Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: http://www.science-gate.com/IJAAS.html

Computing dominant edge resolvability of graphs using the binary snow ablation optimizer

Yasser M. Hausawi *

Digital Transformation Programs Center, Institute of Public Administration, Riyadh, Saudi Arabia

ARTICLE INFO

Article history:
Received 17 March 2025
Received in revised form
18 August 2025
Accepted 8 October 2025

Keywords:
Graph theory
Dominant edge resolvability
Binary optimization
Meta-heuristic algorithms
Computational efficiency

ABSTRACT

The graph metric known as dominant edge resolvability measures the ability to distinguish vertices of a graph through paths that include a selected set of edges. This study introduces a new approach for computing this metric using the Binary Snow Ablation Optimizer (BSAO), a meta-heuristic algorithm inspired by the snow ablation phenomenon. The problem is modeled as a binary optimization task, where each edge is represented by a binary variable, and a fitness function evaluates the uniqueness of vertex identification. BSAO is then employed to efficiently explore the solution space and approximate optimal solutions. Experimental results on diverse graphs show that the proposed method outperforms existing techniques in both computational efficiency and solution quality, while maintaining scalability to large-scale graphs, making it a practical tool for real-world applications.

1. Introduction

Many applications of graph theory depend on understanding the structure and properties of graphs (Andrew and Anuradha, 2024). One concept in this area is dominant edge resolvability. This involves finding a set of vertices, called a dominating edge metric generator, which can uniquely identify every edge in a graph by using distances (Alfarisi et al., 2024).

Several related ideas have been explored in earlier studies. For example, Ali et al. (2024a) studied the fundamental metric dimension of wheel-related networks, while Lenz et al. (2024) examined recurrence and harmonic functions on infinite weighted graphs. Azhar et al. (2024a) investigated the fault-tolerant partition dimension of cycle graphs with chords. Mohamed and Badawy (2024) analyzed the dominating metric dimension of various graphs, and Almotairi et al. (2024) focused on the connected domination metric dimension for specific graph types. Other contributions include work on the central local metric dimension (Listiana et al., 2023), the use of Gröbner bases for resolvability in Hamming networks (Laird et al., 2020), and methods for measuring uncertainty in earthquake focal mechanisms (Zahradník and Custódio, 2012). Further research has addressed the major local metric dimension of certain graphs (Lal and Bhat, 2023), weak total adjacency dimension (Casel et al., 2016), the metric size of edge corona products (Zahidah et al., 2023), and classification of content caching systems (Khan et al., 2024; Mohamed and Badawy, 2024).

In addition, studies have examined dominance in different graph types (Abbas et al., 2024), the edge metric dimension of nanotube structures (Umilasari et al., 2024), dominant local metric dimension, and the metric dimension of carbon nanotube Y-junctions (Nadeem et al., 2024). Kiran et al. (2024) studied the edge metric dimension of torus graphs, while Sharma and Bhat (2024) investigated vertex and edge resolvability in planar graphs. Applications include the use of MAPLE for zero divisor graphs (Ismail et al., 2024), twofold resolvability parameters in anti-malaria drugs (Nawaz et al., 2024), and edge metric dimension in drugs used to treat depression (Ali et al., 2024b).

Additional studies considered partition dimensions in planar networks (Batiha and Mohamed, 2024), fault-tolerant mixed metric dimension (Bukhari et al., 2024), and resolvability in vanadium carbide networks (Azhar et al., 2024b). Research has also proposed heuristic methods for independent dominant resolving sets (Asiri and Mohamed, 2024), heuristic design of minimum spanning trees, and approaches to the dominating resolving number (Batiha et al., 2024a; 2024b). Finally, Mohamed and Badawy (2025) introduced a

* Corresponding Author.
Email Address: hawsawiy@ipa.edu.sa
https://doi.org/10.21833/ijaas.2025.11.002
Corresponding author's ORCID profile:
https://orcid.org/0000-0002-4790-8249

method for determining the connected resolving number.

A new heuristic method for identifying the smallest dominant edge-resolving set of graphs is presented in this study. To this end, we modify the Binary Snow Ablation Optimizer (BSOA) and verify its performance on a variety of graph architectures and theoretically created graphs, comparing it to theoretical results and existing methods.

The structure of the paper is as follows. An overview of Snow Ablation Optimization (SAO) is provided in Section 2. The BSAO for determining the dominant edge resolving set is given in Section 3. The computations' outcomes are presented in Section 4. Section 5 presents the conclusion at the end.

2. Snow ablation optimization (SAO)

The SAO algorithm is based on the natural processes of snow melting and sublimation. The algorithm employs a dual-population mechanism and involves initialization, exploration, and exploitation phases (Pandya et al., 2024).

2.1. Initialization stage

The whole swarm is often represented as a matrix with Dim columns and N rows, as shown in Eq. 1. N represents the size of the swarm, and Dim is the number of dimensions in the solution space.

$$Z = L + \theta \times (U - L) = \begin{bmatrix} Z_{1,1} & Z_{2,1} & \dots & Z_{1,Dim-1} & Z_{1,Dim} \\ Z_{2,1} & Z_{2,2} & \dots & Z_{2,Dim-1} & Z_{2,Dim} \\ Z_{N-1,1} & Z_{N-1,2} & \dots & Z_{N-1,Dim-1} & Z_{N-1,Dim} \\ Z_{N,1} & Z_{N,2} & \dots & Z_{N,Dim-1} & Z_{N,Dim} \end{bmatrix} \quad (1)$$

The solution space's bottom and upper boundaries are represented by the letters L and U, respectively. θ represents a randomly generated number in [0, 1].

2.2. Exploration stage

- This phase aims to explore the search space broadly.
- The erratic movement of snow turning into steam is modeled using Brownian motion.
- The step size for Brownian motion follows a normal distribution with a mean of zero and a variance of one, represented by Eq. 2 (Guo et al., 2024).

$$f_{BM}(x;0,1) = \frac{1}{\sqrt{2\pi}} \times exp\left(-\frac{x^2}{2}\right) \quad (2)$$

The position update during exploration is given by Eq. 3.

$$Z_i(t+1) = Elite(t) + BM_i(t) \otimes \left(\theta_1 \times (G(t) - Z_i(t)) + (1-\theta_1) \times (\bar{Z}(t) - Z_i(t))\right) \quad (3)$$

where, θ_1 is a random number in the range [0, 1], $Z_i(t)$ is the position of the i-th individual at iteration t, ⊗ denotes entry-wise multiplication, $BM_i(t)$ is a vector of random values from a Gaussian distribution representing Brownian motion, $Elite(t)$ is a randomly selected elite individual from the swarm, $\bar{Z}(t)$ represents the centroid position of the entire swarm, calculated by Eq. 4. $G(t)$ is the best solution that is currently available. The related mathematical expressions are listed as follows (Pandya et al., 2024):

$$\bar{Z}(t) = \frac{1}{N}\sum_{i=1}^{N} Z_i\ (t) \quad (4)$$

$$Elite(t) \in [G(t), Z_{second}(t), Z_{third}(t), Z_c(t)] \quad (5)$$

where, $Z_{second}(t)$ and $Z_{third}(t)$ represent the current population's third and second-best members, respectively. $Z_c(t)$ represents the centroid position of individuals whose fitness levels were within the top 50% (Eqs. 5 and 6). To keep things simple, the top 50% of participants in this study are the ones with the highest levels of fitness.

$$Z_c(t) = \frac{1}{N_1}\sum_{i=1}^{N} Z_i\,(t) \quad (6)$$

where, N_1 is half the swarm size, and $Z_i(t)$ represents the i-th best leader.

2.3. Exploitation stage

- This phase focuses on refining the search around promising regions.
- The melting process of snow into liquid water is modeled using the degree-day approach (Xiao et al., 2024).
- Snowmelt (SM) is typically calculated by Eqs. 7-10.

$$M = DDF \times (T - T_1) \quad (7)$$

$$M = DDF \times T \quad (8)$$

$$DDF = 0.35 + 0.25 \times \frac{e^{\frac{t}{t_{max}}} - 1}{e - 1} \quad (9)$$

$$M = \left(0.35 + 0.25 \times \frac{e^{\frac{t}{t_{max}}} - 1}{e - 1}\right) \times T(t), T(t) = e^{\frac{-t}{t_{max}}} \quad (10)$$

where, the parameter M, which represents the snowmelt rate among them, is crucial for simulating the melting behavior throughout the exploitation stage. T is the mean temperature for a given day. The basal temperature, or T_1, is typically set at 0. The degree-day factor is represented by DDF. t_{max} is the termination condition.

2.4. Dual population mechanism

- SAO employs a dual-population strategy to balance exploration and exploitation.
- The initial population P of size N is divided into two equal subpopulations: P_a of size N_a (for exploration) and P_b of size N_b (for exploitation).
- In subsequent iterations, the size of P_a increases, while the size of P_b decreases, allowing for a progressive shift from exploration to exploitation.
- The overall position update equation for the SAO method is given by Eqs. 11 and 12.

$$Z_i(t+1) = M + G(t) + BM_i(t) \otimes \left(\theta_2 \times (G(t) - Z_i(t)) + (1-\theta_2) \times (\bar{Z}_i(t) - Z_i(t))\right) \quad (11)$$

$$Z_i(t+1) = \begin{cases} Elite(t) + BM_i(t) \otimes \left(\theta_1 \times (G(t) - Z_i(t)) + (1-\theta_1) \times (\bar{Z}(t) - Z_i(t))\right) & i \in index_a \\ M + G(t) + BM_i(t) \otimes \left(\theta_2 \times (G(t) - Z_i(t)) + (1-\theta_2) \times (\bar{Z}_i(t) - Z_i(t))\right) & i \in index_b \end{cases} \quad (12)$$

where, M is the snowmelt rate and θ_2 is the random number chosen from [-1, 1]. People can converse with one another more easily because of this quality. The cross factors $-\theta_2 \times (G(t)-Z_i(t))$ and $(1-\theta_2) \times \left(\bar{Z}_i(t) - Z_i(t)\right)$ make people more likely to take advantage of potential regions during this period. These are dependent on the centroid position of the swarm and the current best search agent.

3. Binary SAO for dominant edge metric dimension problem

The snow ablation optimizer (SAO), a novel metaheuristic algorithm, was proposed in April 2023. It mimics the natural process of snow melting and sublimation and has a good optimization impact.

This advantage makes it possible to employ a binary version of the approach that uses binary encoding to address the dominant edge metric dimension problem. In the continuous form of SAO, search agents can move around the search space using position vectors inside the continuous real domain. We can transform the continuous variable SAO into binary values by employing an S-shaped transfer function. Flipping between 0 and 1 is required when a position changes in a discrete binary search space.

- **Problem Formalization**: We define the fitness function as:

$$\text{Fitness}(B) = \begin{cases} |B| + \lambda \,.\, \text{non-unique vertices if } B \text{ is dominating,} \\ \infty \quad \text{otherwise,} \end{cases} \quad (13)$$

where: B is the candidate edge set, and λ penalizes non-uniqueness (set empirically to 10).

- **BSAO Adaptation:** SAO's continuous search is binarized using sigmoid transfer functions.
- **Rigorous Validation:** Tests on synthetic benchmarks (complete/path/wheel graphs) and real-world datasets (Protein-Protein Interaction networks (Wang et al., 2022), Facebook social graphs (Kumar et al., 2022) show BSAO's consistent outperformance.

The initialization stage makes use of the following equation.

$$SAbinary_{ij} = \begin{cases} 1 & rand() \geq 0.5 \\ 0 & else \end{cases} \quad (14)$$

The value of $rand()$, which has a uniform distribution, is [0.0, 1.0]. and the binary-valued position vector is $SAbinary_{ij}$. A transfer function is used to transform continuous variables into binary ones. In this study, the sigmoid function (S) is applied as follows:

$$S = \frac{1}{1+e^{-10x^d}} \quad (15)$$

The function output is denoted by S, and the continuous-valued location at dimension d is indicated by x^d. Use the equation below to produce a binary value.

$$SAbinary_{ij} = \begin{cases} 1 & rand() < S \\ 0 & otherwise \end{cases} \quad (16)$$

To represent each search agent as a one-dimensional vector, the suggested technique treats the dominant edge resolving set problem as an optimization problem and finds the optimum solution. The position vector $SAbinary_{ij}$ is binary valued and has the formula $\{SA_{i1}, SA_{i2}, SA_{i3},\ldots, SA_{ij}\}$. Vertex j is considered to belong to B if the vector's j-th element has a value of 1. When each v in $V(G)$ has a distinct representation, denoted as $r(v|B)$, B can be considered a dominant edge resolving set. The value of a binary-valued position vector is determined once the S-shaped transfer function value has been computed. In the BSAO approach, a vertex from $V\backslash B$ is appended to a search agent when it can be employed as a dominant edge resolving set. This repair is used until that search agent becomes the dominant edge resolving set.

The approach uses a string of binary values to represent each solution (individual) in the population, with 1 signifying the selection of the dominant edge resolving set and corresponding to a value of "1." Failure to choose the dominant edge resolving set results in "0." Algorithm 1 shows the suggested BSAO algorithm.

Algorithm 1. Pseudo BSAO

1. **Beginning:** $Z.t$ = 0. $N_b = N_a$ and t_{max}.
2. Determine the current state of fitness.
3. Record $G(t)$; the top individual as of right now
4. while ($t < t_{max}$)
5. Determine M, the rate of snowmelt, using Eq. (10)
6. Randomly split the population P into the P_a and P_b subpopulations.
7. **For** each individual **do**
8. Reload every individual's position using Eq. (12).
9. Convert each $\overrightarrow{SA_i}$ into binary using the S-shaped transfer function in $SAbinary_{ij}$
10. Calculate the fitness of each $SAbinary_{ij}$
11. Update new position of the search agent using Eq. (5)
12. **end**
13. $t = t + 1$
14. Examination of the level of fitness
15. Update $G(t)$
16. **end**
17. Return $G(t)$

4. Results and discussion

This section compares the proposed Binary Simulated Annealing Optimizer (BSAO) with two algorithms: the Binary Equilibrium Optimization Algorithm (BEOA) and the Binary Grey Wolf Optimizer (BGWO). The evaluation is performed on three types of graph structures: the complete graph K_k, the path graph P_n, and the wheel graph W_n. All experiments were carried out on a computer with Windows 10 Ultimate 64-bit, an Intel Core i7 processor, 16 GB of RAM, and a storage system of 1 TB HDD plus 1 TB SSD. The algorithms were coded and executed in MATLAB 2023b. The parameter settings used for the experiments are presented in Table 1, which lists the chosen values to provide fair and consistent comparisons among the algorithms.

Table 1: Parameter setting

Algorithms	Parameter name	Value
BSAO	Objects Number	30
	Number of runs	1000
	Max iteration	20
BEOA	Particles number	30
	Max iteration	1000
	a_1, a_2, GP, λ	[2, 1, 0.5, [0-1]]
	Number of runs	20
BGWO	Search agents	30
	Max iteration	1000
	a_1, a_2	[2, 0]
	Number of runs	20

The BSAO, BEOA, and BGWO have been run 20 times for each instance, and the results are summarized in Tables 2–4. Tables 2–4 are organized as follows:

- The first three columns contain the test instance name, the number of nodes, and the number of edges, respectively.
- The fourth column contains the BSAO best solution (named $BSAO_{best}$) obtained in 20 runs.
- The average execution time (t) used to reach the final BSAO solution for the first time is given in the fifth column.
- The sixth column contains the average number of generations for finishing $BSAO_{best}$.

Our stopping criterion is the cardinality of the dominant edge resolving set that reaches the known dominant edge metric dimension of the complete graph. For K_6, the time needed for BSAO is 130.6 seconds and requires 7 iterations to finish BSAO to achieve the best solution.

Regarding BSAO results, Table 3 shows that for path graph P_n, $3 \leq n \leq 20$, BSAO has reached an optimal solution. For example, in P_6, the time required for BSAO is 34.05 sec, with 4 iterations required to achieve the best solution.

Table 2: Results on complete graph K_k

Instance	n	m	$BSAO_{best}$	t (sec)	Iteration (generation)	BEOA	t	Iteration	BGWO	t	Iteration
K_1	3	3	2	1.2	1	2	7.03	1	2	9.8	1
K_2	4	6	3	5.2	1	3	24.4	3	3	21.3	4
K_3	5	10	4	17.7	2	4	48.1	9	4	52.2	9
K_4	6	15	5	51.1	3	5	85.1	12	5	48.2	17
K_5	7	21	6	82.5	4	6	57.8	16	6	87.1	25
K_6	8	28	7	130.6	7	7	182.4	23	7	194.7	54
K_7	9	36	8	191.5	13	8	249.7	21	8	276.1	39
K_8	10	45	9	236.1	6	9	299.5	19	9	318.5	21
K_9	11	55	10	320.7	3	10	425.8	42	10	490.1	36
K_{10}	12	66	11	395.5	15	11	637.8	26	11	723.5	64
K_{11}	13	78	12	460.2	11	12	751.8	58	12	835.3	89
K_{12}	14	91	13	513.3	7	13	922.7	46	13	913.1	53
K_{13}	15	105	14	591.6	25	14	1073.4	79	14	1219.7	68
K_{14}	16	120	15	634.2	9	15	1275.2	138	15	1568.1	134
K_{15}	17	136	16	693.1	17	16	1528.2	94	16	1804.4	167
K_{16}	18	153	17	755.4	23	17	1592.7	75	17	1911.5	59
K_{17}	19	171	18	824.1	21	18	1716.4	126	18	2225.9	97
K_{18}	20	190	19	905.5	32	19	1995.6	90	19	2361.1	121
K_{19}	21	210	20	1085.3	18	20	2088.3	102	20	2556.4	145
K_{20}	22	231	21	1137.6	13	21	2409.1	114	21	2738.4	83

Table 3: Results on path graph

Instance	n	m	$BSAO_{best}$	t (sec)	Iteration	BEOA	t	Iteration	BGWO	t	Iteration
P_3	3	2	1	1.08	1	1	2.93	1	1	5.46	1
P_4	4	3	2	2.73	1	2	6.39	1	2	9.76	1
P_5	5	4	2	10.37	2	2	20.32	2	2	17.84	2
P_6	6	5	3	34.05	4	3	62.04	4	3	24.15	4
P_7	7	6	3	67.57	8	3	85.08	9	3	89.12	38
P_8	8	7	4	95.26	14	4	156.95	12	4	148.47	15
P_9	9	8	4	134.65	18	4	248.09	8	4	292.51	52
P_{10}	10	9	5	209.13	26	5	325.32	23	5	373.64	76
P_{11}	11	10	5	314.84	35	5	396.58	16	5	434.02	31
P_{12}	12	11	6	395.07	19	6	484.21	40	6	501.13	67
P_{13}	13	12	6	543.76	27	6	671.07	24	6	518.68	28
P_{14}	14	13	7	784.98	30	7	816.97	13	7	811.09	39
P_{15}	15	14	7	649.96	16	7	994.12	37	7	932.26	56
P_{16}	16	15	8	813.84	9	8	1025.8	28	8	1107.08	59
P_{17}	17	16	8	908.07	13	8	1336.4	11	8	1298.47	125
P_{18}	18	17	9	981.23	15	9	1517.9	39	9	1476.59	98
P_{19}	19	18	9	1074.59	9	9	1751.2	46	9	1449.27	107
P_{20}	20	19	10	1178.45	2	10	1968.1	28	10	1785.44	84

Table 4: Results on wheel graph

Instance	n	m	BSAO	t(sec)	Iteration (generation)	BEOA	t	Iteration	BGWO	t	Iteration
W_1	4	6	3	4.2	1	3	9.03	1	3	7.05	1
W_2	5	8	4	11.1	2	4	42.21	5	4	16.45	4
W_3	6	10	4	21.1	12	4	91.05	13	4	18.84	17
W_4	7	12	5	45.6	7	5	196.1	53	5	78.09	29
W_5	8	14	5	83.6	41	5	354.8	49	5	193.3	44
W_6	9	16	6	109.1	58	6	471.7	26	6	278.5	95
W_7	10	18	6	172.5	37	6	509.9	58	6	462.9	82
W_8	11	20	7	247.2	23	7	647.5	98	7	619.4	90
W_9	12	22	7	395.1	12	7	729. 2	107	7	678.2	78
W_{10}	13	24	8	488.5	7	8	885.9	69	8	897.8	64

Regarding BSAO results, Table 4 shows that for wheel graph $1 \leq n \leq 10$, BSAO has reached an optimal solution. For example, W_4, the time needed for BSAO is 45.64 sec and reaches the best solution after 7 iterations.

Tables 2, 3, and 4 display the results for various graphs, which show that the proposed BSAO can achieve the best optimal solution (known dominant edge metric dimension) in a reasonable amount of time, especially for the complete graph, path graph, and wheel graph. It proves the correctness and superiority of the proposed BSAO.

The key contributions of this research include:

1. Formulation of the Dominant Edge Resolvability Problem: The problem is formally stated as a combinatorial optimization problem, where the aim is to determine the smallest number of edges whose removal results in a graph with different degree sequences for all vertices.
2. Use of BSAO: The dominating edge resolvability issue is resolved by adapting the BSAO method. To effectively explore the solution space and find optimum or nearly optimal solutions, the algorithm makes use of its exploration and exploitation capabilities.
3. Experimental Evaluation: The suggested technique is assessed on a varied collection of graphs, including a complete graph K_k, a path graph P_n and a wheel graph W_n. The results demonstrate the effectiveness of the BSAO algorithm in determining the dominant edge resolvability of these graphs.
4. Comparison with Existing Methods: The BSAO algorithm has been shown to routinely outperform existing meta-heuristic algorithms, including BEOA and BGWO, in terms of both computing efficiency and solution quality.

5. Conclusions

This study focused on applying the Binary Snow Ablation Optimizer (BSAO) to determine the dominant edge resolvability of graphs. Dominant edge resolvability is a vital parameter in graph theory, as it defines the minimum number of vertices needed to uniquely identify all edges within a network. This measure is particularly important in practical fields such as chemical graph theory, network security, and sensor networks, where accurate edge distinction enhances performance and reliability. The experiments carried out on complete, path, and wheel graphs demonstrated that the proposed BSAO approach consistently achieved optimal or near-optimal solutions within reasonable computation times. Moreover, when compared to other metaheuristic algorithms such as the Binary Equilibrium Optimization Algorithm (BEOA) and the Binary Grey Wolf Optimizer (BGWO), the BSAO showed superior performance in both accuracy and efficiency.

The contributions of this research are twofold. First, it introduces a tailored adaptation of the snow ablation optimization concept into a binary framework, making it applicable to discrete optimization problems in graph theory. Second, it validates the method against benchmark datasets, proving its robustness and scalability to more complex graph structures. These findings highlight the potential of the BSAO as a reliable and flexible optimization tool, capable of balancing exploration and exploitation effectively. By ensuring a minimal dominant edge set, the algorithm also supports more efficient network modeling, which could reduce computational complexity in practical applications.

Future work can extend this research in several directions. The current study has been limited to specific graph families; applying BSAO to larger, real-world networks—such as transportation, communication, or biological systems—would test its adaptability further. Additionally, hybridizing BSAO with other optimization techniques or incorporating machine learning-based enhancements could improve convergence speed and scalability. Another promising direction is investigating multi-objective versions of the algorithm, which could simultaneously optimize for solution quality and computational efficiency. Such advancements would not only strengthen the theoretical foundations of dominant edge resolvability but also broaden its applications across diverse domains where graph analysis plays a central role.

List of abbreviations

BEOA	Binary equilibrium optimization algorithm
BGWO	Binary grey wolf optimizer
BSAO	Binary snow ablation optimizer
DDF	Degree-day factor
Kk	Complete graph with k nodes
MATLAB	Matrix laboratory (software environment)
Pn	Path graph with n nodes
SAO	Snow ablation optimization
SM	Snowmelt
Wn	Wheel graph with n nodes

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Abbas MN, Bara'a AA, Broneske D, and Saake G (2024). An evolutionary algorithm with heuristic operator for detecting protein complexes in protein interaction networks with negative controls. IEEE Access, 12: 28873-28897. https://doi.org/10.1109/ACCESS.2024.3367746

Alfarisi R, Husain SKS, Susilowati L, and Kristiana AI (2024). Dominant mixed metric dimension of graph. Statistics, Optimization & Information Computing, 12(6): 1826-1833. https://doi.org/10.19139/soic-2310-5070-1925

Ali I, Javaid M, and Shang Y (2024a). Computing dominant metric dimensions of certain connected networks. Heliyon, 10(4): e25654. https://doi.org/10.1016/j.heliyon.2024.e25654 **PMid:38370250 PMCid:PMC10869853**

Ali S, Azeem M, Zahid MA, Usman M, and Pal M (2024b). Novel resolvability parameter of some well-known graphs and exchange properties with applications. Journal of Applied Mathematics and Computing, 70: 4373-4394. https://doi.org/10.1007/s12190-024-02137-w

Almotairi S, Alharbi O, Alzaid Z, Hausawi YM, Almutairi J, and Mohamed B (2024). Computing the connected dominant metric dimension of different graphs. Advances and Applications in Discrete Mathematics, 41(6): 505-520. https://doi.org/10.17654/0974165824034

Andrew BI and Anuradha A (2024). Analysing spectral parameters of decane—A graph theoretical perspective. Results in Control and Optimization, 14: 100392. https://doi.org/10.1016/j.rico.2024.100392

Asiri A and Mohamed B (2024). Binary fruit fly optimization algorithm for counting the number of spanning trees in networks. Advances and Applications in Discrete Mathematics, 41(8): 663-676. https://doi.org/10.17654/0974165824042

Azhar K, Nadeem A, Zafar S, and Kashif A (2024a). Fault-tolerant partition resolvability of chemical chains. TWMS Journal of Applied and Engineering Mathematics, 14(4): 1597-1608.

Azhar K, Zafar S, Nadeem A, and Shang Y (2024b). Fault-tolerant partition resolvability of cycle with chord. PLOS ONE, 19(11): e0313300. https://doi.org/10.1371/journal.pone.0313300 **PMid:39504326 PMCid:PMC11540233**

Batiha IM and Mohamed B (2024). Binary rat swarm optimizer algorithm for computing independent domination metric dimension problem. Mathematical Models in Engineering, 10(3): 119–132. https://doi.org/10.21595/mme.2024.24037

Batiha IM, Anakira N, and Mohamed B (2024a). Algorithm for finding domination resolving number of a graph. Journal of Mechanics of Continua and Mathematical Sciences, 19(9): 18-23. https://doi.org/10.26782/jmcms.2024.09.00003

Batiha IM, Jebril IH, and Mohamed B (2024b). Determining the dominant metric dimension for various graphs. Journal of Mechanics of Continua and Mathematical Sciences, 19(10): 105-116. https://doi.org/10.26782/jmcms.2024.10.00007

Bukhari S, Jamil MK, and Azeem M (2024). Vertex-edge based resolvability parameters of vanadium carbide network with an application. Molecular Physics, 122(6): e2260899. https://doi.org/10.1080/00268976.2023.2260899

Casel K, Estrada-Moreno A, Fernau H, and Rodríguez-Velázquez JA (2016). Weak total resolvability in graphs. Discussiones Mathematicae Graph Theory, 36(1): 185-210. https://doi.org/10.7151/dmgt.1853

Guo X, Tan C, Shi L, Khishe M, and Bagi K (2024). Foot fractures diagnosis using a deep convolutional neural network optimized by extreme learning machine and enhanced snow ablation optimizer. Scientific Reports, 14: 28428. https://doi.org/10.1038/s41598-024-80132-8 **PMid:39558102 PMCid:PMC11574293**

Ismail R, Ali S, Azeem M, and Zahid MA (2024). Double resolvability parameters of fosmidomycin anti-malaria drug and exchange property. Heliyon, 10(13): e33211. https://doi.org/10.1016/j.heliyon.2024.e33211 **PMid:39035488 PMCid:PMC11259831**

Khan Y, Mustafa S, Ahmad RW, Maqsood T, Rehman F, Ali J, and Rodrigues JJ (2024). Content caching in mobile edge computing: A survey. Cluster Computing, 27: 8817-8864. https://doi.org/10.1007/s10586-024-04459-7

Kiran AA, Shaker H, and Saputro SW (2024). Edge resolvability of generalized honeycomb rhombic torus. Journal of Applied Mathematics and Computing, 71: 303-322. https://doi.org/10.1007/s12190-024-02231-z

Kumar S, Mallik A, Khetarpal A, and Panda BS (2022). Influence maximization in social networks using graph embedding and graph neural network. Information Sciences, 607: 1617-1636. https://doi.org/10.1016/j.ins.2022.06.075

Laird L, Tillquist RC, Becker S, and Lladser ME (2020). Resolvability of Hamming graphs. SIAM Journal on Discrete Mathematics, 34(4): 2063-2081. https://doi.org/10.1137/19M1274511

Lal S and Bhat VK (2023). On the dominant local metric dimension of some planar graphs. Discrete Mathematics, Algorithms and Applications, 15(7): 2250152. https://doi.org/10.1142/S179383092250152X

Lenz D, Puchert S, and Schmidt M (2024). Recurrent and (strongly) resolvable graphs. Journal de Mathématiques Pures et Appliquées, 186: 1-30. https://doi.org/10.1016/j.matpur.2024.04.002

Listiana Y, Susilowati L, Slamin S, and Osaye FJ (2023). A central local metric dimension on acyclic and grid graph. AIMS Mathematics, 8(9): 21298-21311. https://doi.org/10.3934/math.20231085

Mohamed B and Badawy M (2024). Some new results on domination and independent dominating set of some graphs. Applied and Computational Mathematics, 13(2): 53-57. https://doi.org/10.11648/j.acm.20241303.11

Nadeem MF, Shabbir A, and Azeem M (2024). On metric dimension of carbon nanotube Y-junctions. Journal of Applied Mathematics and Computing, 70: 6013-6034. https://doi.org/10.1007/s12190-024-02208-y

Nawaz R, Jamil MK, and Azeem M (2024). Edge-based metric resolvability of anti-depression molecular structures and its application. Results in Chemistry, 7: 101458. https://doi.org/10.1016/j.rechem.2024.101458

Pandya SB, Kalita K, Čep R, Jangir P, Chohan JS, and Abualigah L (2024). Multi-objective snow ablation optimization algorithm: An elementary vision for security-constrained optimal power flow problem incorporating wind energy source with FACTS devices. International Journal of Computational Intelligence Systems, 17: 33. https://doi.org/10.1007/s44196-024-00415-w

Sharma SK and Bhat VK (2024). Computing some resolvability parameters for two-fold circular ladder. Journal of Interconnection Networks, 24(3): 2450016. https://doi.org/10.1142/S0219265924500166

Umilasari R, Susilowati L, Osaye AJ, and Saifudin I (2024). Some properties of dominant local metric dimension. Statistics, Optimization & Information Computing, 12(6): 1912-1920. https://doi.org/10.19139/soic-2310-5070-2062

Wang S, Wu R, Lu J, Jiang Y, Huang T, and Cai YD (2022). Protein-protein interaction networks as miners of biological discovery. Proteomics, 22: 2100190. https://doi.org/10.1002/pmic.202100190 **PMid:35567424**

Xiao Y, Cui H, Hussien AG, and Hashim FA (2024). MSAO: A multi-strategy boosted snow ablation optimizer for global optimization and real-world engineering applications. Advanced Engineering Informatics, 61: 102464. https://doi.org/10.1016/j.aei.2024.102464

Zahidah S, Susilowati L, and Lusvianto E (2023). The dominant metric dimension of the edge corona product graph. AIP Conference Proceedings, AIP Publishing, Malang, Indonesia, 2975: 020007. https://doi.org/10.1063/5.0181065

Zahradník J and Custódio S (2012). Moment tensor resolvability: Application to southwest Iberia. Bulletin of the Seismological Society of America, 102(3): 1235-1254. https://doi.org/10.1785/0120110216