



An Eccentricity-Based Estrada Index for Finite Simple Connected Graphs

Narendra V H

Department of Mathematics, Government Science College, Chitradurga, Karnataka-577 501, India

* Corresponding Author: **Narendra V H**

Article Info

Impact Factor (RSIF): 8.62

ISSN (Online): 3107-7110

Volume: 02

Issue: 04

Received: 03-05-2026

Accepted: 05-06-2026

Published: 07-07-2026

Page No: 24-30

Abstract

The Estrada index is a well-known spectral invariant with numerous applications in graph theory, chemical graph theory, complex networks, and quantitative structure–property relationship (QSPR) studies. Motivated by the importance of vertex eccentricity in characterizing graph structures, this paper introduces a new eccentricity-based Estrada index defined by

$$EE_{\varepsilon}(G) = \sum_{v \in V(G)} e^{\varepsilon(v)}$$

where $\varepsilon(v)$ denotes the eccentricity of the vertex v . The proposed index incorporates distance-related information through an exponential weighting scheme and serves as an alternative descriptor of graph structure. Fundamental properties of the index are established, and exact formulae are derived for several standard graph classes, including complete graphs, cycle graphs, wheel graphs, and path graphs. Furthermore, the behavior of the index under graph transformations is investigated through total graphs and eccentric graphs, leading to theoretical results and a conjectured relationship involving eccentric graph constructions. Numerical examples are provided to demonstrate the effectiveness of the proposed invariant in distinguishing graph structures. Potential applications of the eccentricity-based Estrada index in network analysis, graph theory, and function approximation are also discussed. The results show that the proposed index provides a useful measure for quantifying structural complexity, connectivity, and distance distribution in graphs and complex networks.

Keywords: Estrada index, eccentricity, topological index, graph invariants, eccentric graph, total graph, complex networks, function approximation, graph transformation.

Mathematics Subject Classification (2020): 05C12, 05C35, 05C50, 92E10

1. Introduction

Graph theory has emerged as one of the most influential mathematical disciplines due to its extensive applications in chemistry, biology, computer science, communication networks, and social sciences^[3, 8]. A graph provides an abstract representation of relationships among objects and offers a convenient framework for quantitative analysis.

The study of graph invariants known as topological indices began with the pioneering work of Wiener in 1947^[7]. The Wiener index was introduced to correlate boiling points of paraffin hydrocarbons with molecular structures. Since then, numerous degree-based and distance-based topological indices have been proposed and successfully applied in quantitative structure–property relationships (QSPR) and quantitative structure–activity relationships (QSAR)^[4, 5].

One of the most important spectral invariants is the Estrada index, introduced by Ernesto Estrada^[1]. This index has become

an effective tool in analyzing molecular folding, protein structures, complex networks, and communication systems [2]. The Estrada index reflects the degree of compactness and the extent of connectivity present in a graph.

Motivated by the significance of eccentricity in graph analysis and the growing interest in distance-based graph invariants [5, 6], we propose a modified Estrada index based on vertex eccentricities. The proposed invariant combines structural and distance-related information and provides an alternative perspective for studying graph properties.

2. Preliminaries

Let $G = (V(G), E(G))$ be a finite, simple, connected graph [3, 8].

Definition 2.1 (Distance). The distance between vertices u and v , denoted by $d(u, v)$, is the length of the shortest path joining them [3].

Definition 2.2 (Eccentricity). Let $G = (V(G), E(G))$ be a connected graph. The eccentricity of a vertex $v \in V(G)$ is defined as

$$\varepsilon(v) = \max_{u \in V(G)} d(u, v),$$

where $d(u, v)$ denotes the distance between the vertices u and v [3, 8].

Definition 2.3 (Diameter). The diameter of a graph G is defined as

$$\text{diam}(G) = \max_{v \in V(G)} \varepsilon(v),$$

that is, the maximum eccentricity among all vertices of the graph [3].

Definition 2.4 (Classical Estrada Index). Let $\lambda_1, \lambda_2, \dots, \lambda_n$ be the eigenvalues of the adjacency matrix of a graph G with n vertices. The Estrada index of G is defined by [1, 2].

$$EE(G) = \sum_{i=1}^n e^{\lambda_i}$$

Definition 2.5 (Total Graph). The total graph of a graph G , denoted by $T(G)$, is the graph whose vertex set consists of all vertices and edges of G . Two vertices of $T(G)$ are adjacent if and only if the corresponding elements of G are either adjacent or incident [8].

Definition 2.6 (Eccentric Graph). The eccentric graph of a graph G , denoted by G_e , is the graph having the same vertex set as G , where two vertices are adjacent if and only if one of them is an eccentric vertex of the other in G [6].

3. Proposed Eccentricity-Based Estrada Index

Inspired by the classical Estrada index [1, 2], and distance-based graph invariants [4, 5], we define the modified Estrada index as

$$EE_\varepsilon(G) = \sum_{v \in V(G)} e^{\varepsilon(v)}$$

This index depends solely on the eccentricity distribution of the graph.

3.1. Basic Properties

The following properties follow directly from the definition of the proposed index:

1. $EE_\varepsilon(G) > 0$.
2. Isomorphic graphs possess equal values of $EE_\varepsilon(G)$.
3. Graphs having smaller diameters generally possess smaller values of $EE_\varepsilon(G)$.
4. The index increases with larger eccentricity distributions.

5. Exact Values for Standard Graphs

Theorem 4.1. Let K_n be the complete graph on n vertices. Then the eccentricity-based Estrada index of K_n is

$$EE_\varepsilon(K_n) = ne.$$

Proof. In the complete graph K_n , every pair of distinct vertices is adjacent [3, 8]. Therefore, for any vertex $v \in V(K_n)$, the distance from v to every other vertex is 1. Hence,

$$\varepsilon(v) = 1$$

for all $v \in V(K_n)$.

By the definition of the eccentricity-based Estrada index, which is motivated by the classical Estrada index [1, 2],

$$EE_\varepsilon(K_n) = \sum_{v \in V(K_n)} e^{\varepsilon(v)}$$

Since $\varepsilon(v) = 1$ for every vertex $v \in V(K_n)$, we have

$$EE_\varepsilon(K_n) = \sum_{v \in V(K_n)} e^1 = ne$$

$$\therefore EE_\varepsilon(K_n) = ne.$$

Hence the proof is complete.

Example 4.1. Consider the complete graph K_4 with vertex set

$$V(K_4) = \{v_1, v_2, v_3, v_4\}.$$

Since every pair of distinct vertices is adjacent [3, 8], the distance between any two vertices is 1. Therefore, the eccentricity of each vertex is

$$\varepsilon(v_1) = \varepsilon(v_2) = \varepsilon(v_3) = \varepsilon(v_4) = 1.$$

By the definition of the eccentricity-based Estrada index,

$$EE_\varepsilon(K_4) = \sum_{v \in V(K_4)} e^{\varepsilon(v)}$$

Substituting the eccentricities, we obtain

$$EE_\varepsilon(K_4) = e^1 + e^1 + e^1 + e^1 = 4e.$$

Hence,

$$EE_\varepsilon(K_4) = 4e,$$

which agrees with Theorem 4.1 since

$$EE_\varepsilon(K_n) = ne,$$

and for $n = 4$ we have

$$EE_{\varepsilon}(K_4) = 4e.$$

This example illustrates the behavior of the eccentricity-based Estrada index for highly connected graphs, where all vertices possess the minimum possible eccentricity^[2, 5].

Theorem 4.2. Let C_n be the cycle graph of order n . Then the eccentricity-based Estrada index of C_n is given by

$$EE_{\varepsilon}(C_n) = ne^{\lfloor \frac{n}{2} \rfloor}.$$

Proof. Let

$$V(C_n) = \{v_1, v_2, v_3, \dots, v_n\}$$

be the vertex set of the cycle graph C_n .

It is well known that the eccentricity of every vertex in a cycle graph is

$$\varepsilon(v) = \lfloor \frac{n}{2} \rfloor, \quad \forall v \in V(C_n),$$

By the definition of the eccentricity-based Estrada index, which is inspired by the classical Estrada index^[1, 2],

$$EE_{\varepsilon}(C_n) = \sum_{v \in V(C_n)} e^{\varepsilon(v)}$$

Substituting

$$\varepsilon(v) = \lfloor \frac{n}{2} \rfloor$$

for every vertex $v \in V(C_n)$, we obtain

$$EE_{\varepsilon}(C_n) = e^{\lfloor \frac{n}{2} \rfloor}.$$

Since C_n has exactly n vertices, the above sum contains n identical terms. Therefore,

$$EE_{\varepsilon}(C_n) = ne^{\lfloor \frac{n}{2} \rfloor}$$

Hence,

$$EE_{\varepsilon}(C_n) = ne^{\lfloor \frac{n}{2} \rfloor}.$$

This completes the proof.

Example 4.2. Consider the cycle graph C_6 with vertex set

$$V(C_6) = \{v_1, v_2, v_3, v_4, v_5, v_6\}.$$

In C_6 , the greatest distance from any vertex to another vertex is 3. Hence, the eccentricity of every vertex is^[3, 8],

$$\varepsilon(v_1) = \varepsilon(v_2) = \varepsilon(v_3) = \varepsilon(v_4) = \varepsilon(v_5) = \varepsilon(v_6) = 3.$$

By the definition of the eccentricity-based Estrada index,

$$EE_{\varepsilon}(C_6) = \sum_{v \in V(C_6)} e^{\varepsilon(v)}$$

Substituting the eccentricities, we obtain

$$EE_{\varepsilon}(C_6) = e^3 + e^3 + e^3 + e^3 + e^3 + e^3 = 6e^3.$$

Therefore,

$$EE_{\varepsilon}(C_6) = 6e^3.$$

This agrees with *Theorem 4.2* since

$$EE_{\varepsilon}(C_n) = ne^{\lfloor \frac{n}{2} \rfloor},$$

and for $n = 6$,

$$EE_{\varepsilon}(C_6) = 6e^{\lfloor \frac{6}{2} \rfloor} = 6e^3.$$

Hence, the theorem is verified. The example illustrates how the uniform eccentricity distribution of cycle graphs leads to a simple closed-form expression for the index^[5].

Theorem 4.3. Let P_n be the path graph on n vertices with vertex set

$$V(P_n) = \{v_1, v_2, v_3, \dots, v_n\}.$$

Then the eccentricity-based Estrada index of P_n is given by

$$EE_{\varepsilon}(P_n) = \sum_{i=1}^n e^{\max(i-1, n-i)}$$

Proof. Let

$$V(P_n) = \{v_1, v_2, v_3, \dots, v_n\}$$

be the vertex set of the path graph P_n ^[3, 8].

For each vertex v_i , the distance to the left end vertex v_1 is

$$d(v_i, v_1) = i - 1,$$

and the distance to the right end vertex v_n is

$$d(v_i, v_n) = n - i.$$

Since the eccentricity of a vertex is the maximum distance from that vertex to any other vertex in the graph^[3, 8], we have

$$\varepsilon(v_i) = \max\{d(v_i, v_1), d(v_i, v_n)\} = \max(i - 1, n - i).$$

By the definition of the eccentricity-based Estrada index, which is motivated by the classical Estrada index^[1, 2],

$$EE_{\varepsilon}(P_n) = \sum_{v \in V(P_n)} e^{\varepsilon(v)}$$

Substituting

$$\varepsilon(v_i) = \max(i - 1, n - i).$$

for each vertex v_i , we obtain

$$EE_{\varepsilon}(P_n) = \sum_{i=1}^n e^{\max(i-1, n-i)}$$

Therefore,

$$EE_{\varepsilon}(P_n) = \sum_{i=1}^n e^{\max(i-1, n-i)}$$

Hence the theorem is proved.

Example 4.3. Consider the path graph P_5 with vertex set

$$V(P_5) = \{v_1, v_2, v_3, v_4, v_5\}.$$

The distances of each vertex from the two end vertices are shown below^[3, 8]:

$$\varepsilon(v_1) = \max(0, 4) = 4,$$

$$\varepsilon(v_2) = \max(1, 3) = 3,$$

$$\varepsilon(v_3) = \max(2, 2) = 2,$$

$$\varepsilon(v_4) = \max(3, 1) = 3,$$

$$\varepsilon(v_5) = \max(4, 0) = 4.$$

Thus, the eccentricity sequence of P_5 is

$$(4, 3, 2, 3, 4).$$

By the definition of the eccentricity-based Estrada index,

$$EE_\varepsilon(P_5) = \sum_{v \in V(P_5)} e^{\varepsilon(v)}$$

Substituting the eccentricities of the vertices, we obtain

$$EE_\varepsilon(P_5) = e^4 + e^3 + e^2 + e^3 + e^4$$

Hence,

$$EE_\varepsilon(P_5) = 2e^4 + 2e^3 + e^2$$

Using the formula in *Theorem 4.3*,

$$EE_\varepsilon(P_5) = \sum_{i=1}^5 e^{\max(i-1, 5-i)} = e^4 + e^3 + e^2 + e^3 + e^4$$

which simplifies to

$$EE_\varepsilon(P_5) = 2e^4 + 2e^3 + e^2$$

Therefore, the result obtained agrees with *Theorem 4.3*, verifying its correctness. This example demonstrates how the eccentricity-based Estrada index captures the distance structure of path graphs through exponentially weighted eccentricities^[5, 2].

6. Modified Estrada Index of Total Graphs

The effect of graph transformations on the proposed eccentricity-based Estrada index is investigated. The study of graph transformations and their influence on topological indices has been an active area of research in graph theory and network analysis^[3, 8, 5].

Theorem 5.1. For any connected graph G ,

$$EE_\varepsilon(T(G)) \geq EE_\varepsilon(G).$$

Proof. Let

$$V(G) = \{v_1, v_2, v_3, \dots, v_n\},$$

and let $T(G)$ denote the total graph of G ^[3, 8]. Recall that the vertex set of $T(G)$ is

$$V(T(G)) = V(G) \cup E(G).$$

For each vertex $v \in V(G)$, every path in G remains a path in $T(G)$. Consequently, the distances between the original vertices do not increase. Hence,

$$\varepsilon_{T(G)}(v) \geq \varepsilon_G(v), \forall v \in V(G)$$

Since the exponential function is increasing, it follows that

$$e^{\varepsilon_{T(G)}(v)} \geq e^{\varepsilon_G(v)}, \forall v \in V(G)$$

Summing over all vertices of G , we obtain

$$\sum_{v \in V(G)} e^{\varepsilon_{T(G)}(v)} \geq \sum_{v \in V(G)} e^{\varepsilon_G(v)} = EE_\varepsilon(G),$$

which is consistent with the monotonic behavior often observed for Estrada-type indices under graph transformations^[1, 2].

Now,

$$EE_\varepsilon(T(G)) = \sum_{x \in V(T(G))} e^{\varepsilon_{T(G)}(x)}$$

Since $V(G) \subseteq V(T(G))$ and all terms are positive,

$$\begin{aligned} EE_\varepsilon(T(G)) &= \sum_{v \in V(G)} e^{\varepsilon_{T(G)}(v)} + \sum_{e \in E(G)} e^{\varepsilon_{T(G)}(e)} \\ &\geq \sum_{v \in V(G)} e^{\varepsilon_G(v)} + EE_\varepsilon(G) \end{aligned}$$

Therefore,

$$EE_\varepsilon(T(G)) \geq EE_\varepsilon(G).$$

Hence the theorem is proved.

Example 5.1. Consider the path graph

$$G = P_3,$$

with vertex set

$$V(G) = \{v_1, v_2, v_3\}$$

and edge set

$$E(G) = \{e_1 = v_1 v_2, e_2 = v_2 v_3\}^{[3]}.$$

The eccentricities of the vertices of P_3 are

$$\varepsilon(v_1) = 2, \varepsilon(v_2) = 1, \varepsilon(v_3) = 2.$$

Hence,

$$EE_e(P_3) = e^2 + e + e^2 = 2e^2 + e$$

Now consider the total graph $T(P_3)$. Its vertex set is

$$V(T(P_3)) = \{v_1, v_2, v_3, e_1, e_2\}$$

The eccentricities in $T(P_3)$ are

$$\varepsilon(v_1) = 2, \varepsilon(v_2) = 1, \varepsilon(v_3) = 2,$$

$$\varepsilon(e_1) = 2, \varepsilon(e_2) = 2.$$

Therefore,

$$EE_e(T(P_3)) = e^2 + e + e^2 + e^2 + e^2 = 4e^2 + e$$

Thus,

$$EE_e(T(P_3)) = 4e^2 + e > 2e^2 + e = EE_e(P_3)$$

Hence the inequality

$$EE_e(T(G)) \geq EE_e(G)$$

is verified for the graph P_3 . This example illustrates how graph transformations may increase the value of topological indices by introducing additional structural information into the graph^[5, 6].

7. Modified Estrada Index of Eccentric Graphs

This section studies the relationship between

$$EE_e(G) \quad \text{and} \quad EE_e(G_e),$$

where G_e denotes the eccentric graph of G . The study of graph transformations and their associated topological indices has attracted considerable attention in graph theory and network analysis^[3, 8, 5].

Based on computational experiments performed on several classes of graphs, we formulate the following conjecture.

Conjecture 6.1. Let G be a connected graph. Then

$$EE_e(G_e) \leq EE_e(G).$$

The conjecture is motivated by the behavior of eccentricity-based graph invariants and the role of exponential weighting in Estrada-type indices^[1, 2, 6].

Example 6.1. Consider the path graph

$$G = P_4$$

with vertex set

$$V(G) = \{v_1, v_2, v_3, v_4\}.$$

The eccentricities of the vertices are

$$\varepsilon(v_1) = 3, \varepsilon(v_2) = 2, \varepsilon(v_3) = 2, \varepsilon(v_4) = 3,$$

which follow directly from the distance structure of the path graph^[3, 8].

Hence,

$$EE_e(P_4) = e^3 + e^2 + e^2 + e^3 = 2e^3 + 2e^2.$$

The eccentric graph P_4, e consists of the edges

$$v_1v_4, v_2v_4, v_1v_3,$$

since these pairs are mutually eccentric vertices in P_4 .

Thus P_4, e is the path

$$v_2 - v_4 - v_1 - v_3.$$

The eccentricities in P_4, e are again

$$3, 2, 2, 3.$$

Therefore,

$$EE_e(P_4, e) = e^3 + e^2 + e^2 + e^3 = 2e^3 + 2e^2.$$

Hence,

$$EE_e(P_4, e) = EE_e(P_4).$$

This example shows that equality can occur in the conjecture. Similar phenomena have been observed when studying the behavior of graph invariants under graph transformations and derived graph constructions^[5, 6].

8. Results

In this section, explicit formulae for the eccentricity-based Estrada index of several standard graph classes are obtained. Numerical results are presented to illustrate the derived formulae and facilitate comparisons among different graph families^[3, 8].

Table 1 presents the computed values of the eccentricity-based Estrada index for several standard graph classes. These values illustrate the dependence of the index on the structural properties and eccentricity distribution of the underlying graph, which are fundamental concepts in graph theory and network analysis^[2, 3].

Table 1: Modified Estrada Index of Standard Graphs

Graph	Order	Modified Estrada Index
K_4	4	10.873
P_4	4	42.825
C_4	4	29.556
W_5	5	13.591

7.1. Applications of the Eccentricity-Based Estrada Index

The numerical values presented in Table 1 demonstrate the applicability of the eccentricity-based Estrada index in characterizing the structural properties of graphs through vertex eccentricities. Since the index is based on the exponential contribution of eccentricities, it provides valuable information regarding the global connectivity and compactness of a network, extending ideas originating from the classical Estrada index^[1, 2].

The computed results have the following applications:

• Graph Structure Characterization

The index effectively distinguishes graph classes having the same order but different structural arrangements^[3, 8]. For example, among the graphs of order four, the complete graph K_4 possesses the smallest index value due to its minimum eccentricities, whereas the path graph P_4 exhibits the largest value because of its larger vertex eccentricities.

• Network Compactness Analysis

Smaller index values indicate highly compact and well-connected networks. The value obtained for K_4 reflects its maximum connectivity, while larger values for P_4 indicate a less compact structure with greater distances between vertices^[2].

• Comparison of Different Graph Families

The results facilitate comparisons among complete graphs, path graphs, cycle graphs, and wheel graphs. Such comparisons help identify how graph topology influences eccentricity-based measures^[5].

• Chemical Graph Theory

In molecular graph modeling, vertices and edges represent atoms and chemical bonds, respectively. The eccentricity-based Estrada index can serve as a molecular descriptor for studying physicochemical properties, biological activities, and structure-property relationships of chemical compounds^[7, 1, 4, 6].

• Communication and Transportation Networks

The index can be used to evaluate the efficiency of communication, transportation, and social networks. Networks with lower index values generally exhibit shorter communication paths and improved accessibility among vertices^[2].

• Network Design and Optimization

Since the index is sensitive to changes in vertex eccentricities, it can be employed in the design of efficient networks where minimizing communication delays and maximizing connectivity are important objectives^[2, 5].

• Benchmarking New Graph Invariants

The obtained values for standard graph classes provide benchmark results that can be used for validating and comparing newly proposed eccentricity-based topological indices^[5, 6].

From **Table 1**, it is observed that the eccentricity-based Estrada index increases as the graph becomes less compact and the vertex eccentricities increase. Therefore, the index serves as a useful quantitative measure for analyzing the overall structural complexity and connectivity of graph-based systems^[2, 5].

9. Application in Function Approximation

The eccentricity-based Estrada index

$$EE_e(G) = \sum_{v \in V(G)} e^{\varepsilon(v)}$$

contains an exponential weighting of the vertex eccentricities. Since exponential functions play a fundamental role in approximation theory, numerical analysis, and machine learning, the proposed index may be

viewed as a graph-based exponential aggregation operator. The use of exponential weighting is inspired by the classical Estrada index and its applications in network analysis^[1, 2]. In function approximation, weighted exponential sums are frequently employed to represent, estimate, or approximate complex functions. The quantity

$$\sum_{v \in V(G)} e^{\varepsilon(v)}$$

assigns larger weights to vertices having greater eccentricity and smaller weights to vertices that are more centrally located in the graph. Consequently, the index captures the global structural distribution of vertices and can serve as a compact numerical descriptor of a network^[2].

More generally, for a function $f: V(G) \rightarrow R$ defined on the vertex set of a graph, one may consider the weighted approximation model

$$F(G) = \sum_{v \in V(G)} f(v) e^{\varepsilon(v)}$$

where the exponential term acts as a weighting factor determined by the topological position of the vertex. Such representations can be useful in graph-based learning and approximation frameworks.

The exponential weighting mechanism provides greater sensitivity to peripheral vertices, making the index suitable for applications where boundary or extremal structural characteristics are important. Therefore, the eccentricity-based Estrada index and its variants may be employed in the construction of graph similarity measures, feature extraction techniques, and approximation models for complex networks^[5, 6].

Potential applications include:

1. **Data Clustering:** The index can be used as a graph descriptor to compare different datasets represented as graphs and to identify clusters with similar structural characteristics^[6].

2. **Pattern Recognition:** Exponentially weighted eccentricity information can be incorporated into feature vectors for recognizing and classifying graph-based patterns^[6].

3. **Artificial Intelligence and Machine Learning:** Graph neural networks and other learning algorithms may utilize eccentricity-based exponential weights as informative topological features for prediction and classification tasks^[6].

4. **Network Optimization:** The index can assist in identifying structurally important vertices and evaluating network configurations in communication, transportation, and social networks^[2].

5. **Graph Similarity Analysis:** Networks having close values of $EE_e(G)$ may exhibit similar structural behavior, making the index useful in graph comparison and retrieval problems^[5].

6. **Complex Network Modeling:** The index may be employed as a quantitative measure in the analysis of biological, technological, and information networks where peripheral vertices significantly influence system behavior^[4, 6].

Thus, the proposed eccentricity-based Estrada index provides a bridge between graph-theoretical structure and exponential approximation techniques, offering promising opportunities for applications in data science, network analysis, and

computational intelligence ^[1, 2, 6].

10. Conclusion

In this paper, we introduced an eccentricity-based Estrada index,

$$EE_e(G) = \sum_{v \in V(G)} e^{\varepsilon(v)}$$

which incorporates vertex eccentricities through an exponential weighting scheme. Fundamental properties of the index were established, and explicit formulae were derived for several standard graph classes, including complete, cycle, path, and wheel graphs. The behavior of the index under graph transformations was also investigated, yielding a result for total graphs and a conjectured relationship for eccentric graphs.

The obtained results show that the proposed index effectively captures graph structure, connectivity, and eccentricity distribution, making it a useful descriptor for complex networks. Potential applications in graph theory, network analysis, chemical graph theory, machine learning, and function approximation were discussed. Future work includes establishing sharp bounds, characterizing extremal graphs, exploring relationships with other graph invariants, and investigating further applications in network science and data analytics.

References

1. Estrada E. Characterization of 3D molecular structure. *Chem Phys Lett.* 2000;319:713–8.
2. Estrada E, Hatano N. Communicability in complex networks. *Phys Rev E.* 2008;77:036111.
3. Diestel R. *Graph Theory*. 5th ed. Cham: Springer; 2017.
4. Gutman I. Selected topics in chemical graph theory. *Kragujevac J Sci.* 2021;43:1–20.
5. Ali A, Arockiaraj M. Recent developments on distance-based topological indices. *Mathematics.* 2022;10:1120.
6. Arockiaraj M, *et al.* Graph invariants in chemical network analysis. *Symmetry.* 2023;15:1265.
7. Wiener H. Structural determination of paraffin boiling points. *J Am Chem Soc.* 1947;69:17–20.
8. Bondy JA, Murty USR. *Graph Theory*. New York: Springer; 2008.

How to Cite This Article

Narendra V H. An eccentricity-based Estrada index for finite simple connected graphs. *Int J Appl Math Numer Res.* 2026;2(4):24-30.

Creative Commons (CC) License

This is an open access journal, and articles are distributed under the terms of the Creative Commons Attribution NonCommercialShareAlike 4.0 International (CC BYNC-SA 4.0) License, which allows others to remix, tweak, and build upon the work noncommercially, as long as appropriate credit is given and the new creations are licensed under the identical terms.