrosophic set introduced by Wang et al. (2010) enables neutrosophic information to be represented within the unit interval. Alkhazaleh (2015) subsequently introduced the neutrosophic vague set (NVS), which combines the interval-based structure of vague sets with the three membership components of neutrosophic sets. This representation provides a potentially useful mechanism for modelling uncertain routing information.

Several studies have incorporated fuzzy or neutrosophic information into shortest-path algorithms. Jeyanthi and Radhika (2018) applied Floyd’s algorithm to neutrosophic shortest-path problems, whereas Broumi et al. (2019) extended the Bellman algorithm using interval-valued neutrosophic numbers. Sahoo et al. (2022) modified the Floyd–Warshall algorithm for uncertain wireless sensor networks. More recently, Habib et al. (2023) developed a picture-fuzzy Floyd–Warshall algorithm for a multi-parameter computer-routing network.

Despite these developments, three methodological issues remain. First, a conventional Floyd–Warshall comparison requires one ordered and additive edge cost, whereas a routing edge may contain several criteria measured in different directions. Length, delay, monetary cost, hop count, and network load are cost criteria that should be minimised. In contrast, bandwidth, maximum transmission unit (MTU), throughput, and reliability are benefit criteria that should be maximised. Directly minimising all nine criteria may therefore produce a misleading result. Second, a vector containing several criterion values cannot be inserted into the scalar Floyd–Warshall recurrence without a clearly defined comparison or aggregation rule. Third, selecting successive edges using the largest number of favourable Boolean comparisons is a greedy decision rule and does not necessarily reconstruct the globally shortest path represented by the Floyd–Warshall matrices.

Accordingly, this study proposes a direction-aware Neutrosophic Vague Floyd–Warshall framework. The framework first converts linguistic assessments into valid NVS representations, calculates their score values, transforms benefit and cost criteria into a common penalty direction, aggregates the normalised criteria into a scalar edge penalty, and finally

applies the Floyd–Warshall recurrence. The study has two objectives: (1) to develop a mathematically consistent NVS-based Floyd–Warshall framework for uncertain multi-criteria routing and (2) to demonstrate its application using a five-node computer-routing network adapted from Habib et al. (2023).

Literature Review

Classical and fuzzy shortest-path problems

The Floyd–Warshall algorithm determines the shortest distance between every ordered pair of nodes in a weighted directed graph. Let $d_{ij}^{(k)}$ represent the shortest distance from node i to node j when only nodes $1, \dots, k$ are permitted as intermediate nodes. Its recurrence is:

$$d_{ij}^{(k)} = \min \{d_{ij}^{(k-1)}, d_{ik}^{(k-1)} + d_{kj}^{(k-1)}\}$$

The algorithm performs this comparison for all combinations of i, j , and k , resulting in a computational complexity of $O(n^3)$, where n is the number of nodes (Floyd, 1962). It can accommodate positive and negative edge weights, provided the network does not contain a negative-weight cycle.

Classical edge weights are inadequate when distance, duration, cost, or network quality cannot be measured precisely. Zadeh's (1965) fuzzy set theory allows an object to possess a membership value between zero and one. Atanassov (1986) extended this idea by separately representing membership and non-membership, while Gau and Buehrer (1993) represented possible membership through a vague interval. These developments facilitated the formulation of fuzzy shortest-path algorithms in which imprecise edge information is ranked or transformed before shortest-path calculations are performed.

Sahoo et al. (2022), for instance, employed a modified Floyd–Warshall algorithm to determine maximum connectivity in wireless sensor networks under uncertainty. Their work demonstrated that uncertain edge information can be incorporated into network optimisation, but it also showed that the meaning and ordering of uncertain weights must be defined before comparisons are made. In a related real-world application, Marpaung and Harliana (2023) employed the Floyd–Warshall algorithm to optimise road networks in Medan City, demonstrating its effectiveness in determining optimal routes within complex transportation networks. More recently, Shaik and Ravishankar (2025) proposed Floyd-Warshall algorithm to find the critical path in network analysis using haar octagonal fuzzy numbers.

Neutrosophic representations in shortest-path analysis

A neutrosophic set represents an evaluation through independent truth, indeterminacy, and falsity membership values. A single-valued neutrosophic representation restricts the membership values to the interval $[0, 1]$ (Wang et al., 2010). An NVS extends this structure by representing each component as an interval:

$$A = \langle [T_A^-, T_A^+], [I_A^-, I_A^+], [F_A^-, F_A^+] \rangle$$

where:

$$0 \leq T_A^- \leq T_A^+ \leq 1, 0 \leq I_A^- \leq I_A^+ \leq 1, 0 \leq F_A^- \leq F_A^+ \leq 1$$

For an NVS, truth and falsity are dependent through:

$$T_A^+ = I - F_A^-, \quad F_A^+ = I - T_A^-$$

while indeterminacy is represented independently (Alkhazaleh, 2015). This interval structure is useful when a linguistic network assessment cannot be represented confidently by a single membership value.

Jeyanthi and Radhika (2018) applied Floyd's algorithm to a network with neutrosophic edge weights. Broumi et al. (2019) proposed an interval-valued neutrosophic Bellman algorithm and demonstrated how a ranking procedure could be used to identify a shortest path. These studies support the applicability of neutrosophic representations but mainly emphasise uncertain arc length rather than a routing problem containing multiple cost and benefit criteria.

Habib et al. (2023) addressed multi-parameter routing through trapezoidal picture-fuzzy information. Their network contained nine routing parameters: length, bandwidth, delay, cost, MTU, throughput, hop count, load, and reliability. The study demonstrated the importance of evaluating multiple network characteristics simultaneously. However, multi-criteria shortest-path problems require an explicit rule for comparing criterion vectors because different routes can be efficient under different objectives (Martins, 1984).

Research gap and proposed contribution

The literature establishes the usefulness of fuzzy and neutrosophic representations for uncertain routing. However, limited attention has been given to the direction of the routing criteria before their aggregation. Treating a high bandwidth or reliability value in the same way as a high delay or cost value reverses the meaning of the benefit criteria. Furthermore, a majority-based selection among edge-level Boolean comparisons cannot guarantee global path optimality. The present framework addresses these gaps through three improvements. First, all NVS intervals are constructed with valid lower and upper bounds. Second, each criterion is transformed according to whether it is a cost or benefit criterion. Third, the transformed criteria are aggregated into a scalar nonnegative penalty before the Floyd–Warshall recurrence is applied. This procedure retains the uncertainty-modelling role of NVS while preserving the mathematical requirements of the shortest-path algorithm.

Methodology

Research design and network data

This study employed a quantitative algorithm-development design supported by an illustrative numerical case. The directed network and its linguistic edge assessments were adapted from Habib et al. (2023). Table 1 shows the linguistic variable for each edge corresponding to each parameter and the network consisted of five nodes and 11 directed edges as shown in Figure 1:

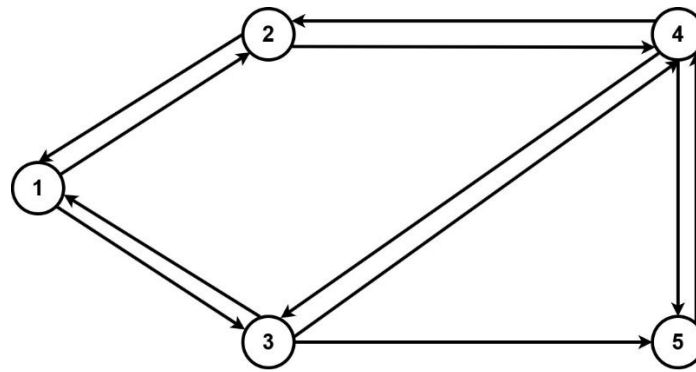


Figure 1: Directed network

Each edge was evaluated using nine criteria: C_1 : length, C_2 : bandwidth, C_3 : delay, C_4 : cost, C_5 : MTU, C_6 : throughput, C_7 : hop count, C_8 : load and C_9 : reliability. The cost criteria were C_1 , C_3 , C_4 , C_7 , and C_8 , while the benefit criteria were C_2 , C_5 , C_6 , and C_9 .

Table 1: Linguistic variable for each edge corresponding to each parameter

Edge (i, j)	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
(1,2)	VL	L	L	M	BM	H	VH	VL	AM
(1,3)	L	M	H	VL	VH	AM	BM	L	H
(2,1)	L	BM	VL	VH	AM	H	M	M	H
(2,4)	M	L	H	AM	BM	VL	VH	M	AM
(3,1)	L	L	H	BM	M	VH	AM	VL	VL
(3,4)	L	VL	AM	VL	BM	VH	AM	H	H
(3,5)	L	L	BM	BM	AM	H	VL	VH	M
(4,2)	H	H	H	VH	VL	BM	AM	AM	M
(4,3)	L	M	L	H	M	VH	AM	AM	M
(4,5)	M	M	M	AM	AM	BM	H	VL	VH
(5,4)	VH	VH	VH	VH	AM	M	H	AM	BM

Corrected NVS linguistic scale

Seven linguistic levels were used: very low (VL), low (L), below medium (BM), medium (M), above medium (AM), high (H), and very high (VH). The indeterminacy intervals were arranged so that $I^- \leq I^+$. The resulting scale is presented in Table 2.

Table 2: Corrected NVS linguistic scale and score values

Level	NVS representation	Score
VL	$\langle [0.20, 0.30], [0.15, 0.85], [0.70, 0.80] \rangle$	0.675
L	$\langle [0.30, 0.40], [0.25, 0.75], [0.60, 0.70] \rangle$	0.780
BM	$\langle [0.40, 0.50], [0.35, 0.65], [0.50, 0.60] \rangle$	0.905
M	$\langle [0.50, 0.50], [0.50, 0.50], [0.50, 0.50] \rangle$	1.000
AM	$\langle [0.60, 0.70], [0.35, 0.65], [0.30, 0.40] \rangle$	1.115
H	$\langle [0.70, 0.80], [0.25, 0.75], [0.20, 0.30] \rangle$	1.200
VH	$\langle [0.80, 0.90], [0.15, 0.85], [0.10, 0.20] \rangle$	1.305

The score for an NVS was calculated using the function adapted from Hashim et al. (2023):

$$s(A) = (T_A^- + T_A^+) / 2 + [1 - ((I_A^- + I_A^+) / 2) \times I_A^+] - ((F_A^- + F_A^+) / 2) \times (1 - F_A^+)$$

For example, the corrected score for VL is:

$$s(VL) = (0.20 + 0.30) / 2 + [1 - ((0.15 + 0.85) / 2) \times 0.85] - ((0.70 + 0.80) / 2) \times (1 - 0.80) = 0.675$$

The scores increase monotonically from VL to VH, thereby preserving the intended ordering of the linguistic assessments.

Directional normalisation and criterion aggregation

A high score does not have the same meaning for every criterion. For a cost criterion, a higher score represents a larger penalty. Therefore,

$$z_{ijr} = (s_{ijr} - s_r^{\min}) / (s_r^{\max} - s_r^{\min}), r \in \{1, 3, 4, 7, 8\}$$

For a benefit criterion, a higher score is preferable and must be converted into a lower penalty:

$$z_{ijr} = (s_r^{\max} - s_{ijr}) / (s_r^{\max} - s_r^{\min}), r \in \{2, 5, 6, 9\}$$

Consequently, every normalised value satisfies $0 \leq z_{ijr} \leq 1$, where a lower value consistently represents a more desirable condition.

Because no empirical or expert-derived criterion weights were provided in the secondary dataset, equal weights were used:

$$w_r = 1/9, \sum_{(r=1 \text{ to } 9)} w_r = 1$$

The scalar composite penalty for edge (i, j) was then calculated as:

$$c_{ij} = \sum_{(r=1 \text{ to } 9)} w_r \times z_{ijr}$$

Equal weights provide a transparent baseline but do not imply that all routing criteria are universally equally important. In a practical implementation, the weights should be elicited from network administrators or estimated using an objective weighting procedure.

Floyd–Warshall implementation

The initial distance matrix was defined as:

$$\begin{aligned} D_{ij}^{(0)} &= 0, \text{ for } i = j \\ D_{ij}^{(0)} &= c_{ij}, \text{ for } (i, j) \in E \\ D_{ij}^{(0)} &= \infty, \text{ for } (i, j) \notin E \end{aligned}$$

The matrix was updated using:

$$D_{ij}^{(k)} = \min \{D_{ij}^{(k-1)}, D_{ik}^{(k-1)} + D_{kj}^{(k-1)}\}, k = 1, \dots, n$$

A next-node matrix N was maintained for path reconstruction. Initially, $N_{ij} = j$ for every existing edge. Whenever the route through node k improved the current distance, the update was $N_{ij} = N_{ik}$. This is preferable to selecting an edge greedily using the number of favourable criteria because the next-node matrix reconstructs the route associated with the globally minimum accumulated penalty.

Verification and sensitivity assessment

The calculations were verified by independently enumerating all simple paths from node 1 to node 5. The four feasible simple paths were:

- $1 \rightarrow 3 \rightarrow 5$
- $1 \rightarrow 3 \rightarrow 4 \rightarrow 5$
- $1 \rightarrow 2 \rightarrow 4 \rightarrow 5$
- $1 \rightarrow 2 \rightarrow 4 \rightarrow 3 \rightarrow 5$

The total penalty of each path was calculated by summing the composite penalties of its constituent edges. A sensitivity assessment should also be performed in the final paper by varying the criterion weights because a routing decision may change when a particular criterion is given substantially greater importance.

Analysis and Discussion

Composite edge penalties

After correcting the NVS scale, normalising the criteria according to their directions, and applying equal weights, the composite penalties in Table 3 were obtained.

Table 3: Composite penalties for the directed edges

Edge	Composite penalty	Edge	Composite penalty
(1, 2)	0.4021	(3, 5)	0.4092
(1, 3)	0.2760	(4, 2)	0.7055
(2, 1)	0.3854	(4, 3)	0.4462
(2, 4)	0.7037	(4, 5)	0.4427
(3, 1)	0.4868	(5, 4)	0.6614
(3, 4)	0.4665		

Among the outgoing edges from node 1, edge (1, 3) had a lower composite penalty than edge (1, 2). Nevertheless, an edge-level comparison alone was insufficient to determine the optimal route because the remaining penalty from each subsequent node also had to be considered.

Final all-pairs distance matrix

The final distance matrix generated by the corrected Floyd–Warshall procedure was:

Matrix D*				
0	0.4021	0.2760	0.7425	0.6852
0.3854	0	0.6614	0.7037	1.0706
0.4868	0.8889	0	0.4665	0.4092
0.9330	0.7055	0.4462	0	0.4427
1.5944	1.3669	1.1076	0.6614	0

For example, the minimum composite penalty from node 1 to node 5 was 0.6852. Path reconstruction using the next-node matrix produced: $1 \rightarrow 3 \rightarrow 5$. The total penalty was:

$$c_{13} + c_{35} = 0.2760 + 0.4092 = 0.6852.$$

Comparison of alternative paths

Table 4: Comparison of feasible paths from node 1 to node 5

Rank	Path	Number of edges	Total penalty
1	$1 \rightarrow 3 \rightarrow 5$	2	0.6852
2	$1 \rightarrow 3 \rightarrow 4 \rightarrow 5$	3	1.1852
3	$1 \rightarrow 2 \rightarrow 4 \rightarrow 5$	3	1.5485
4	$1 \rightarrow 2 \rightarrow 4 \rightarrow 3 \rightarrow 5$	4	1.9612

The results demonstrate that $1 \rightarrow 3 \rightarrow 5$ is the optimal route under equal criterion weights. It has the smallest total penalty and requires only two directed edges. The route $1 \rightarrow 2 \rightarrow 4 \rightarrow 3 \rightarrow 5$, which has a penalty of 1.9612, is approximately 2.86 times as costly as the optimal route on the composite scale.

The corrected result differs from a decision obtained by choosing the outgoing edge with the largest number of favourable Boolean labels. Such a procedure selects each edge locally without evaluating the total effect of the remaining route. Greedy edge selection is therefore not an appropriate method for reconstructing a Floyd–Warshall solution. The predecessor or next-node matrix must be used instead.

The analysis also highlights the importance of criterion direction. For example, higher bandwidth, MTU, throughput, and reliability should reduce the composite penalty, whereas higher length, delay, cost, hop count, and load should increase it. Without this transformation, the algorithm would incorrectly penalise edges that possess favourable benefit values.

The findings should nevertheless be interpreted as an illustrative numerical demonstration rather than evidence of operational network superiority. The dataset contains only five nodes, 11 edges, linguistic assessments adapted from an earlier study, and no empirically estimated criterion weights. No comparison with real network measurements, conventional Floyd–Warshall results, or other uncertain shortest-path algorithms was conducted. Consequently, the present application demonstrates mathematical feasibility but does not establish large-scale computational efficiency or practical routing performance.

Future empirical validation should use time-stamped network observations, such as actual latency, bandwidth, packet loss, throughput, and link reliability. The proposed framework should also be compared with classical Floyd–Warshall, fuzzy Floyd–Warshall, picture-fuzzy Floyd–Warshall, and Pareto-based multi-objective shortest-path procedures. Computational time, route stability, sensitivity to weights, and agreement with observed network performance should be reported.

Conclusion

This study developed a direction-aware Neutrosophic Vague Floyd–Warshall framework for multi-criteria routing under uncertainty. The framework represents uncertain linguistic information using valid NVS intervals, converts the intervals into score values, distinguishes

benefit criteria from cost criteria, and aggregates the normalised evaluations into a scalar edge penalty. The scalar penalties allow the conventional Floyd–Warshall recurrence and its global optimality logic to be applied consistently.

Application to the five-node routing network showed that the optimal route from node 1 to node 5 was $1 \rightarrow 3 \rightarrow 5$, with a total composite penalty of 0.6852. This result was confirmed by enumerating and comparing all feasible simple paths. The analysis also demonstrated that selecting edges according to the largest number of favourable Boolean values can produce a route that is inconsistent with the Floyd–Warshall distance and path matrices.

The principal contribution of the framework is the integration of NVS-based uncertainty representation with directionally consistent multi-criteria aggregation and valid path reconstruction. However, the findings remain dependent on a small illustrative network and equal criterion weights. Further research should validate the framework using large-scale, dynamic, and real-time network data; elicit criterion weights from relevant experts; conduct comprehensive sensitivity analysis; and compare the proposed framework with established fuzzy, neutrosophic, and multi-objective shortest-path algorithms.

Acknowledgement

The authors gratefully acknowledge Universiti Teknologi MARA (UiTM) Cawangan Kelantan for providing the institutional support, resources, and facilities necessary for the successful completion of this research.

References

- Alkhazaleh, S. (2015). Neutrosophic vague set theory. *Critical Review*, 10, 29–39.
- Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, 20(1), 87–96.
- Broumi, S., Dey, A., Talea, M., Bakali, A., Smarandache, F., Nagarajan, D., Lathamaheswari, M., & Kumar, R. (2019). Shortest path problem using Bellman algorithm under neutrosophic environment. *Complex & Intelligent Systems*, 5, 409–416.
- Floyd, R. W. (1962). Algorithm 97: Shortest path. *Communications of the ACM*, 5(6), 345.
- Gau, W.-L., & Buehrer, D. J. (1993). Vague sets. *IEEE Transactions on Systems, Man, and Cybernetics*, 23(2), 610–614.
- Habib, S., Majeed, A., Akram, M., & Ali Al-Shamiri, M. M. (2023). Floyd–Warshall algorithm based on picture fuzzy information. *Computer Modeling in Engineering & Sciences*, 136(3), 2873–2894.
- Hashim, H., Awang, N. A., & Abdullah, L. (2023). A normalized weighted Bonferroni mean aggregation operator in neutrosophic vague multi-criteria decision-making. *International Journal of Neutrosophic Science*, 22(1), 86–103.
- Jeyanthi, V., & Radhika, V. S. (2018). Applying Floyd’s algorithm for solving neutrosophic shortest path problems. *International Journal of Mathematics Trends and Technology*, 61(1), 58–63.
- Marpaung, F., & Harliana, P. (2023). Floyd-Warshall algorithm for web-based route optimization for a road network study in Medan City. *Jurnal Multidisiplin Madani (MUDIMA)*, 3(11), 2192–2208.
- Martins, E. Q. V. (1984). On a multicriteria shortest path problem. *European Journal of Operational Research*, 16(2), 236–245.
- Sahoo, L., Sen, S., Tiwary, K., Samanta, S., & Senapati, T. (2022). Modified Floyd–Warshall’s algorithm for maximum connectivity in wireless sensor networks under uncertainty. *Discrete Dynamics in Nature and Society*, 2022, Article 5973433.
- Shaik, R., & Ravishankar, N. R. (2025). An algorithmic approach of solving fuzzy critical path problem using Haar ranking octagonal fuzzy number method. *Communications on Applied Nonlinear Analysis*, 32(1), 344–351.
- Wang, H., Smarandache, F., Zhang, Y. Q., & Sunderraman, R. (2010). Single valued neutrosophic sets. *Multispace and Multistructure*, 4, 410–413.
- Warshall, S. (1962). A theorem on Boolean matrices. *Journal of the ACM*, 9(1), 11–12.
- Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8(3), 338–353.