

Spectral properties of some matrices related to topological indices

SAMANEH ZANGI[°]

Department of Mathematics, Faculty of Science, Shahid Rajaee Teacher Training University, Tehran, 16785 – 136, I R. Iran

ABSTRACT. A topological index is a kind of molecular descriptor which anticipates some properties of chemical compound. The aim of this paper is to compute the spectrum of PA adjacency matrix associated to a well-known topological index.

Keywords: spectrum of graph, topological index, adjacency matrix.

1. INTRODUCTION

Here, we introduce some basic notation and terminology used throughout the paper. All graphs considered here are finite and simple. A simple graph X is a graph without loops and multiple edges. The vertex set and the edge set of graph X are denoted by $V(X)$ and $E(X)$, respectively. When two vertices u and v are endpoints of an edge, we say that they are adjacent and write $u \sim v$ to indicate this. The adjacency matrix A is an $n \times n$ matrix whose xy-th entry is 1 if $xy \in E$ and zero otherwise. **ABSTRACT.** A topological index is a kind of molecular descriptor which anticipates some
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The spectrum of a graph is based on the adjacency matrix of graph and it is strongly dependent on the form of this matrix. A number of possible disadvantages can be derived by using only the spectrum of a graph. For example, some information about expansion and randomness of a graph can be derived from the second largest eigenvalue of a graph. One of the main applications of graph spectra in chemistry is

the application in Hückel molecular orbital theory for the determination of energies of molecular orbitals of π-electrons.

The real number λ is called the eigenvalue of graph Γ with adjacency matrix A if the equation $Ax = \lambda x$ has a nontrivial solution x. Then x is called eigenvector corresponding to the eigenvalue λ . The characteristic polynomial of the matrix A is $\chi_{\lambda}(G) = det(A - \lambda I)$ where the eigenvalues of A are roots of $\chi_{\lambda}(G)$.

2. MAIN RESULTS

For given graph G, if the maximum degree of every vertex reaches to four, then G is called a molecular graph. A topological index is a kind of molecular descriptor which anticipates some properties of chemical compound. Many topological indices were defined and many properties are discovered, see [1,2]. The first **inverse sum indeg** index (ISI index) defined as follows [3]:

$$
ISI(G) = \sum_{uv \in E(G)} \frac{d_u d_v}{d_u + d_v}.
$$

Let $V(G) = \{v_1, v_2, ..., v_n\}$ be the vertex set of graph G. For 1, 2, ...,n, let d_i be the degree of the vertex v_i . Then define the ISI adjacency matrix PA to be [4]

$$
PA(G) = \begin{cases} \frac{d_i d_j}{d_i + d_j} & v_i \sim v_j \\ 0 & \text{ o.w} \end{cases}.
$$

If the graph G is regular of degree r, then $PA(G) = \frac{r}{2} A(G)$ and 2 $PA(G) = \frac{r}{2}A(G)$ and

$$
PA^{2}(G) = \frac{1}{4}r^{2}A^{2}(G).
$$
 (1)

Example 1. Let G be an r-regular graph. Since $tr(A^2) = 2m$, we have $tr(A^2(G)) = nr$. This means that $tr(P A²(G)) = nr³/4$.

Example 2. By using Eq.(1), we have $tr(PA^2(S_n)) = 2(n-1)^3 / n^2$. Let P_n denotes to the path graph, then

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$$
v_i
$$
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\n
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\n
$$
PA(P_n) = \begin{bmatrix}\n0 & 2/3 & 0 & 1 \\
2/3 & 0 & 1 & 0 \\
1 & 0 & \ddots & 0 \\
0 & 1 & 0 & 2/3 \\
0 & 2/3 & 0\n\end{bmatrix}
$$
\nThe diagonal elements of *PA*² are $\frac{4}{9}, \frac{13}{9}, 2, 2, ..., 2, \frac{13}{9}, \frac{4}{9}$. Therefore

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$$
tr(PA^{2}(P_{n})) = \frac{34}{9} + 2(n-4) = 2n - \frac{38}{9}
$$

Lemma 4. Let $PA(G) = \frac{r}{2}A(G)$, t 2 $PA(G) = \frac{r}{2}A(G)$, then

$$
\chi_{\lambda}(PA(G)) = \left(\frac{r}{2}\right)^{n} \chi_{\frac{2}{r}\lambda}(A(G)). \tag{2}
$$

Proof. It is straightforward. For an example, $PA(S_n) = \frac{n-1}{n}A(S_n)$ and n and by using Lemma4 $\chi_{\lambda}(PA(S_n)) = (\frac{n-1}{n})^n \chi_{n\lambda}$ $(PA(S_n)) = (\frac{n-1}{n})^n \chi_{n\lambda}(A(S_n)).$ $PA(S_n^-)) = \left(\frac{n-1}{n}\right)^n \chi_{n\lambda}^-(A(S_n^-))$ n

It is not difficult to see that $PA(K_{m,n}) =$ $PA(K_{m,n}) = \frac{mn}{m+n}A(K_{m,n})$ as $\frac{mn}{m+n}A(K_{m,n})$ and hence

÷,

n

1

$$
\chi_{\lambda}(PA(K_{m,n})) = (\frac{mn}{m+n})^n \chi_{\frac{(m+n)\lambda}{mn}}(A(K_{m,n}))
$$
\n(3)

Theorem 5 [4]. Let G be a graph with vertices set $\{1, 2, ..., n\}$ and *ISI* matrix PA. Then i) $tr(PA) = 0$, (4)

ii)
$$
tr(PA^2) = 2 \sum_{i \sim j} \left(\frac{d_i d_j}{d_i + d_j}\right)^2
$$
, $(PA^2)_{ij} = d_i d_j \sum_{k \sim i, k \sim j} \frac{d_k^2}{(d_i + d_k)(d_j + d_k)}$ (5)

iii)
$$
tr(PA^3) = 2 \sum_{i \sim j} \frac{(d_i d_j)^2}{d_i + d_j} \left(\sum_{k \sim i, k \sim j} \frac{(d_k)^2}{(d_i + d_k)(d_j + d_k)} \right),
$$
 (6)

iv)
$$
tr(PA^4) = \sum_{i=1}^{n} \left(\sum_{i \sim l} \left(\frac{d_i d_l}{d_i + d_l}\right)^2\right)^2 + \sum_{i \neq j} d_i d_j \left(\sum_{l \sim i, l \sim j} \frac{\left(d_l\right)^2}{\left(d_i + d_l\right) \left(d_j + d_l\right)}\right)^2
$$
. (7)

The probabilistic neural network $PNN(n, k, m)$ can be constructed as follows:

There are three types of vertices in $PNN(n, k, m)$, namely of degree km, of degree $n + 1$, and of degree m. Thus, we have

 $V_1 = \{v \in V \mid \text{PNN}(n, k, m)\} | d_v = km\}, V_2 = \{v \in V \mid \text{PNN}(n, k, m)\} | d_v = n + 1\},$ and $V_3 = \{v \in V \mid \text{PNN}(n, k, m)\}$ $(PNN(n, k,m))|d_v = m$, where $|V_1| = n$, $|V_2| = km$ and $|V_3| = k$. Consequently, $|V(PNN(n, k,m))| = k$ (k, m)] = $v = |V_1| + |V_2| + |V_3| = n + k(m+1)$. There are two types of edges with respect to degrees of end vertices in PNN(n, k,m), namely with degrees of end vertices $\{km, n+1\}$ and degrees of end vertices $\{n+1,m\}$. Thus, we have **Theorem 5 [4].** Let *G* be a graph with vertices set {1, 2, ..., *n*} and *ISI* matrix PA. Then
 ii $tr(PA^2) = 2\sum_{i=1}^{\infty} \left(\frac{d_i d_j}{d_i + d_j}\right)^2$, $(PA^2)_{ij} = d_i d_j \sum_{k=1, k \neq j} \frac{d_k^2}{(d_i + d_k)(d_j + d_k)}$ (5)
 iii $tr(PA^2) = 2\sum_{$

$$
E_1 = E_{\{km,n+1\}} = \{uv \in E(\text{PNN}(n, k,m)) | d_u = km, d_v = n+1\},\
$$

 $E_2 = E_{n+1,m} = \{uv \in E(PNN(n, k,m)) | d_u = n + 1, d_v = m\}$, where $|E_{k,m,n+1}| = kmn$ and $|E_{n+1,m}\| = km$. Consequently, $|E(PNN(n, k,m))| = e = |E_1| + |E_2| = km(n + 1)$. The probabilistic neural network PNN(4, 2, 3) is depicted in Figure 1.

Figure 1. probabilistic neural network PNN(4, 2, 3).

The aim of this paper is to compute the spectrum of PA matrix of probabilistic neural network PNN(n, k, m).

Theorem A. The spectrum of PA matrix of $PNN(n, k, m)$ is as follows:

$$
\cdot \Big\{ [0]^{km+n-k}, [\pm a\sqrt{m}]^{k-1}, [\pm \sqrt{ma^2 + kmb^2n}]^1 \Big\}.
$$

Proof. One can easily prove that the PA matrix is as follows:

$$
PA = \begin{bmatrix} 0_{k \times k} & C_{k \times mk} & 0_{k \times n} \\ C_{mk \times k}^t & 0_{mk \times mk} & D_{mk \times n} \\ 0_{n \times k} & D_{n \times mk}^t & 0_{n \times n} \end{bmatrix}
$$

where

$$
C = \begin{bmatrix} a & \cdots & a & 0 & 0 & \cdots & \cdots & \cdots & 0 \\ 0 & \cdots & 0 & a & \cdots & a & 0 & \cdots & 0 \\ \vdots & & & & & & & \vdots \\ 0 & 0 & \cdots & \cdots & \cdots & 0 & a & \cdots & a \end{bmatrix}
$$

$$
D = bJ, b = \frac{mk(n+1)}{mk+n+1}, a = \frac{m(n+1)}{m+n+1}.
$$

This yields that if $det(PA - \lambda I) = 0$ then and so

$$
\chi(PNN(n, k, m), \lambda) = (ma^2 - \lambda^2)^{k-1} \times \lambda^{km+n-k} \times (-kmb^2n - ma^2 + \lambda^2).
$$

Hence,

$$
\begin{vmatrix} xI_k & 0 & 0 \\ 0 & M & 0 \\ \frac{mba}{\lambda} J & P & S \end{vmatrix} = 0,
$$

where

$$
S = \begin{bmatrix} -\lambda & 0 & 0 & 0 \\ 0 & \ddots & \ddots & 0 \\ 0 & 0 & -\lambda & 0 \\ \lambda & \cdots & \lambda & y \end{bmatrix}_{n \times n}, y = -\frac{kmb^2n}{x} - \lambda.
$$

This means that

$$
Spec(PA) = \begin{pmatrix} 0 & a\sqrt{m} & -a\sqrt{m} & \sqrt{ma^2 + kmb^2n} & -\sqrt{ma^2 + kmb^2n} \\ km+n-k & k-1 & k-1 & 1 & 1 \end{pmatrix}.
$$

CONCUSION

In the studies of quantitative structure-activity relationship and quantitative structure-property relationship, the topological indices are utilized to guess the physical features related to the bioactivities and chemical reactivities in certain networks. $S = \begin{bmatrix} -\lambda & 0 & 0 & 0 \\ 0 & \ddots & \ddots & 0 \\ 0 & 0 & -\lambda & 0 \\ 2 & \cdots & \lambda & y \end{bmatrix}_{n \infty}$, $y = -\frac{kmb^2n}{x} - \lambda$.

This means that
 $Spec(PA) = \begin{pmatrix} 0 & a\sqrt{m} & -a\sqrt{m} & \sqrt{ma^2 + kmb^2n} & -\sqrt{ma^2 + kmb^2n} \\ km + n - k & k - 1 & k - 1 & 1 & 1 \end{pmatrix}$.

CONCUSION

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In this paper, we first defined a new matrix associated to the ISI index and then we computed it for several well-known graphs. In continuing of this paper, we computed its spectrum for probabilistic neural network $PNN(n, k, m)$.

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