NONLINEAR DYNAMIC NETWORK TOPOLOGY CONSTRUCTION FOR IDENTIFYING DISTANCE ESTIMATION BASED ON HILBERT QUEUING ALGEBRAIC MODEL FOR NETWORK COMMUNICATION

Abstract

The development network structure creates complex topology for non-residual communication due to nonlinear communication sinks one over the other. By identifying the dynamic network distance is difficult because the nonlinear structure creature mitigated structure. Most of the distance theory algebraic models failed to reduce the analytical process for identifying best solution for path construction because of data Queuing are non-analytical process. To resolve this problem, we propose Nonlinear Dynamic network topology (NLDNT) construction for identifying distance estimation based on Hilbert Queuing Algebraic model (HQAM) for network communication. Initially the Barrier Log Neighbor path utility analysis (BLNPUA) gets the node possibility of transmission. To get the closest support node using Distance estimation of convergence based on Hilbert and estimated through Laplacian scale (LS) procedere to get the node covergence. Then the Linearity path construction analyses in M/M/G-k-queuing make support node to construct the neighbor path to make efficient transmission. The proposed mathematical algebraic model reduce the analytical process burden to provide equivalence support to identifying the structural path to transfer the data to less time and network improvement than other analytical solution. This proposed system produce high performance evaluation compared to the other systems.

Keywords: network topology, analytical process, Algebraic topology: distance theory estimation, Hilbert theory, and Queuing process.

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I. INTRODUCTION

The proposed system estimate the network to expand the algebraic connection into the cognitive context in which the network receives the design of the mean Laplace an matrix, averages it by the random function of the primary user, and calculates the algebraic connection. Based on this mathematical model, it has been shown to be useful in capturing some key properties of network paths and developing an application function based on distance theory estimation that can be used to compare them for routing purposes by definition of Hilbert process. Then, by modeling the path with a map and its Laplace formation, we design a routing plan that captures the connection properties of the path and correctly selects the best route in the uncertain and variable connection environment.

II. RELATED WORK

S. Dong et al. [1], the author investigates network topology must be designed to provide immunity to connection failures. The most recovering network is called the survival network. A reliability polynomial is a consistent measure of network efficiency, and it isn't easy to calculate that factor. Nondeterministic Polynomial-time (NP) problem has in network topology. So the author introduces the Logarithmic Barrier Method (LBM) for network traffic prediction. This method first uses the LBM to analyze network traffic's key factors. It then uses the LBM for queue congestion to adjust the network distribution's distributed packet transfer rate.

M. Li et al. [2], the study explore the growing power consumption problems of wireless sensor network applications. The study introduces Relay Node Replacement based on Optimal Transmission Distance (RNROTD) to decrease power consumption and enhance network lifetime in a two-tiered sensor network. T. Etzion et al. [3] the novel focus to demonstrate the strong link between optimal Grassmannian encoding for commonly integrated networks and network encoding solutions. To generalize multiple distances in a Grossmanian, it define two new dual distance measurements in the Grossmanian measure. Describes the maximum size and new distance weights of the new classman code.

K. Wu et al. [4] the study introduces Minimum Distance Dominating (MDD) approach for dominates complex networks by recognizing the driving nodes. The recommended approach first integrate the main concepts of distance control theory into graphs and applies them to complex networks' controllability analysis. Turovska et al. [5] Distance estimating equipment is one of the most commonly used navigation in the aviation industry. The Markov chain model is utilized to obtain continuous stationary equations. If the number of aerospace users varies, the response capability of the device repeater and the probability of query loss will be explored.

S. Choi et al. [6], the study carries out the Distance estimation method of wireless sensor networks. The suggested method analyses two neighbor nodes distance estimation to analyze the information. L. Pan et al. [7], the algebraic connection averages the random function of the primary user and calculate the algebraic connection in the cognitive context that derives the design of the network's average Laplacean matrix.

J. Heredia-Juesas et al. [8], the novel explains Rigged Hilbert Spaces (RHS) important feature of this mathematical rigour that combines conventional and general functions under a single framework. Bo Jiao et al. [9] novel investigates the problem of range free like the hop count-based method using Laplacian spectra for multicast routing for networks. However, these methods are less accurate on low-end networks and harder to use on wireless networks other than densely populated sensor networks.

X. Yin et al. [10] the study explores the balanced system driven by the Levy process Hilbert space. To get complete control, it needs to make some assumptions. Whereas Banach fixed theorem and appropriate control are obtained using the semiconductor theory of different operators. Abbagnale et al. [11] the author explains connectivity Driven Routing for Ad-hoc networks. The recommended approach to illustrate the algebraic connection in a cognitive context, obtain the average Laplacian matrix for the network, which averages the random function of the primary user, and calculate the algebraic connection for ad-hoc networks. W. S. Lai et al. [12] the study explores Deep Laplacian Pyramid Networks (DLPN) method for accurate super-resolution. The model takes a rough resolution feature map as the input at each pyramid level, predicts high-frequency residues, and uses curves modified to smooth positions.

C. McGee et al. [13] a connection is established between the stability of the Graph Laplacian for the network forensics. The number of negative eigenvalues of the signed Laplacian is related to the network's number of negatively weighted margins.

III. METHODS OF EVALUATION

The Network path analysis was carried by the definition depends on barrier log carried out neighbor distance estimation by calculating the least square analysis of nodes at coverage in transmission medium. Each transmission medium distance coverage get the node convergence by estimating the congestion control. The following are the definitions,

1. **Barrier Log Neighbor Path Utility Analysis:** Let is considering the singular topology on dynamic path which is contains the N number of nodes at x and y positions having max number of nodes. The performance analysis was intent a through put measurement by considering column matrix at H positions for all the available paths to carry out Log table. The utility of nodes represented as single path and multi path be considered as regular medium ‘r’ at constant time c is,

$$\max_{x \geq 0} \sum_s u_s * n\left(\sum_{r \in s} x_r - \omega \sum_l f(y_l)\right) \dots\dots \qquad (1)$$

   At that point of network, Matrix be constructed as $Hx + r = c$ in constant time,

   From the equation1, the convex position is estimated by source and destination by covering the node path region, by searching the nodes carried over by greedy search estimation based on each flow of the packet. Some losses are recovered by ‘x’ and ‘y’ position to gain the throughput by considering the constant nodes ‘c’ to reduce the traffic ‘Tf’.

$$\underset{x \geq 0}{Tf} \sum_s u_s(\sum_{r \in s} x_r) + \sum_l \omega_l ln_l \ldots\ldots \quad (2)$$

The constant position at equivalence theory Subject to $Hx + r = c$ in all node consideration

$$\underset{x \geq 0}{Log\ (max)} \sum_s u_s(\sum_{r \in s} x_r) + \mu \sum_r lnx_r + \sum_l w_l ln_l \ldots (3)$$

The $equvance\ node\ at\ constant\ position\ is\ Hx + r \leq c$

By considering the node variation from new and existing transmission on path to get the defined variable $\lambda \in R_+^L, let\ p_r = \sum_{tf} \lambda_l$ at time t.

2. **Maximum Distance at New and Existence Equivalence:** In this stage maximum distance was estimated based on the node representation by arriving the path region in new and existing node of evaluation. The estimation of node at path at position 'r' P, the new and existing node representation is,

$$D(\lambda) := \underset{x,r}{max} L(x, r, \lambda) = \sum_s B(p_s) + \sum B(\lambda_l) + c^T \lambda \ldots\ldots\ldots\ldots \quad (4)$$

By getting the distance D at maximum closeness point,

$$B(p_s) = \underset{x_s}{max} U_s(\sum_{r \subset s} x_r) + \sum_{r \subset s}(\mu \ln x_r - p_r x_r) \ldots.. \quad (5)$$

$$B(\lambda_l) = \underset{r_l \leq c_l}{max} \omega_l lnr_l - \lambda_l r_l \ldots \quad (6)$$

By getting new and existing node representation is,

$$\underset{\lambda \geq 0}{min} \sum_s B(p_s) + \sum_L B(\lambda_L) + C^T \lambda \ldots.. \quad (7)$$

They attain the node convergence by estimating support of the node by representing dynamic variance nodes

3. **Node Convergence on Distributed Node Control:** The distributed nodes are dynamic in nature by constructing path in equivalence theory the support nodes get analyzed by convergence level by covering the difference of time representation. By analyzing the dynamic variation of node, the distance be evaluated by distributed probability function, $\beta\left(r_j(t) + \sum_{r.l\epsilon r} x_r(t) - c_j\right)$ at regular interval of node arrival time,

$$\lambda_l(t+1) - \left[\lambda_j(t) + \beta\left(r_j(t) + \sum_{r.l\epsilon r} x_r(t) - c_j\right)\right]^t \ldots \quad (8)$$

To get all the minimum value we get,

$$r_l(t) = \min\left(c_j, \frac{\omega_l}{\lambda_l(t)}\right)\ldots.. \quad (9)$$

Similarly the source s, be get max utility from the regular level.

$$x_s(t) = \arg\max_{x_s} U_s(\textstyle\sum_{r\epsilon s} x_r) + \sum \mu \ln x_r - p_r(t)x_r \ \ldots \quad (10)$$

Where $p_r(t) = \sum_{l.J\epsilon r} \lambda_j(t)$, $\lambda(t)$ .... (11) is the link

Congestion metric, and the remaining capacity r_l is determined according to the control parameters ω_l and the link congestion level at time t: $r_l(t) = \min\left(c_l, \frac{\omega_l}{\lambda_l(t)}\right)$. The formula (11) shows the maximizing net utility of the source s at time t based on path congestion level.

4. **Distance Estimation of Convergence Node:** Each convergence of node in path get validated by cyclic pre- presentation based on Hilbert theory of approach. The network topology can be signified by an undirected by Hilbert theory of approach and simple graph *G=(V,E)* where *V={V],V2,··· ,vn }* and *E={eJ,e2,·· . ,em}* correspondingly mean the node set and superiority set. Let *dv* denote the degree of node v in G, then the nominalized Laplacian matrix of G can be defined as

$$L(G)(u,v) = \begin{cases} 1 & if\ u = v\ and\ d_v \neq 0 \\ -\frac{1}{\sqrt{d_n.d_v}} & if\ u\ and\ v\ are\ adjacent\ldots \\ 0 & otherwise \end{cases} \quad (12)$$

The normalized Laplacian scale is self-possessed of all the eigen calues of $L(G)$: $\lambda_1 \leq \lambda_2 \leq \cdots \leq \lambda_n$.

$$W(G,N) = \textstyle\sum_{i=1,2,\ldots n}(1-\lambda_i)^N \ldots \quad (13)$$

From 13 the Eigen values are pointed regular nodes with suitable value for parameter N[12,13]. Moreover, the graph poi n G can be represented as N number of nodes

$$W(G,N) \approx \textstyle\sum_{\theta\epsilon\Omega}(1-\theta)^N . f(\lambda = \theta) \ldots. \quad (14)$$

By the congestion the Link of Transmission time T at λ_l variation depends on the N number of nodes arrived at queuing Length at t time in congestion c be $\sum_C x_t(t)$ be refereed at link state of time difference, ie,

$$\lambda_l(t+T) = \left[\lambda_l(t) + \beta\left(r_l(t) + \frac{N_T}{T} - c_l\right)\right]^t \ldots. \quad (15)$$

For a given price vector$\lambda(t)$, from formula (11) $x_s(t)$ is the solution of every sub problem if

$$\frac{1}{x_s(t)} + \frac{\mu}{x_r(t)} - p_r(t) = 0, \forall r \in s\ldots. \quad (16)$$

Considering the r as path from the regular source medium s pointed as in X positions, in ach process Pr,

$$p_r(t) > \frac{1}{x_s(t)} + \frac{\mu}{x_r(t)}, i.e. \frac{1}{p_r(t)} - \frac{x_r(t)x_s(t)}{x_r(t)+x_s(t)} < 0, \ldots \quad (20)$$

The congestion metric is relatively high, it is necessary to reduce the send rate of the flow, and the difference $\frac{1}{p_r(t)} - \frac{x_r(t)x_s(t)}{x_r(t)+x_s(t)}$ can be used in updating.

Where the remaining capacity of the link l is

$$r_l(t) = \min\left(c_l, \frac{\omega_l}{\lambda_l(t)}\right)\ldots \quad (21)$$

This gets maximum attaining distance coverage node based on the capacity of the nodes with minimum representation of the time

5. **Linearity Path Construction on Queuing:** In this the Node distance convergence are queued based on M/M/G- k-partitioned nodes graph, Let $G(\sigma, \mu)$ be a path location .we define the successive linearity graph of G.

G_{k_p}: $\left(\sigma_{k_{p(G)}} \quad , \quad \mu_{k_{p(G)}}\right)$ As follows.

The node set σ is partitioned into k disjoin subsets namely,$\sigma_{X1,}$ σ_X2 〖,σ〗 $\_X3$,............σ_Xk.

Such that the sum of the membership of the nodes of the subsets is more or less equal to each other. i.e., the sum of membership of nodes in Xi σ satisfies the condition$\left|\sum \sigma_{Xi} \quad - \sum \sigma_{Xj} < \varepsilon\right|$ Where 1, 2, 3 ….k and $i \neq j$ We have to partition σ such that an edge in $\mu_{k_{p(G)}}$originates at $\sigma_{Xi}$and ends edge inσ_{Xj}And ,

$$\mu_{k_p}(G)\ (u_i v_j) = \begin{cases} \mu_G(u_i, v_j) u_i \in \sigma_{Xi} \\ 0, otherwise \end{cases} and\ v_j \in \sigma_{Xj}\ \ \forall i\ \neq j\ \ldots \quad (22)$$

$\mu_{k_p}(G) \in [0,1]$ By definition Laplacian modified resultant of each node, $\mu_{k_p}(G)(u_i v_j) \leq \sigma_{Xi}(u_i) \wedge \sigma_{Xj}$ Here,$\mu_{k_p}(G)$ is a node relation on the subsets$\sigma_{k_p}(G)$.This proposed distance estimation by considering the support modes efficiency to get support on node relation. This proves the high supportive to get least path to improve the transmission.

IV. CONCLUSION

To conclude the proposed Nonlinear Dynamic network topology (NLDNT) construction makes efficient path construction by identifying distance estimation based on Hilbert Queuing Algebraic model (HQAM) to improve the network communication. The analysis models create slog support performed well by Barrier Log Neighbor path utility analysis to get the node possibility of improved transmission. This attain highly closest support node using Distance estimation of convergence based on Hilbert and estimated through Laplacian scale (LS) procedere to get the node covergence. This produce effeint quqing on path which have high mpact in node coverance by distance estimation.The proposed system produce high performance compared to the other solutions. This proved the distance estimation network transmission under the evaluation of Hilbert theory connecting the network of path carried over the distance estimation.

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