Modified box dimension and average weighted receiving time on the weighted fractal networks

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In this paper a family of weighted fractal networks, in which the weights of edges have been assigned to different values with certain scale, are studied. For the case of the weighted fractal networks the definition of modified box dimension is introduced, and a rigorous proof for its existence is given. Then, the modified box dimension depending on the weighted factor and the number of copies is deduced. Assuming that the walker, at each step, starting from its current node, moves uniformly to any of its nearest neighbors. The weighted time for two adjacency nodes is the weight connecting the two nodes. Then the average weighted receiving time (AWRT) is a corresponding definition. The obtained remarkable result displays that in the large network, when the weight factor is larger than the number of copies, the AWRT grows as a power law function of the network order with the exponent, being the reciprocal of modified box dimension. This result shows that the efficiency of the trapping process depends on the modified box dimension: the larger the value of modified box dimension, the more efficient the trapping process is.

Recently, self-similar fractals have attracted much attention. The renormalization procedure tiles a network according to the box-covering algorithm. Self-similarity is then obtained if the network structure remains invariant under the renormalization. Gallos et al. reviewed the findings of self-similarity in complex networks. Using the box-covering technique, it was shown that many networks present a fractal behavior, which is seemingly in contrast to their small-world property. Then they used scaling theory to quantify the degree of correlations in the particular case of networks with a power-law degree distribution. Starting from the fractal network, Rozenfeld et al. applied renormalization group theory to study complex networks using the box covering technique, which is useful to classify network topologies into universality classes in the space of configurations. After defining a unified mathematical framework for both immunization and spreading, Morone and Makse provided its optimal solution in random networks by mapping the problem onto optimal percolation and found that the top influencers are highly counterintuitive.

Motivated by the hierarchal and scale-free networks, Komjáthy and Simon introduced deterministic the scale-free graphs derived from a graph directed self-similar fractal. Chen et al. constructed a class of scale-free networks with fractal structure based on the subshift of finite type and base graphs. When embedding the growing network into the plane, its image is a graph-directed self-affine fractal, whose Hausdorff dimension is related to the power law exponent of cumulative degree distribution.

Unfortunately, many previous works have focused on the un-weighted networks. In real networks, the relations between two nodes have been affected by specific physical properties of network elements, including the number of passengers traveling yearly between two airports in airport networks, to the intensity of predator-prey interactions in ecosystems or the traffic measured in packets per unit time between routers in the Internet. So weighted networks commendably represent the natural framework to describe natural, social, and technological systems, in which the intensity of a relation or the traffic between elements is an important parameter. In general terms, weighted networks are extension of networks or graphs, in which each edge between nodes i and j is associated with a variable \( w_{ij} \), called the weight.

A key quantity related to weighted networks is the mean weighted first-passage time (MWFPPT), that is, the expected weighted first time for the walker starting from a source node to a given target node. The average weighted
receiving time (AWRT) is the sum of mean weighted first-passage times (MFPTs) for all nodes absorbt at the trap located at a given target node\(^{19-21}\). In 2013, Dai et al. introduced the non-homogeneous weighted Koch networks depending on the three weight factors\(^ {19}\). They defined the average weighted receiving time (AWRT) for the first time and studied the AWRT on random walk. Recently, fractals have also attracted an increasing attention in physics and other scientific fields, owning to the striking beauty intrinsic in their structures and the significant impact of the idea of fractals. These structures have been a focus of research objects and many underlying properties have been found. So it makes sense to combining weighted networks with fractals which are called weighted fractal networks. Daudert and Lapidus\(^ {20}\) studied weighted graphs and random walks on the Koch snowflake. Carletti and Righi\(^ {21}\) defined a class of weighted complex networks whose topology can be completely analytically characterized in terms of the involved parameters and of the fractal dimension.

This paper is organized as follow. Based on weighted fractal networks\(^ {21}\), we introduce a family of the weighted fractal networks depending on the number of copies of the edge and the weight factor \( r \) in the next section. In Section 3, the definition of modified box dimension and a rigorous proof for its existence are given in the case of the weighted fractal networks. In Section 4, the average weighted receiving time (AWRT) on random walk is obtained by recursive formulas for \( F_1(n) \) and \( T_{out}(n) \). When the weight factor is larger than the number of copies, we show that the efficiency of the trapping process depends on the modified box dimension: the larger the value of modified box dimension, the more efficient the trapping process is. In the last section we draw conclusions.

**Weighted fractal networks**

In this section a family of weighted fractal networks is introduced.

Let \( r (r > 1) \) be a positive real numbers, and \( s (s > 1) \) be a positive integer.

(1) Let \( G_n \) be our base graph, composed by \( N + 1 \) nodes \( \Sigma_1 = \{0, 1, \ldots, N\} \) and \( r \) copies of edges \( \Sigma_0 \). We partition \( \Sigma_0 \) into two non-empty sets \( V_1 = \{0\} \), labeled attaching node, \( V_2 = \{1, \ldots, N\} \) all other nodes except for the attaching node, satisfying the symmetry of nodes in \( G_n \). The edge set \( E(G_n) \) is defined by \( (0,1,2,\ldots,N) \). If the pair \( x, y \in \Sigma_0 \) is connected by an edge, then this edge is denoted by \( (x, y) \). Each of \( (0,1,2,\ldots,N) \) is \( E(G_n) \) with unit weight.

**Remark:** The symmetry of nodes \( 1, \ldots, N \) in \( G_n \) means that the network \( G_n \) is invariable no matter how two arbitrary nodes \( i \) and \( j \) are exchanged \( (i, j) \in [1, \ldots, N] \).

(2) For any \( n \geq 1 \), \( G_n \) is obtained from \( G_{n-1} \) (see Fig. 1): \( G_n \) has one attaching node labelled by \( \{00\ldots0\} \). Let \( G_n^{(1)}, G_n^{(2)}, \ldots, G_n^{(s)} \) be \( s \) copies of \( G_n \), \( G_n^{(1)}, G_n^{(2)}, \ldots, G_n^{(s)} \) be \( s \) copies of the union of \( s \) copies of \( G_n^{(1)}, G_n^{(2)}, \ldots, G_n^{(s)} \). Let \( V(G_n) \) be the set of nodes in \( G_n \) with \( \Sigma_0 = \{x = (x_1, x_2, \ldots, x_n) \in \Sigma_0, 1 \leq i \leq n\} \). If the pair \( x, y \in \Sigma_0 \) is connected by an edge, then this edge is denoted by \( (x, y) \). Let \( E(G_n) \) be the set of edges in \( G_n \). For \( i = 1, \ldots, s \), let us denote by \( (a) \in \Sigma_0 \), the node in \( G_n^{(i)} \) image of the labeled node \( (a) \in V(G_{n-1}) \). Let \( \{x_0, 0\ldots0\} \in V(G_n) \), \( \{x_0, 0\ldots0\} \in V(G_n) \), then link all those label nodes to the attaching node \( \{00\ldots0\} \in V(G_n) \).

The weighted fractal networks are set up.

According to the construction of the weighted fractal networks, one can see that \( G_n \) the weighted fractal networks of \( n \) generation, is characterized by three parameters \( n, s \) and \( r \): \( n \) being the number of generations, \( s \) being the number of copies, and \( r \) representing the weight factor. The total number of nodes in \( G_n \) is as follows.

\[
N_n = |V(G_n)| = 1 + s + s^2 + \cdots + s^{n-1} + s^{n-1}N = \frac{s^n - 1}{s - 1} + s^{n-1}N \approx \frac{(Ns + s - N)s^{n-1}}{s - 1}.
\]

(1)

**Modified box dimension**

**Definition 3.1.** The weighted shortest path of nodes \( i \) and \( j \) in the weighted graphs \( G_n \) is given by

\[
P(i, j) = \min_{l \in \Gamma} \{w_{ik} + w_{kj} + \cdots + w_{lj}\},
\]

where \( \Gamma \) is the set of paths linking \( i \) and \( j \) in \( G_n \).

The self-similar property of real-world networks, box-counting method turns to be practical\(^ {22}\). The method works as follows: we partition the nodes into boxes of size \( l_0 \). The maximal distance between vertices within a box is at most \( l_0^2 - 1 \). The resulting number of boxes needed to tile the networks denoted by \( N_B(l_0) \). Then the box dimension \( d_B \) is defined by \( d_B \equiv \log N_B(l_0)/\log l_0 \).

Modified box dimension was motivated by the fact that in the case of the weighted fractal networks the original definition of box dimension is infinite. It is worth mentioning, our new concept of dimension does exist and is finite for this model as Theorem 3.3 shows.
Definition 3.2. The modified box dimension is defined by

\[
\dim(\{G_n\}_{n \in \mathbb{N}}) = \lim_{k \to \infty} \lim_{n \to \infty} \frac{\log |V(G_n)|}{-\log l_k}
\]

where \(l_k = \text{diam}(G_k) + 1\) and \(B^n_k\) denotes the minimal number of boxes of size \(l_k\) that we need to cover \(G_n\).

Theorem 3.3. For the weighted fractal networks the modified box dimension:

\[
\dim(\{G_n\}_{n \in \mathbb{N}}) = \log r s,
\]

where \(s\) is the number of copies, \(r\) is the weighted factor.

For convenience of description, we recall the following notations.

(i) Let \(V(G_n)\) be the set of nodes in \(G_n\), which is \(\Sigma_n = \{x = (x_1, \ldots, x_n): x_i \in \Sigma_i, i = 1, \ldots, n\}\) where \(\Sigma_i = \{0, 1, \ldots, N\}\), and \(E(G_n)\) be the set of edges in \(G_n\).

(ii) Given \(x = (x_1, \ldots, x_n), y = (y_1, \ldots, y_m) \in \Sigma_n\), we denote the common prefix by \(x \wedge y = (z_1, \ldots, z_k)\) s.t. \(x_i = y_i = z_i, \forall i = 0, \ldots, k\) and \(x_{k+1} = y_{k+1}\).

(iii) We fix an arbitrary self-map \(p\) of \(\Sigma_i\) such that for \(x = 1, 2, \ldots, N, (x, p(x)) \in E(G_i)\), i.e., \(p(x) = 0\).

For a word \(z = (z_1, \ldots, z_m) \in \Sigma_m\), we define...
\[ p(z) = \begin{cases} (z_1 \cdots z_{m-1} p(z_m)) = (z_1 \cdots z_{m-1}, 0), & \text{if } z_m = 0, \\ (z_1 \cdots p(z_k) z_{k+1} \cdots z_m), & \text{if } z_{k+1} = \cdots = z_m = 0 \text{ and } z_k \neq 0. \end{cases} \]

Then \((tz, tp(z))\) is an edge in \(G_{n+m}, \forall z = (t_1 \cdots t_n) \in \Sigma^*_n\).

**The diameter of \(G_n\)**

**Lemma 3.4.** The diameter of \(G_n\) is

\[ \text{diam}(G_n) = \frac{2(r^n - 1)}{r - 1}, \quad (n \geq 2). \] (3)

**Proof.** We will prove this from two respects.

1. Considering the worst case scenario, i.e., choosing \(x = (x_1 \cdots x_n) \in V(G_n)\) and \(y = (y_1 \cdots y_n) \in V(G_n)\) such that (i) \(x \land y = 0\). (ii) \(x_1 \cdot x_2 \cdot \cdots x_n \cdot y_1 \cdot y_n = 0\), yields that

\[ P(x, y) \geq 1 + r + \cdots + r^{n-1} + r^{n-1} + \cdots + r + 1 = \frac{2(r^n - 1)}{r - 1}. \]

2. We construct a path \(P(x, y)\) between two arbitrary nodes \(x, y\) that is no longer than \(\frac{2(r^n - 1)}{r - 1}\). Let \(x = (x \land b_1 b_2 \cdots b_\mu 0 \cdots 0)\) where \(b_i \in \Sigma_1, \mu \leq n\), and \(y = (x \land c_1 c_2 \cdots c_\nu 0 \cdots 0)\) where \(c_j \in \Sigma_1, \nu \leq n\).

Starting from \(x\) the first half of the path \(P(x, y)\) is as follows:

\[
\begin{align*}
x^0 &= x, \\
x^1 &= (x \land yb_1b_2 \cdots b_\mu 0 \cdots 0) \\
&= (x \land yb_1b_2 \cdots b_\mu 0 \cdots 0), \\
&\vdots \\
x^{\mu-1} &= (x \land yp(b_1) \cdots p(b_{\mu-1}) 0 \cdots 0) \\
&= (x \land yp(b_1) \cdots p(b_{\mu-1}) 0 \cdots 0). 
\end{align*}
\]

Starting from \(y\) the first half of the path \(p(x, y)\) is as follows:

\[
\begin{align*}
y^0 &= y, \\
y^1 &= (x \land yc_1c_2 \cdots c_\nu 0 \cdots 0) \\
&= (x \land yc_1c_2 \cdots c_\nu 0 \cdots 0), \\
&\vdots \\
y^{\nu-1} &= (x \land yc_1p(c_2) \cdots p(c_{\nu-1}) 0 \cdots 0) \\
&= (x \land yc_1p(c_2) \cdots p(c_{\nu-1}) 0 \cdots 0). 
\end{align*}
\]

In this way

\[ P(x, y) = (x^0, x^1, \ldots, x^{\mu-1}, y^0, y^1, \ldots, y^{\nu-1}). \]

Clearly,

\[
P(x, y) \leq \frac{r^i + r^{i+1} + \cdots + r^{i+\mu-1}}{\mu} \\
+ \frac{r^j + r^{j+1} + \cdots + r^{j+\nu-1}}{\nu}
\]

\[
(0 \leq i \leq n - \mu, 0 \leq j \leq n - \nu)
\]

\[
\leq 1 + r + \cdots + r^{n-1} + 1 + r + \cdots + r^{n-1}
\]

\[
= \frac{2(r^n - 1)}{r - 1}. \#
\]

**Lower bound of modified box dimension**

**Lemma 3.5.** The following inequality holds for \(\forall n \geq 1\),
\[ B^n_k \leq \frac{s^n - 1}{s - 1}. \]  

**Proof.** It is easy to see that we need one \( l_i \)-box to cover \( G_i \). It follows from the weighted structure of \( G_n \) that \( G_n \) contains \( s^{n-1} \) copies of \( G_1 \) and \( s^{n-2} + \cdots + s + 1 \) nodes. This implies that we can cover \( G_n \) with \( s^{n-1} + (s^{n-2} + \cdots + s + 1) = \sum_{s=1}^{n} l_i \)-boxes. 

**Lemma 3.6.**

If \( n \leq k \) then \( B^n_k = 1 \).

If \( n > k \geq 2 \) then \( B^n_k \leq B^{n-1}_{k-1} \).  

**proof.** Suppose that \( x = (x_1, \ldots, x_{n-k+1}) \) and \( y = (y_1, \ldots, y_{n-k+1}) \) two arbitrary nodes in \( G_{n-k+1} \) contained by the same \( l_i \)-box, i.e., the distance between \( x \) and \( y \) is not greater than \( \text{diam}(G_i) \). If we blow them up, we get two cylinder sets of nodes:

\[ X = \{ (\tilde{x}_1, \ldots, \tilde{x}_n) | (\tilde{x}_1, \ldots, \tilde{x}_{n-k+1}) = x \}, \]

and

\[ Y = \{ (\tilde{y}_1, \ldots, \tilde{y}_n) | (\tilde{y}_1, \ldots, \tilde{y}_{n-k+1}) = y \}. \]

Next, we calculate the maximal distance between the elements of \( X \) and \( Y \). Considering the worst case scenario \( x_1, \ldots, x_{n-k+1} \neq 0, y_1, \ldots, y_{n-k+1} \neq 0 \) and \( |x \land y| = n - k \). Namely, that

\[ X^1 = \{ (\tilde{x}_1, \ldots, \tilde{x}_n) | (\tilde{x}_1, \ldots, \tilde{x}_{n-k+1}) = x \} \quad \text{and} \quad \tilde{x}_{n-k+2} \cdots \tilde{x}_n = 0 \subset X. \]

and

\[ Y^1 = \{ (\tilde{y}_1, \ldots, \tilde{y}_n) | (\tilde{y}_1, \ldots, \tilde{y}_{n-k+1}) = y \} \quad \text{and} \quad \tilde{y}_{n-k+2} \cdots \tilde{y}_n = 0 \subset Y. \]

Starting from \( \tilde{\bar{x}} \in X^1 \) at most takes \((r + 1) + \cdots + r^{k-1}\) steps to reach the \((x \land y)0\ldots0\). Similarly, starting from \( \tilde{\bar{y}} \in Y^1 \) we need at most \((1 + r + \cdots + r^{k-1}) \) steps to reach \((x \land y)0\ldots0\).

Thus the distance between \( \tilde{\bar{x}} \) and \( \tilde{\bar{y}} \) is not greater than \( 2(1 + r + \cdots + r^{k-1}) = 2(r^k - 1) = \text{diam}(G_k) < l_k \).

Therefore, the same \( l_i \)-boxing that we have used in \( G_{n-k+1} \) is an appropriate \( l_i \)-boxing for \( G_n \).

From Eqs (4) and (5), we can see that, if \( n > k \), \( B^n_k \leq B^{n-1}_{k-1} \leq \frac{s^{n-1} - 1}{s - 1} \). Then from Eqs (1–3), we obtain

\[ \lim_{k \to \infty} \log \left( \frac{(s + x - n)s^{-1}}{s - 1} \right) = \log \frac{s^{n-1} - 1}{s - 1} \]

\[ = \log s. \]

**Upper bound of modified box dimension**

**Lemma 3.7.** The following inequality holds for \( \forall n \geq 1 \)

\[ B^n_n \geq s^{n-1}. \]

**Proof.** For every digit \( x \in \{1, 2, \ldots, s\} \), we define the cylinder set \( Z_x \) of words \((z_1, z_2, \ldots, z_n)\) with \( z_1 = x \).

Let \( x, y \in \{1, 2, \ldots, s\}, x = y \). Now we give a lower bound on the shortest path between \( Z_x \) and \( Z_y \), thus we need at least \( 2s^{n-1} > 2 \geq \text{diam}(G_i) \) steps on any path between \( z_x \in Z_x \) and \( z_y \in Z_y \). These witness must be in distinct \( l_i \)-boxes, so we need at least \( s^{n-1} - 1 \)-boxes to cover \( G_n \).

**Lemma 3.8.** The following inequality holds

\[ B^n_n \geq s^{n-k-1} \text{ for } n > k. \]

**Proof.** We have constructed \( s^{n-1} \) nodes in \( G_i \) whose pairwise distance is greater than \( \text{diam}(G_i) \). It is enough to show that we can find the same number of nodes (i.e., \( s^{n-1} \)) in \( G_{n+i} \) for \( i \geq 1 \) such that the pairwise distances between them are greater than \( \text{diam}(G_i) \), this implies

\[ B^{n+i} \geq s^{i-1}. \]

Let
\[ x = (x_1, x_2, \cdots, x_i) \in \Sigma_i \mapsto z_x \in \mathcal{Z}_x \]

where the cylinder set of nodes

\[ \mathcal{Z}_x = \{(\tilde{z}_1, \tilde{z}_2, \cdots, \tilde{z}_{i+j}) \in \Sigma_{i+j} | (\tilde{z}_1, \tilde{z}_2, \cdots, \tilde{z}_i) = x\} \]

Now we give a lower bound on the shortest path between \( z_x \) and \( z_y \), where \( x, y \in \Sigma_i \). We need at least

\[ 2(s^2 + 1 + s + 1) = \text{diam}(G) < l_j \] steps on any path between \( z_x \) and \( z_y \). Hence these witness must be in distinct \( l_j \) boxes. So we need at least \( s^{i+j} \) boxes to cover \( G_{i+j} \), i.e., substituting \( n = i + j \) and \( k = j \) yields that

\[ B_k^n = B_k^{n-2+k} \geq s^{n-k-1} \].

From Eq. (7) we can see that \( B_k^n \geq s^{n-k-1} \). Then from Eqs (1–3), we obtain

\[
\widetilde{\dim}(\{G_n\}_{n \in \mathbb{N}}) = \lim_{k \to \infty} \lim_{n \to \infty} \frac{\log V(G_n) - \log B_k^n}{\log(\text{diam}(G_n) + 1)} \\
\leq \lim_{k \to \infty} \lim_{n \to \infty} \frac{\log \left(\frac{(N_s + s - N)}{s-1} \right)^{s-1} - \log s^{n-k-1}}{\log \left(\frac{2(s-1)}{s-1} \right)^{s-1} + 1} \\
= \log s.
\] (8)

**Proof of Theorem 3.3.** Combining lower bound and upper bound of modified box dimension i.e., Eqs (6) and (8) yields Theorem 3.3, hence:

\[
\widetilde{\dim}(\{G_n\}_{n \in \mathbb{N}}) = \log s.
\]

**The average weighted receiving time on random walk**

The purpose of this section is to determine explicitly the average weighted receiving time (AWRT) \( \{T_n\} \) and to show how \( \{T_n\} \) scales with network order. We consider a particular case on \( G_n \) with the trap placed on the attaching node \( (00\cdots0)_n \), let us denote by \( 0 \). All other nodes, except for the attaching node, are denoted by \( 1, 2, \cdots, N_n - 1 \).

Assuming that the walker, at each step, starting from its current node, moves uniformly to any of its nearest neighbors.

For two adjacency nodes \( i \) and \( j \), the weighted time is defined as the corresponding edge weight \( w_{ij} \). The mean weighted first-passing time (MWFTP) is the expected first arriving weighted time for the walks starting from a source node to a given target node. Let \( F_{ij}(n) \) be the mean weighted first-passage time (MWFTP) for a walker starting from node \( i \) to node \( j \). Let \( F_i(n) \) be the MWFTP from Node \( i \) to the trap. \( \{T_n\} \) is the average weighted receiving time (AWRT) which is defined as the average of \( F_{ij}(n) \) over all starting nodes other than the trap. \( \{T_n\} \) is the key question concerned in this paper.

**Theorem 4.1.** For a large system, i.e., \( N_n \to \infty \),

1. if \( r > s \), we have the following expression for the dominating term of \( \{T_n\} \):

\[
\{T_n\} \sim N_n^{\log r} = N_n^{\dim(G_{n \in \mathbb{N}})} \]

2. if \( r < s \), we have the following expression for the dominating term of \( \{T_n\} \):

\[
\{T_n\} \sim N_n^s.
\]

3. if \( r = s \), we have the following expression for the dominating term of \( \{T_n\} \):

\[
\{T_n\} \sim N_n \cdot \log N_n.
\]

**Remark.** This confirms that in the large \( n \) limit, if \( r > s \) then the AWRT grows as a power law function of the network order with the exponent, represented by \( \theta = \frac{1}{\dim(G_{n \in \mathbb{N}})} \), being the reciprocal of \( \dim(G_{n \in \mathbb{N}}) \). When \( \dim(G_{n \in \mathbb{N}}) \) grows from 0 to 1, the exponent decreases from \( +\infty \) approaches 1. This also means that the efficiency of the trapping process depends on the modified box dimension: the larger the value of modified box dimension, the more efficient the trapping process is.

**Proof.** By definition, \( \{T_n\} \) is given by
Here, we denote by $T_{\text{ntot}}$ the sum of MWFPTs for all nodes to absorption at the trap located the attaching node $n$. Thus, the problem of determining $T_n$ is reduced to finding $T_{\text{ntot}}$. We will compute $T_{\text{ntot}}$ by segmenting $G_n$.

From the self-similarity construction method of $G_n \geq 2$, $G_n$ can be regarded as merging $s+1$ groups, sequentially denoted by $G_n^{(0)}$, $G_n^{(1)}$, $G_n^{(2)}$, ..., $G_n^{(s)}$. The $s+1$ groups are obtained as follows. $G_n^{(0)}$ includes the central Node 0 and $s$ nodes denoted by $1 = \left\{ \begin{array}{cc} 0 & n \end{array} \right\} \vdots 2 = \left\{ \begin{array}{cc} 0 & n \end{array} \right\} \vdots s = \left\{ \begin{array}{cc} 0 & n \end{array} \right\}$. Each node in $s$ nodes is linked to the central Node 0 through the weighted time $r_n$. $G_n^{(i)}$ is a copy of $G_{n-1}^{(i)}$ ($i = 1, 2, \ldots, s$). In order to completely express the division of the general weighted fractal networks, we present the special division of the 'Sierpinski' weighted fractal networks when $s = 3$ (see Fig. 2).

Through this division, we can rewrite the sum $T_{\text{ntot}}$ as follows:

\[
T_{\text{ntot}}(n) = \left[ T_{\text{ntot}}(n-1) + N_{n-1}F_1(n) \right] + \left[ T_{\text{ntot}}(n-1) + N_{n-1}F_2(n) \right] + \cdots + \left[ T_{\text{ntot}}(n-1) + N_{n-1}F_s(n) \right] = sT_{\text{ntot}}(n-1) + N_{n-1}F_s(n) + F_2(n) + \cdots + F_s(n) = sT_{\text{ntot}}(n-1) + sN_{n-1}F_s(n),
\]

where $F_i(n) = F_2(n) = \cdots = F_s(n)$.

Figure 2. Take the 'Sierpinski' weighted fractal networks $G_n$, for example, $G_2$ is regarded as merging $G_2^{(0)}$, $G_1^{(1)}$, $G_1^{(2)}$, $G_1^{(3)}$. 

$T_n = \frac{1}{N_n - 1} \sum_{i=1}^{N_n-1} F_i(n)$. 

Through this division, we can rewrite the sum $T_{\text{ntot}}(g)$ as follows:

\[
T_{\text{ntot}}(n) = \left[ T_{\text{ntot}}(n-1) + N_{n-1}F_1(n) \right] + \left[ T_{\text{ntot}}(n-1) + N_{n-1}F_2(n) \right] + \cdots + \left[ T_{\text{ntot}}(n-1) + N_{n-1}F_s(n) \right] = sT_{\text{ntot}}(n-1) + N_{n-1}F_s(n) + F_2(n) + \cdots + F_s(n) = sT_{\text{ntot}}(n-1) + sN_{n-1}F_s(n),
\]

where $F_i(n) = F_2(n) = \cdots = F_s(n)$. 

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Thus, the problem of determining \( T_{\text{tot}}(n) \) is reduced to finding \( F_i(n) \). Note that the strength of Node \( i \) \((i = 1, 2, \ldots, s)\) is \( 1 + s \) according to the construction of \( G_n \). Using the division of \( G_n \), we have

\[
F_i(n) = \frac{r^{n-1}}{1 + s} + \frac{s}{1 + s} \left[ r^{n-2} + F_i(n - 1) + F_i(n) \right].
\]

(13)

Through the reduction of Eq. (13), we obtain

\[
F_i(n) = sF_i(n - 1) + r^{n-1} + s^{-1}.
\]

(14)

In the given initial network \( G_1 \), let \( F_1 \) be the the mean weighted first-passage times (MWFPTs) for a walker from Node \( i \) in \( V_2 = \{1, \ldots, N\} \) to the attaching node 0 in \( V_1 = \{0\} \). Here, we denote by \( T_{\text{tot}}(1) \) the sum of MWFPTs for all nodes to the attaching node 0, i.e., \( T_{\text{tot}}(1) = \sum_{i=1}^{N} F_i \). Because of the symmetry of nodes \( 1, 2, \ldots, N \), \( F_1(1) = F_2(1) = \cdots = F_N(1) \) and \( F_1(1) = T_{\text{tot}}(N) \). \( T_{\text{tot}}(1) \) is a constant number for the given initial network \( G_1 \).

Considering the initial network \( G_1 \), one can prove

\[
F_1(2) = \frac{r}{1 + N} + \frac{N}{1 + N} \left[ 1 + \frac{T_{\text{tot}}(1)}{N} + F_1(1) \right]
\]

(15)

Through the simplifications of Eq. (15), we obtain

\[
F_1(2) = r + N + T_{\text{tot}}(1).
\]

(16)

From Eq. (16), we can solve Eq. (14) recursively to yield

\[
F_i(n) = \begin{cases} 
\frac{r + N + T_{\text{tot}}(1)}{s} r^{n-1} + \frac{s + r}{s - r} r^{n-2}, & \text{if } r \neq s, \\
(N + T_{\text{tot}}(1) - s)s^{-2} + 2(n - 1)s^{n-1}, & \text{if } r = s.
\end{cases}
\]

(17)

Using the construction of \( G_2 \), we have

\[
T_{\text{tot}}(2) = sT_{\text{tot}}(0) + s(1 + N)F_2(2) = (N + 2)T_{\text{tot}}(1) + (1 + N)(r + N).
\]

(18)

When \( r = s \) from Eqs (17) and (18), we can solve Eq. (10) inductively to yield

\[
T_{\text{tot}}(n) = \left[ (N + 2)T_{\text{tot}}(1) + (1 + N)(r + N) - \frac{s(Ns + s - N)(s + r)}{(s - 1)^2} \left( r + N + T_{\text{tot}}(1) + \frac{r(s + r)}{s - r} \right) - \frac{s^2(Ns + s - N)(s + r)}{(s - 1)(s - r)} \right] r^{n-1}
\]

\[
+ \frac{Ns + s - N}{s^2(s - 1)^2} \left( r + N + T_{\text{tot}}(1) + \frac{r(s + r)}{s - r} \right) r^{n-2} + \frac{(Ns + s - N)(s + r)}{s(1 - r)(s - 1)(s - r)} (sr)^n.
\]

Hence, \( \langle T \rangle_n \), which we are concerned about, could be expressed as follows:

\[
\langle T \rangle_n = \frac{T_{\text{tot}}(n)}{N_n - 1} = \left[ \frac{(s - 1)(N + 2)T_{\text{tot}}(1) + (s - 1)(1 + N)(r + N)}{Ns + s - N} - \frac{s}{s - 1} \left( r + N + T_{\text{tot}}(1) + \frac{r(s + r)}{s - r} \right) - \frac{s^2(Ns + s - N)(s + r)}{(1 - r)(s - r)} \right] r^{n-1}
\]

\[
+ \frac{1}{s(s - 1)} \left( r + N + T_{\text{tot}}(1) + \frac{r(s + r)}{s - r} \right) r^{n-2} + \frac{s + r}{(1 - r)(s - r)} (sr)^n.
\]

(19)
(1) If \( r > s \), the dominating term of \( \langle T \rangle_n \) is written as follows:
\[
\langle T \rangle_n \approx \frac{s + r}{(1 - r)(s - r)} r^n.
\]

For a large system, i.e., \( N_n \to \infty \), from Eq. (1) we have the following expression for the dominating term of \( \langle T \rangle_n \):
\[
\langle T \rangle_n \approx N_n^{\log_2 r} = N_n^{\dim_{\text{top}}(G)_{n \geq N}}.
\]
where \( 0 < \dim_{\text{top}}(G)_{n \geq N} = \log_2 r < 1 \).

(2) If \( r < s \), the dominating term of \( \langle T \rangle_n \) is written as follows:
\[
\langle T \rangle_n \approx \frac{1}{s - 1} \left[ r + N + T_{\text{tot}}(1) + \frac{r(s + r)}{s - r} \right] n^{-1}.
\]

For a large system, i.e., \( N_n \to \infty \), from Eq. (1) we have the following expression for the dominating term of \( \langle T \rangle_n \):
\[
\langle T \rangle_n \approx \frac{1}{Ns + s - N} \left[ r + N + T_{\text{tot}}(1) + \frac{r(s + r)}{s - r} \right] N_n.
\]

(3) If \( r = s \), from Eqs (17) and (18), we can solve Eq. (12) inductively to yield
\[
T_{\text{tot}}(n) = \left[ (N + 2)T_{\text{tot}}(1) + r + N + (s + N) \right]
- \frac{s(Ns + s - N)(N + T_{\text{tot}}(1) - s)}{s(s - 1)^2}
+ \frac{2(Ns + s - N)}{(s - 1)^3}
+ \frac{2(Ns + s - N)}{s(s - 1)^2} n^{2n}.
\]

For a large system, i.e., \( N_n \to \infty \), from Eq. (1) we have the following expression for the dominating term of \( \langle T \rangle_n \):
\[
\langle T \rangle_n = \frac{(s - 1)(N + 2)T_{\text{tot}}(1) + (s - 1)(1 + N)(s + N)}{Ns + s - N}
- \frac{s(N + T_{\text{tot}}(1) - s)}{s - 1}
+ \frac{2s}{(s - 1)^2}
+ \frac{N + T_{\text{tot}}(1) - s}{s(s - 1)} n^2
+ \frac{2s}{s - 1} n^2.
\]

Conclusions
In this paper, we introduced a family of weighted fractal networks with weight factor \( r \). We mainly studied its modified box dimension and AWRT on the weighted fractal networks. For the case of \( r > s \), the AWRT grows as a power law function of the network order with the exponent, being the reciprocal of \( \dim_{\text{top}}(G)_{n \geq N} \). We found that when \( \dim_{\text{top}}(G)_{n \geq N} \) grows from 0 to 1, the exponent decreases from \( +\infty \) approaches 1. This result showed that the efficiency of the trapping process depends on the modified box dimension: the larger the value of modified box dimension, the more efficient the trapping process is. Otherwise, for the case of \( r < s \), the AWRT grows linearly with the network size \( N_n \), and for the case of \( r = s \), the AWRT grows with increasing order \( N_n \) as \( \log_2 N_n \).

It should be mentioned that we only studied a particular family of weighted fractal networks, whether the conclusion also holds for other more general networks, which needs further investigation.

References
1. L. K. Gallos, C. Song & H. A. Makse. A review of fractality and self-similarity in complex networks. Physica A 386, 686–691 (2007).
2. L. K. Gallos, C. Song & H. A. Makse. Scaling of Degree Correlations and Its Influence on Diffusion in Scale-Free Networks. Phys. Rev. Lett. 100, 248701 (2008).
3. H. D. Rozenfeld, C. Song & H. A. Makse. Small-World to Fractal Transition in Complex Networks: A Renormalization Group Approach. Phys. Rev. Lett. 104, 025701 (2010).
4. F. Morone & H. A. Makse. Influence maximization in complex networks through optimal percolation. *Nature* **524**, 65–68 (2015).

5. R. Albert & A.-L. Barabási. Hierarchical organization in complex networks. *Rev. Mod. Phys.* **74**, 47 (2002).

6. A. L. Barabási, E. Ravasz & T. Vicsek. Deterministic scale free networks. *Physica A* **299**(3), 559–564 (2001).

7. J. Komjáthy & K. Simon. Generating hierarchical scale free graphs from fractals. *Chaos, Solitons & Fractals* **44**(8), 651–666 (2011).

8. J. Chen, M. F. Dai, Z. X. Wen & L. F. Xi. A class of scalefree network with fractal structure based on subshif of finite type. *Chaos* **24**, 043133 (2014).

9. A. Barrat, M. Barthélemy, R. Pastor-Satorras & A. Vespignani. The architecture of complex weighted networks. *Proc. Natl. Acad. Sci. USA* **101**, 3747–3752 (2004).

10. A. E. Krause, K. A. Frank, D. M. Mason, R. E. Ulanowicz & W. W. Taylor. Compartments revealed in food-web structure. *Nature* **426**, 282–285 (2003).

11. R. Pastor-Satorras & A. Vespignani. Evolution and Structure of the Internet. *A Statistical Physics Approach*. Cambridge, Cambridge University Press (2004).

12. M. Barthélémy, A. Barrat, R. Pastor-Satorras & A. Vespignani. Characterization and modeling of weighted networks. *Physica A* **346**, 34–43 (2005).

13. A. Barrat, M. Barthélemy & A. Vespignani. Large scale structure and dynamics of complex networks: From Information Technology to Finance and Natural Science, World Scientific (2007).

14. R. Albert & A. L. Barabási. Statistical mechanics of complex networks. *Rev. Mod. Phys.* **74**, 47–100 (2002).

15. S. N. Dorogovtsev & J. F. F. Mendes. Evolution of networks: from biological nets to the internet and WWW. Stanford, Oxford University Press (2003).

16. K. I. M. KyungSik, G. H. KIM & Y. S. KONG. Multifractal measures characterized by the iterative map with two control parameters. *Fractals* **08**(02), 181–187 (2000).

17. S. Redner. *A guide to first-passage processes*. Cambridge, Cambridge University Press (2001).

18. J. D. Noh & H. Rieger. Random Walks on Complex Networks. *Phys. Rev. Lett.* **92**, 118701 (2004).

19. M. F. Dai, X. Y. Li & L. F. Xi. Random walks on non-homogenous weighted Koch networks. *CHAOs* **23**, 033106–033113 (2013).

20. B. Daudert & M. Lapidus. Localization on snowflake domains. *Fractals* **15**, 255–267 (2007).

21. T. Carletti & S. Righi. Weighted fractal networks. *Physica A* **389**, 2134–2142 (2010).

22. C. Song, S. Havlin & H. A. Makse. Self-similarity of complex networks. *Nature* **431**, 392–395 (2005).

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**Author Contributions**

M.D. and W.S. designed the research. S.S. and L.X. collected the data. M.D. and Y.S. wrote the manuscript and Y.S. prepared figures 1–2. All authors discussed the results and reviewed the manuscript.

**Additional Information**

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