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Efficiency Enhancement through Optimization on Sequence Path Defining and Temporal Streamlining of Coupled Networks

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Abstract

The optimization of coupled linear networks is a pervasive challenge with diverse applications across scientific and engineering disciplines. This study delves into recent research efforts aimed at enhancing the performance and efficiency of interconnected systems characterized by linear relationships. The pursuit of algorithmic advancements stands as a cornerstone in this domain, with researchers focusing on the development of existing algorithms capable of swiftly addressing extensive linear systems arising from network interactions. An emerging trend involves linear network optimization. The proposed approach seamlessly integrates insights from numerical linear algebra, optimization, and graph theory, leading to accelerated computations and heightened accuracy. This synergistic interplay paves the way for transformative applications in fields like telecommunications, signal processing, and control systems. The robust optimization of linear coupled networks addresses the inherent uncertainties and variations that affect network performance in real-world scenarios.

Keywords: *Coupled Linear Network, Node, Non-Adjacent, Optimization, Transmission.*

Introduction

Logical estimation is a method that entails making educated predictions or approximations based on existingknowledge and sound reasoning rather than relying solely on empirical data or complex computations [1]. It is a valuable analytical approach employed in diverse domains, including mathematics, science, economics, engineering, and more. Recent research in the realm of logical estimation has concentrated on refining methodologies and enhancing the accuracy of predictions, while also considering ethical implications and real-world applications. One area of advancement pertains to algorithmic enhancements [2-5]. Researchers may be focused on devising novel algorithms that amalgamate logical reasoning with machine learning techniques. These algorithms could leverage historical data to make predictions in scenarios where direct data is limited or unreliable, effectively bridging gaps in information. Another avenue of exploration could involve Binary logical estimation. By integrating Bayesian statistical methods with logical reasoning, researchers might strive to produce more nuanced and probabilistic predictions [6,7]. This approach would permit the incorporation of priorbeliefs and the ability to adapt estimates as fresh information becomes available, resulting in more adaptable and dynamic predictions. The interplay between causal inference and logical estimation is an emerging topic.

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Researchers could be investigating how to effectively combine these two disciplines to estimate the effects of interventions or changes within intricate systems [8-10]. By identifying causal relationships and applying logical reasoning, researchers could offer insights into cause-and-effect dynamics. The integration of qualitative and quantitative data is an intriguing dimension of recent research in logical estimation. Developments in this area could lead to frameworks that seamlessly integrate these data mining concepts, enabling more comprehensive and accurate estimations. Ethical considerations in logical estimation are gaining attention. Recent research might emphasize transparency, fairness, and accountability in the estimation process.Ensuring that logical estimates are not only accurate but also ethically sound is becoming a significant focus, particularly as these estimates influence decision-making. In the realm of expert elicitation and aggregation, researchers may be working to enhance the methodologies employed to elicit estimates from experts and to aggregate these opinions effectively. The goal is to devise approaches that address uncertainty and biases inherent in expert judgments, resulting in more reliable and robust estimates. Logical estimation also finds application in tackling real-world challenges. Researchers could be using this method to forecast outcomes related to climate change, pandemic trends, economic shifts, and more. As these challenges become increasingly complex and multifaceted, logical estimation offers a valuable tool for making informed predictions [11,12].

Logical optimization refers to the process of systematically finding the best possible solution to a problem byemploying logical reasoning and structured methodologies [13]. This approach involves leveraging logical deductions and principles to optimize a system or process, often with the aim of maximizing desired outcomes while minimizing undesirable ones. Recent research in the realm of logical optimization has led to the development of advanced techniques, novel applications, and the exploration of ethical considerations. One significant area of advancement in logical optimization involves algorithmic innovations. Researchers have been focused on devising efficient algorithms that harness logical principles to solve complex optimization problems. These algorithms may incorporate elements of artificial intelligence, machine learning, or constraint programming to navigate intricate solution spaces and reach optimal or near-optimal outcomes [14,15].

The integration of logical optimization with real-world applications is another noteworthy aspect of current research. From supply chain management to energy level efficient distribution and urban planning, logical optimization techniques are being applied to solve intricate problems faced by cloud servers. By employing logical reasoning to model real-world scenarios, researchers can formulate strategies for optimizing resource allocation, scheduling, and decision-making processes. Ethical considerations play a vital role in the field of logical optimization [16]. Recent research delves into the ethical implications of using optimized solutions, particularlyin scenarios where competing objectives or values must be balanced. Ensuring that optimized solutions are fair, unbiased, and aligned with societal values is a critical aspect of advancing this field responsibly.

Simulation of Linear Coupled Networks

The performance of linear coupled network having 5, 6 and 7 nodes in different architecture are simulated usingNS2 tool in this work.

Example 1

Consider the following linear network with 5 nodes, N0, N1, N2, N3 and N4. Three types of architecture areconsidered as shown in Fig 1(a), Fig 1(b) and Fig 1(c).

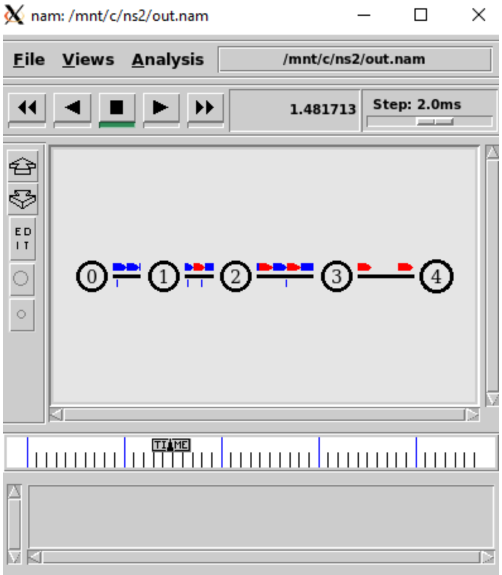

Figure 1a: Network with 5 nodes in linear architecture

From simulation, it is inferred that nodes N1, N2, N3 forms the dominant nodes in Fig 1(a) and Figure 1(b) asthese nodal values highly impact the Transmission Efficiency (TE).

Table 1a: Efficiency Table for the network with 5 nodes

N0	N1	N2	N3	N4	TE (%) N0-N4
0	0	0	0	0	0
0	0	0	0	1	0
0	0	0	1	0	0
0	0	0	1	1	0
0	0	1	0	0	0
0	0	1	0	1	0
0	0	1	1	0	0
0	0	1	1	1	0
0	1	0	0	0	0
0	1	0	0	1	0
0	1	0	1	0	0
0	1	0	1	1	0
0	1	1	0	0	0
0	1	1	0	1	0
0	1	1	1	0	0
0	1	1	1	1	0
1	0	0	0	0	0
1	0	0	0	1	19
1	0	0	1	0	0
1	0	0	1	1	59
1	0	1	0	0	0
1	0	1	0	1	65
1	0	1	1	0	0
1	0	1	1	1	87
1	1	0	0	0	0
1	1	0	0	1	35
1	1	0	1	0	0
1	1	0	1	1	89
1	1	1	0	0	0
1	1	1	0	1	71
1	1	1	1	0	0
1	1	1	1	1	100

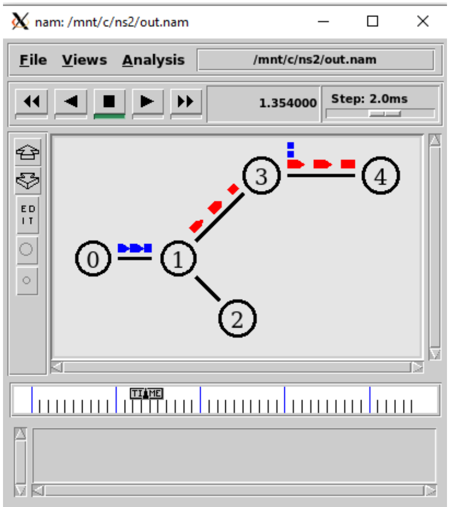

Figure 1b: Network with 5 nodes in branched architecture

In Figure 1b, the data from node 1 can travel in two ways via N2 and N3. The passing of data via N2 ends in N2 itself (will not provide any output) and the data through N3 goes to the output Node N4.

Table 1b: Efficiency Table for the network with 5 nodes

N0	N1	N2	N3	N4	TE (%) N0-N1-N3 – N4
0	0	0	0	0	0
0	0	0	0	1	0
0	0	0	1	0	0
0	0	0	1	1	0
0	0	1	0	0	0
0	0	1	0	1	0
0	0	1	1	0	0
0	0	1	1	1	0
0	1	0	0	0	0
0	1	0	0	1	0
0	1	0	1	0	0
0	1	0	1	1	0
0	1	1	0	0	0
0	1	1	0	1	0
0	1	1	1	0	0
0	1	1	1	1	0
1	0	0	0	0	0
1	0	0	0	1	26
1	0	0	1	0	0
1	0	0	1	1	72
1	0	1	0	0	0
1	0	1	0	1	36
1	0	1	1	0	0
1	0	1	1	1	82
1	1	0	0	0	0
1	1	0	0	1	66
1	1	0	1	0	0
1	1	0	1	1	100
1	1	1	0	0	0
1	1	1	0	1	78
1	1	1	1	0	0
1	1	1	1	1	92

From the Table 1a and 1b, it is inferred that the value of N3 decides the network efficiency to greater extent andis considered as Major node.

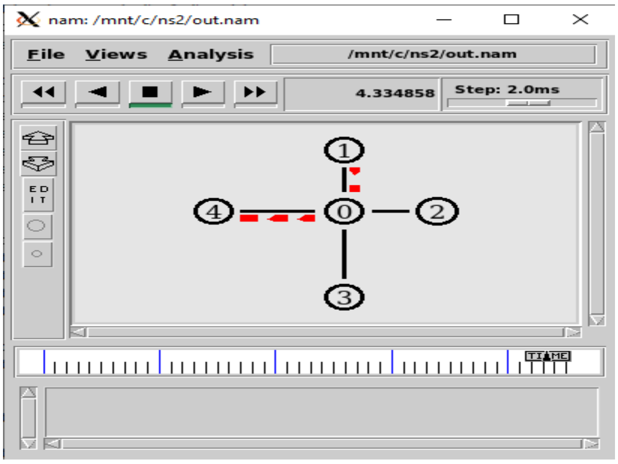

Figure 1c: Network with 5 nodes in X- shaped architecture

For the architecture shown in Figure 1(c), N0 is the dominant node since 4 different 1 hop network will be having this node N0 as a common point.

Table 1c: Efficiency Table for the network with 5 nodes in X-shaped architecture

N0	N1	N2	N3	N4	TE(%)	
					N1- N3	N2-N4
0	0	0	0	0	0	0
0	0	0	0	1	0	0
0	0	0	1	0	0	0
0	0	0	1	1	0	0
0	0	1	0	0	0	0
0	0	1	0	1	0	46
0	0	1	1	0	0	0
0	0	1	1	1	0	48
0	1	0	0	0	0	0
0	1	0	0	1	0	0
0	1	0	1	0	0	0
0	1	0	1	1	48	0
0	1	1	0	0	0	0
0	1	1	0	1	0	49
0	1	1	1	0	46	0
0	1	1	1	1	46	46
1	0	0	0	0	0	0
1	0	0	0	1	0	0
1	0	0	1	0	0	0
1	0	0	1	1	0	0
1	0	1	0	0	0	0
1	0	1	0	1	0	46
1	0	1	1	0	0	0
1	0	1	1	1	0	100
1	1	0	0	0	0	0
1	1	0	0	1	0	0
1	1	0	1	0	100	0
1	1	0	1	1	48	0
1	1	1	0	0	0	0
1	1	1	0	1	0	100
1	1	1	1	0	100	0
1	1	1	1	1	100	100

From Table 1c, N0 decides the flow of data and hence it is the dominant as well as major node. It should be noted that whichever node comes with degree 4 (Here, N0) will be dominant. The dominant node in general isrepresented as Ni where, i = 0,1,2,3,4. (as discussed earlier).

Example 2

Consider the following linear network with 6 nodes, N0, N1, N2, N3, N4 and N5. Two types of architecture are considered as shown in Fig 2(a) and Fig 2(b).

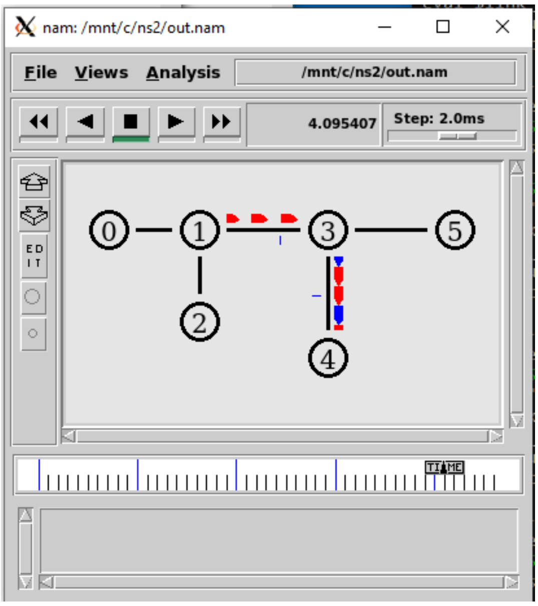

Figure 2a: Network with 6 nodes in 2 branch architecture

From simulation, it is inferred that nodes N1, N3 forms the dominant nodes in Fig 2(a) and nodes N1, N2 and N4 forms the dominant nodes in Figure 2(b). Also, the nodes N2, N4 are split ends in Figure 2(a) and are not considered for TEcalculation. Similarly, node N3 is the split end in Figure 2(b).

Table 2a: Efficiency Table for the network with 6 nodes

N0	N1	N2	N3	N4	N5	TE (%) N0-N1-N3-N5
0	0	0	0	0	0	0
0	0	0	0	0	1	0
0	0	1	0	1	0	0
0	0	1	0	1	1	0
0	1	0	1	0	0	0
0	1	0	1	0	1	0
0	1	1	1	1	0	0
0	1	1	1	1	1	0
1	0	0	0	0	0	0
1	0	0	0	0	1	24
1	0	0	0	1	0	0
1	0	0	0	1	1	18
1	0	0	1	0	0	0
1	0	0	1	0	1	92
1	0	0	1	1	0	0
1	0	1	1	1	1	33
1	0	1	0	0	0	0
1	0	1	0	0	1	0
1	0	1	0	1	0	0
1	0	1	0	1	1	0
1	0	1	1	0	0	0
1	0	1	1	0	1	34
1	0	1	1	1	0	0

1	0	1	1	1	1	21
1	1	0	0	0	0	0
1	1	0	0	0	1	47
1	1	0	0	1	0	0
1	1	0	0	1	1	33
1	1	0	1	0	0	0
1	1	0	1	0	1	100
1	1	0	1	1	0	0
1	1	0	1	1	1	92
1	1	1	0	0	0	0
1	1	1	0	0	1	36
1	1	1	0	1	0	0
1	1	1	0	1	1	44
1	1	1	1	0	0	0
1	1	1	1	0	1	57
1	1	1	1	1	0	0
1	1	1	1	1	1	94

From Table 2a, it is inferred that N1 and N3 are the dominant nodes and N3 is the major node in the network.

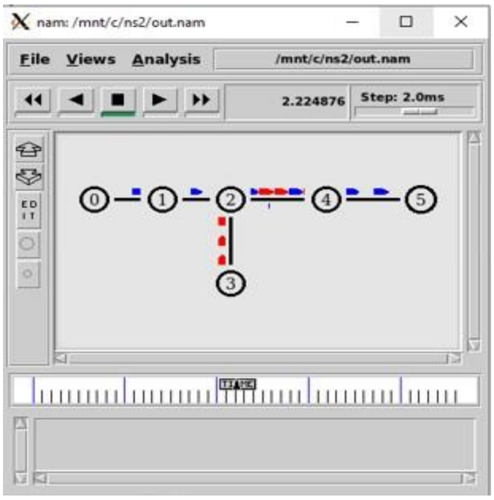

Figure 2b: Network with 6 nodes in single branch architecture

Table 2b: Efficiency Table for the network with 6 nodes

N0	N1	N2	N3	N4	N5	TE(%) N0-N1-N2-N4-N5
0	0	0	0	0	0	0
0	0	0	0	0	1	0
0	0	1	0	1	0	0
0	0	1	0	1	1	0
0	1	0	1	0	0	0
0	1	0	1	0	1	0
0	1	1	1	1	0	0
0	1	1	1	1	1	0
1	0	0	0	0	0	0
1	0	0	0	0	1	24
1	0	0	0	1	0	0
1	0	0	0	1	1	79
1	0	0	1	0	0	0
1	0	0	1	0	1	56
1	0	0	1	1	0	0
1	0	1	1	1	1	83
1	0	1	0	0	0	0
1	0	1	0	0	1	71
1	0	1	0	1	0	0

1	0	1	0	1	1	89
1	0	1	1	0	0	0
1	0	1	1	0	1	59
1	0	1	1	1	0	0
1	0	1	1	1	1	82
1	1	0	0	0	0	0
1	1	0	0	0	1	47
1	1	0	0	1	0	0
1	1	0	0	1	1	88
1	1	0	1	0	0	0
1	1	0	1	0	1	71
1	1	0	1	1	0	0
1	1	0	1	1	1	87
1	1	1	0	0	0	0
1	1	1	0	0	1	64
1	1	1	0	1	0	0
1	1	1	0	1	1	100
1	1	1	1	0	0	0
1	1	1	1	0	1	63
1	1	1	1	1	0	0
1	1	1	1	1	1	92

From Table 2b, it is inferred that N1, N2 and N4 are the dominant nodes and N4 is the major node in the network as the change of state of these 3 nodes greatly affect the transmit efficiency. Also, whenever N0, N4, N5 have the state as 1, optimized network performance is obtained.

Example3

Consider the following linear network with 7 nodes, N0 –N6. A simple architecture is considered as shown in Figure 3.

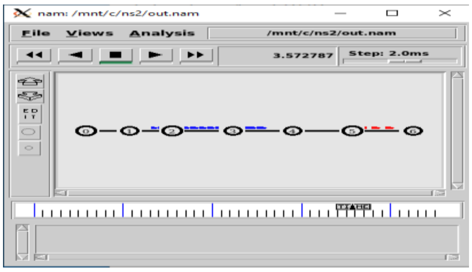

Figure 3: Network with 7 nodes in simple linear architecture

From simulation, it is inferred that nodes N1, N2, N3, N4, and N5 forms the dominant nodes.

Table 3 Efficiency Table for the network with 7 nodes

N0	N1	N2	N3	N4	N5	N6	TE(%) N0-N6
0	0	0	0	0	0	0	0
0	0	0	1	0	0	1	0
0	0	1	0	0	1	0	0
0	0	1	1	0	1	1	0
0	1	0	0	1	0	0	0
0	1	0	1	1	0	1	0
0	1	1	0	1	1	0	0
0	1	1	1	1	1	1	0
1	0	0	0	0	0	0	0
1	0	0	0	0	0	1	18
1	0	0	0	0	1	0	0
1	0	0	0	0	1	1	73
1	0	0	0	1	0	0	0

1	0	0	0	1	0	1	71
1	0	0	0	1	1	0	0
1	0	0	0	1	1	1	83
1	0	0	1	0	0	0	0
1	0	0	1	0	0	1	47
1	0	0	1	0	1	0	0
1	0	0	1	0	1	1	79
1	0	0	1	1	0	0	0
1	0	0	1	1	0	1	71
1	0	0	1	1	1	0	0
1	0	0	1	1	1	1	84
1	0	1	0	0	0	0	0
1	0	1	0	0	0	1	45
1	0	1	0	0	1	0	0
1	0	1	0	0	1	1	52
1	0	1	0	1	0	0	0
1	0	1	0	1	0	1	63
1	0	1	0	1	1	0	0
1	0	1	0	1	1	1	90
1	0	1	1	0	0	0	0
1	0	1	1	0	0	1	0
1	0	1	1	0	1	0	0
1	0	1	1	0	1	1	0
1	0	1	1	1	0	0	0
1	0	1	1	1	0	1	0
1	0	1	1	1	1	0	0
1	0	1	1	1	1	1	0
1	1	0	0	0	0	0	0
1	1	0	0	0	0	1	24
1	1	0	0	0	1	0	0
1	1	0	0	0	1	1	79
1	1	0	0	1	0	0	0
1	1	0	0	1	0	1	56
1	1	0	0	1	1	0	0
1	1	0	0	1	1	1	83
1	1	0	1	0	0	0	0
1	1	0	1	0	0	1	71
1	1	0	1	0	1	0	0
1	1	0	1	0	1	1	89
1	1	0	1	1	0	0	0
1	1	0	1	1	0	1	59
1	1	0	1	1	1	0	0
1	1	0	1	1	1	1	86
1	1	1	0	0	0	0	0
1	1	1	0	0	0	1	47
1	1	1	0	0	1	0	0
1	1	1	0	0	1	1	84
1	1	1	0	1	0	0	0
1	1	1	0	1	0	1	71
1	1	1	0	1	1	0	0
1	1	1	0	1	1	1	87
1	1	1	1	0	0	0	0
1	1	1	1	0	0	1	64
1	1	1	1	0	1	0	0
1	1	1	1	0	1	1	89
1	1	1	1	1	0	0	0
1	1	1	1	1	0	1	78
1	1	1	1	1	1	0	0
1	1	1	1	1	1	1	100

From Table 3, it is inferred that N5 is the major node in the network which decides the transmission efficiencyto greater extent.

Optimization of Linear Coupled Networks

The coupled networks having transmit efficiency of 75% and above from the above tables (Table 1-Table3) are considered to be optimized and the states of nodes that provides optimized linear path are separated and listed below in Table 4, Table 5 and Table 6.

Table 4: Optimized nodal states for the network with 5 nodes

Network with 5 nodes in Linear Architecture						
N0	N1	N2	N3	N4	TE (%)N0-N4	
1	0	1	1	1	87	
1	1	0	1	1	89	
1	1	1	1	1	100	
Network with 5 nodes in Branched Architecture						
N0	N1	N2	N3	N4	TE(%) N0-N1-N3 – N4	
1	0	1	1	1	82	
1	1	0	1	1	100	
1	1	1	0	1	78	
1	1	1	1	1	92	
Network with 5 nodes in X-shaped Architecture						
N0	N1	N2	N3	N4	TE (%)	
					N1- N3	N2-N4
1	0	1	1	1	0	100
1	1	0	1	0	100	0
1	1	1	0	1	0	100
1	1	1	1	0	100	0
1	1	1	1	1	100	100

Table 5: Optimized nodal states for the network with 6 nodes

Network with 6 nodes in 2 Branch Architecture						
N0	N1	N2	N3	N4	N5	TE(%) N0-N1-N3-N5
1	0	0	1	0	1	92
1	1	0	1	0	1	100
1	1	0	1	1	1	92
1	1	1	1	1	1	94
Network with 6 nodes in 1 Branch Architecture						
N0	N1	N2	N3	N4	N5	TE(%) N0-N1-N2-N4-N5
1	0	0	0	1	1	79
1	0	1	1	1	1	83
1	0	1	0	1	1	89
1	0	1	1	1	1	82
1	1	0	0	1	1	88
1	1	0	1	1	1	87
1	1	1	0	1	1	100
1	1	1	1	1	1	92

Table 6: Optimized nodal states for the network with 7 nodes

N0	N1	N2	N3	N4	N5	N6	TE(%) N0-N6
1	0	0	0	1	1	1	83
1	0	0	1	0	1	1	79
1	0	0	1	1	1	1	84
1	0	1	0	1	1	1	90
1	1	0	0	0	1	1	79
1	1	0	0	1	1	1	83
1	1	0	1	0	1	1	89
1	1	0	1	1	1	1	86
1	1	1	0	0	1	1	84

1	1	1	0	1	1	1	87
1	1	1	1	0	1	1	89
1	1	1	1	1	0	1	78
1	1	1	1	1	1	1	100

Based on the simulations done using NS2 and the inference from Table 4, Table 5 and Table 6, there are fewfindings which are listed below.

Finding 1: In coupled linear network with 'n' nodes, having the following prepositions, there exists 'n-2' different linear paths with different combinations of input and with corresponding output states.

Finding 2: In coupled linear network with 'n' nodes, there will be minimum 'n-1' number of different dominationservers along with different inputs and with corresponding output states.

Conclusion and Future Work

A linear coupled network with 5, 6 & 7 nodes are simulated using "NS2" tool to find the network efficiency. Eachnetwork is tested with different combinations of node states and the optimized values are found. Based on the simulation experiment, there are some findings as listed above. The output is obtained whenever the starting node is active and having '1' as a state and if more number of nodes have the state of '0's then the network becomes inefficient. Also, the network is not optimized if starting and ending nodes have its value as '1' and if the intermediate nodes have '0'state.

The future work is the performance analysis of coupled networks without loss of generality and with linked nodes other than input and output in active state in time series for dynamic manner. The optimized network having more than 75%efficiency and the corresponding state of nodes (as listed in Table 4-6) will be involved and evolved through machine learning techniques.

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