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Optimization of fiber optic backbone networks using minimum spanning tree based on Kruskal and prim algorithms

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ABSTRACT

Fiber optic cable has become the primary backbone infrastructure for modern campus communication networks due to its high transmission speed, large bandwidth capacity, and long-distance reliability. However, the deployment cost of fiber optic infrastructure is relatively expensive, particularly in star-topology network architectures that require extensive cable utilization. Therefore, network optimization is essential to reduce infrastructure costs while maintaining network connectivity and performance. This study proposes a graph-theoretical optimization approach for the fiber optic backbone network at Syiah Kuala University (USK), Indonesia, using the Minimum Spanning Tree (MST) concept implemented through Kruskal's and Prim's algorithms. The existing network infrastructure was modeled as a weighted graph consisting of 29 vertices representing campus buildings and weighted edges representing fiber optic cable distances. Furthermore, a reconstructed network model was developed by assuming direct connectivity between neighboring buildings to obtain a more efficient topology configuration. The results demonstrate that both Kruskal's and Prim's algorithms produced identical MST structures with a total cable length of 5,632 meters. Compared with the currently installed network length of 11,175 meters, the optimized MST configuration reduced cable usage by 5,543 meters, corresponding to approximately 49.6% network efficiency improvement. The resulting topology also transformed the existing star-ring hybrid architecture into a more efficient tree-based backbone network. The findings indicate that Minimum Spanning Tree modeling provides an effective mathematical framework for optimizing fiber optic infrastructure in smart campus environments.

1. Introduction

The rapid development of information and communication technology has significantly increased the demand for high-speed and reliable network infrastructure. Internet connectivity has become an essential component in modern educational institutions, particularly in universities implementing smart campus systems that integrate academic, administrative, and digital services into a centralized communication framework. In this context, fiber optic cable technology has become one of the most widely used transmission media because of its ability to provide high bandwidth, long-distance transmission, low signal attenuation, and resistance to electromagnetic interference [1, 2].

Fiber optic networks are commonly implemented as backbone infrastructure in large-scale computer networks due to their superior transmission performance compared to conventional copper cables. Despite these advantages, the deployment and maintenance costs of fiber optic infrastructure remain relatively expensive. The installation process requires specialized equipment, technical expertise, and careful network planning to ensure both economic efficiency and network reliability. Consequently, inefficient network topology design may lead to excessive cable utilization and unnecessary infrastructure expenditure [3–5].

Network topology plays a fundamental role in determining the effectiveness of data transmission and infrastructure efficiency. Among commonly used topologies, star topology is widely implemented because of its reliability and ease of maintenance. However, this topology requires each node to connect directly to a central node, resulting in substantial cable consumption. Meanwhile, ring topology offers better cable efficiency but suffers from limited scalability and vulnerability to network failure if one segment is disconnected. Therefore, selecting an optimal network topology becomes an important challenge in designing large-scale fiber optic infrastructure [6, 7].

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Optimization problems in telecommunication networks can be effectively modeled using graph theory. In graph representation, buildings or communication points are modeled as vertices, while communication links are represented as weighted edges whose weights correspond to cable length, installation cost, or transmission distance. One of the most important concepts in graph theory for solving network optimization problems is the Minimum Spanning Tree (MST). The MST concept aims to connect all vertices in a graph using the minimum possible total edge weight without forming cycles, thereby producing an efficient and cost-effective network structure [8–10].

Several algorithms have been developed to determine the Minimum Spanning Tree of a weighted graph, among which Kruskal's algorithm and Prim's algorithm are the most widely applied. Kruskal's algorithm constructs the MST by selecting edges globally from the smallest weight while avoiding cycles, whereas Prim's algorithm grows the spanning tree incrementally from an initial vertex by selecting the minimum adjacent edge at each iteration. Both algorithms have been extensively used in transportation systems, electrical distribution networks, telecommunication infrastructure, and computer network optimization problems [3, 11].

Previous studies have demonstrated the effectiveness of MST algorithms in minimizing infrastructure utilization. Latifah (2015) applied Kruskal's and Prim's algorithms to optimize water distribution pipelines and successfully reduced pipeline length significantly. Similarly, Sam (2016) optimized electrical transmission networks using Prim's algorithm and obtained considerable reductions in transmission cable distance. However, studies focusing on the optimization of real-world campus fiber optic backbone infrastructure using graph-theoretical reconstruction approaches remain limited, particularly in the context of smart campus telecommunication systems [12, 13].

Syiah Kuala University (USK), one of the largest public universities in Indonesia, has implemented a fiber optic backbone network connecting various academic and administrative buildings across the campus. The current network infrastructure follows a hybrid combination of star and ring topologies centered at the ICT Center building. Although this configuration supports network connectivity, the large amount of cable required indicates potential inefficiency in infrastructure utilization. Furthermore, the ongoing campus expansion and construction of new buildings increase the importance of developing a more scalable and efficient network design [6, 14, 15].

This study proposes a graph-theoretical optimization framework for evaluating and reconstructing the fiber optic backbone network at Syiah Kuala University using the Minimum Spanning Tree concept. Unlike previous studies that only evaluate existing networks, this research reconstructs an alternative network model by assuming direct connectivity between neighboring buildings to obtain a more optimal topology configuration. The reconstructed network is then analyzed using Kruskal's and Prim's algorithms to determine the minimum cable length required while maintaining complete network connectivity.

The novelty of this study lies in the integration of graph reconstruction modeling with MST optimization for real-world smart campus infrastructure. The study not only evaluates the efficiency of the existing fiber optic network but also proposes a mathematically optimized alternative topology that significantly reduces cable utilization. The results are expected to contribute to the development of cost-efficient telecommunication infrastructure planning strategies for universities and other large-scale institutional environments.

Therefore, the main objective of this study is to optimize the fiber optic backbone network at Syiah Kuala University using Minimum Spanning Tree modeling implemented through Kruskal's and Prim's algorithms. Specifically, this study aims to 1). Model the existing fiber optic network into a weighted graph representation; 2). Reconstruct an alternative network topology based on neighboring-building connectivity assumptions; 3). Apply Kruskal's and Prim's algorithms to determine the optimal MST configuration; and 4). Evaluate the efficiency improvement achieved through the optimized network model.

2. Materials and Methods

2.1. *Study area and data collection*

This study was conducted at Syiah Kuala University (USK), Banda Aceh, Indonesia. The object of the study was the fiber optic backbone network connecting academic and administrative buildings across the university campus. The existing network infrastructure is managed by the Information and Communication Technology (ICT) Center of USK. The data used in this research consisted of:

1. Campus map data of Syiah Kuala University;
2. Existing fiber optic network distribution scheme;
3. Connectivity information between buildings; and
4. Fiber optic cable route measurements.

A total of 29 buildings connected by fiber optic cable were identified in the existing network system. The ICT Center building functions as the central server node of the network infrastructure. The network topology currently implemented at USK combines star topology and ring topology configurations.

The cable route measurements were performed using Google Earth Pro by tracing the actual outdoor installation paths of the fiber optic cables. Cable measurements were constrained to routes surrounding building perimeters and roadside areas because the physical cable installation does not pass beneath buildings. This approach ensured that the measured distances closely represented the actual field implementation [4, 16].

2.2. *Graph representation of fiber optic networks*

The fiber optic backbone network was modeled mathematically using graph theory [17, 18]. The network was represented as a weighted undirected graph in equation (1).

$$G = (V, E) \qquad (1)$$

where: V represents the set of vertices corresponding to campus buildings, E represents the set of edges corresponding to fiber optic cable connections. Each edge in the graph was assigned a positive weight representing cable length $\omega(e) > 0$, $\omega(e)$ denotes the cable length associated with edge e. The existing network topology was first represented as the initial graph G_A, consisting of 29 vertices, and 29 weighted edges. Subsequently, an alternative reconstructed network graph G_B was developed by assuming that neighboring buildings could be directly connected through fiber optic cables. This reconstructed graph was designed to explore more efficient connectivity possibilities and contained 29 vertices, and 50 weighted edges.

2.3. *Research framework*

The research framework of this study consisted of four main stages: network identification, graph modeling, Minimum Spanning Tree optimization, and comparative evaluation. Fig. 1 illustrates the overall methodological workflow used in this research [3, 6, 16].

Stage 1: Existing Network Identification, the first stage involved collecting spatial and connectivity data from the ICT Center USK. The existing fiber optic backbone infrastructure was identified, including:

- Connected buildings,
- Cable routes,
- Network topology structures,
- Server locations.

The actual cable lengths between buildings were then measured using Google Earth Pro to obtain weighted edge values for graph construction.

Stage 2: Graph Construction and Network Reconstruction. The existing network was transformed into a weighted graph representation G_A. In this graph:

- Buildings were modeled as vertices,
- Fiber optic links were modeled as weighted edges,
- Cable lengths were used as edge weights.

To improve network efficiency, a reconstructed graph G_B was developed by introducing additional potential connections between neighboring buildings. This reconstruction process aimed to provide more candidate edges for MST optimization [19–21].

Stage 3: Minimum Spanning Tree Optimization. The reconstructed graph GB was optimized using Kruskal's algorithm, and Prim's algorithm. Both algorithms were applied independently to determine the Minimum Spanning Tree configuration that minimizes total cable length while maintaining complete network connectivity. The total MST weight was calculated as equation (2).

$$W(T) = \sum_{e \epsilon T} \omega(e) \qquad (2)$$

where: T is the Minimum Spanning Tree, $w(e)$ is the weight of edge e.

Stage 4: Comparative Efficiency Analysis. The optimized MST topology was compared with the existing network infrastructure based on total cable length, topology structure, and cable reduction efficiency. The percentage efficiency improvement was computed using equation (3).

$$E = \frac{L_{existing} - L_{MST}}{L_{existing}} \times 100\% \qquad (3)$$

where: E is network efficiency improvement, $L_{existing}$ is the total length of the existing network, L_{MST} is the total length of the optimized MST network.

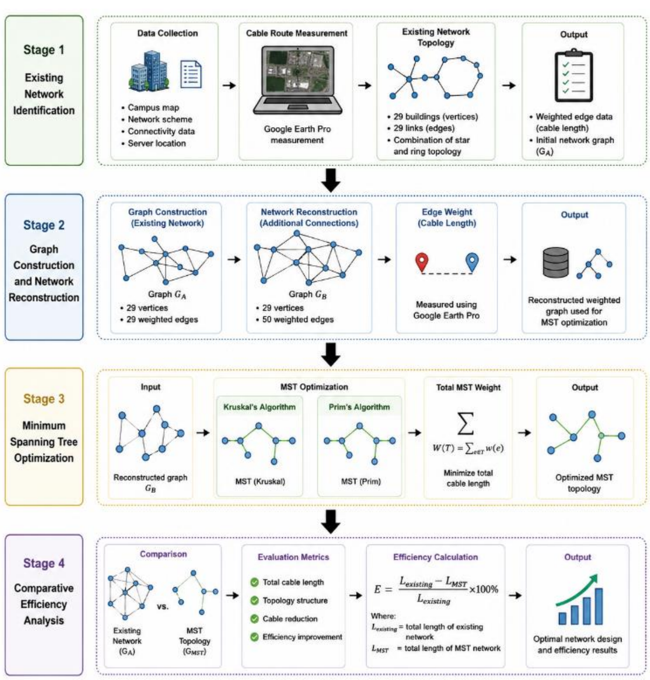

Fig. 1. Research framework of fiber optic backbone network optimization at Universitas Syiah Kuala using the Minimum Spanning Tree (MST) approach.

The next stage involved conducting a normality test using the Liliefors method. This statistical test was applied to determine whether the return data followed a normal distribution assumption required in stochastic modeling. The test results indicated that the stock return data were not normally distributed in their original form, thus justifying the use of logarithmic transformation before further analysis. Following the preprocessing stage, several statistical parameters required in the Generalized Wiener Process model were estimated. These included the expected return (μ), standard deviation (S), and volatility (σ). The expected return represents the average stock return or drift component in the stochastic process, while volatility measures the intensity of stock price fluctuations. These parameters play critical roles in defining both deterministic and random components of stock price movement [3, 6, 16].

2.4. *Minimum spanning tree (MST)*

A Minimum Spanning Tree is a spanning tree of a connected weighted graph (Fig 2) that minimizes the total edge weight while connecting all vertices without forming cycles [6, 14, 15]. Mathematically, the MST problem can be formulated as equation (3).

$$T^* = arg\ \min_{T \subseteq G} \sum_{e \epsilon T} \omega(e) \qquad (3)$$

subject to: T is connected, T contains all vertices, and T contains no cycles. The MST concept is particularly important in communication network optimization because it minimizes infrastructure utilization while preserving full network connectivity.

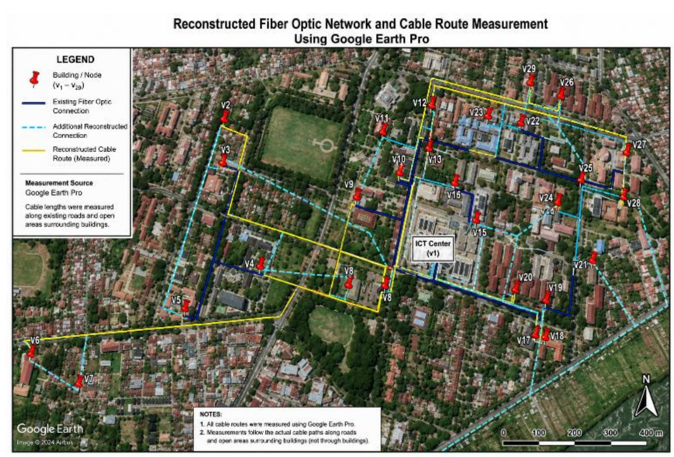

Fig. 2. Spatial reconstruction of the USK fiber optic backbone network showing existing and additional inter-building cable connections measured using Google Earth Pro.

2.5. *Kruskal's algorithm*

Kruskal's algorithm is a greedy optimization algorithm used to determine the Minimum Spanning Tree by selecting edges globally from the smallest weight to the largest while avoiding cycles [19–21]. The algorithm proceeds as follows:

- Sort all edges in ascending order based on edge weight;
- Select the edge with the minimum weight;
- Add the edge to the spanning tree if it does not form a cycle;
- Repeat until all vertices are connected.

The cycle constraint can be represented in equation (4).

$$|E(T)| = |V| - 1 \qquad (4)$$

where: $|E(T)|$ is the number of edges in the MST, $|V|$ is the number of vertices. The computational complexity of Kruskal's algorithm is $O(E \log E)$ making it suitable for sparse graph optimization problems.

2.6. Prim's algorithm

Prim's algorithm is another greedy algorithm for finding the Minimum Spanning Tree by expanding the tree incrementally from an initial vertex. The algorithm operates through:

- Selecting an arbitrary initial vertex;
- Choosing the minimum-weight edge connected to the current tree;
- Expanding the tree iteratively until all vertices are included.

At each iteration, the selected edge satisfies see equation (5).

$$\omega(e) = \min\{\omega(u,v) | u \epsilon T, v \notin T\} \qquad (5)$$

where: u is a vertex already in the tree, v is a vertex outside the tree. The computational complexity of Prim's algorithm is $O(E \log V)$ which is efficient for dense graph structures.

2.7. Performance evaluation

The optimized network configurations generated by Kruskal's and Prim's algorithms were evaluated based on total cable length, topology efficiency, and percentage reduction in cable utilization. The cable reduction value was computed as equation (6).

$$\boldsymbol{R = L_{existing} - L_{MST}} \qquad (6)$$

where: R represents cable reduction, $L_{existing}$ is the installed network length, L_{MST} is the optimized MST network length. The resulting optimized topology was then analyzed to determine its applicability for future smart campus network infrastructure planning [14, 22, 23].

3. Results and discussion

3.1. Existing fiber optic backbone network

The existing backbone network at Universitas Syiah Kuala (USK) consists of interconnected faculty buildings and administrative facilities using fiber optic cable as the main transmission medium. The network infrastructure was originally designed using a combination of star topology and ring topology to ensure reliable communication and centralized control through the ICT Center server [24].

Table 1
Existing fiber optic backbone network at Universitas Syiah Kuala

Edge	Connected Vertices	Cable Length (m)	Edge	Connected Vertices	Cable Length (m)
(e1)	(v1 - v8)	124	(e16)	(v10 - v14)	173
(e2)	(v1 - v6)	1131	(e17)	(v_{14}-v_{15})	142
(e3)	(v6 - v7)	156	(e18)	(v_{10}-v_{16})	376
(e4)	(v1 - v2)	771	(e19)	(v_{16}-v_{19})	327
(e5)	(v1 - v29)	902	(e20)	(v_{19}-v_{20})	74
(e6)	(v1 - v27)	1158	(e21)	(v_{19}-v_{21})	215
(e7)	(v1 - v10)	298	(e22)	(v_{16}-v_{17})	360
(e8)	(v10 - v9)	246	(e23)	(v_{17}-v_{18})	26
(e9)	(v10 - v4)	634	(e24)	(v_{22}-v_{23})	347
(e10)	(v4 - v3)	432	(e25)	(v_{22}-v_{26})	526
(e11)	(v4 - v5)	300	(e26)	(v_{22}-v_{27})	438
(e12)	(v10 - v22)	613	(e27)	(v_{22}-v_{25})	302
(e13)	(v10 - v11)	223	(e28)	(v_{22}-v_{24})	403
(e14)	(v10 - v12)	216	(e29)	(v_{27}-v_{28})	114
(e15)	(v10 - v13)	148	–	–	–

The implementation of the star topology provides direct communication between the ICT Center and several buildings, resulting in high reliability and easier troubleshooting. However, this topology requires a significantly larger amount of cable because every node must be directly connected to the central server. On the other hand, the ring topology reduces cable usage but introduces vulnerability because damage to one segment may interrupt the entire communication path [20, 21, 25].

Based on field observations and measurements using Google Earth Pro, the total length of the existing installed fiber optic cable at USK was recorded at 11,175 meters (Table 1). The network connects 29 buildings, represented as vertices in the graph model [16, 26, 27]. The existing network was then transformed into a weighted graph $G_A = (V,E)$, where; vertices (V) represent buildings, edges (E) represent fiber optic cable connections, and edge weights represent cable lengths in meters. The resulting graph contains 29 vertices, and 29 weighted edges.

Based on Google Earth Pro measurements, the total installed fiber optic cable length in the existing USK backbone network reached 11,175 meters. The longest connection was identified between the ICT Center and the Faculty of Medicine (e6) with a cable length of 1,158 meters, while the shortest connection was observed between the Integrated Laboratory and the Training Center (e23) with a distance of only 26 meters. These findings indicate significant disparities in cable distribution efficiency across the existing network topology. The analysis indicates that the existing topology prioritizes connectivity reliability rather than cable efficiency. Consequently, several connections exhibit unnecessarily long cable routes.

3.2. Reconstruction of the fiber optic network

To optimize cable utilization, a new network model was reconstructed based on the assumption that adjacent buildings could be directly connected using shorter cable routes (Fig. 3). The reconstruction process aimed to generate a more efficient weighted graph while preserving complete network connectivity among all buildings.

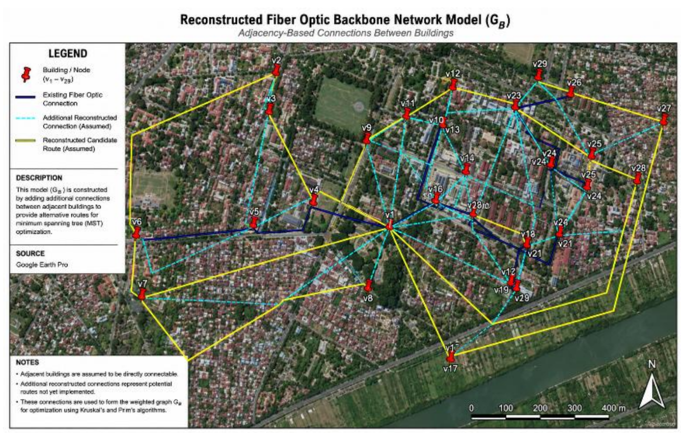

Fig. 3. Reconstruction of the USK fiber optic backbone network showing additional inter-building connections used to generate the weighted graph G_B for MST optimization.

The reconstructed network was represented as a new weighted graph denoted by equation (1). $G_B = (V,E)$, where; vertices (V) represents the same 29 buildings, edges (E) represents newly proposed connections between nearby buildings. Unlike the initial graph, the reconstructed graph contains 29 vertices, and 50 weighted edges. The additional edges provide alternative routes that enable optimization algorithms to search for shorter spanning connections [28, 29].

Table 2
Comparison between existing and reconstructed networks

Network Model	Graph Symbol	Number of Vertices	Number of Edges	Edge Definition	Purpose
Existing fiber optic network	(G_A)	29	29	Actual installed fiber optic cable links	Represents the current USK backbone network
Reconstructed fiber optic network	(G_B)	29	50	Actual links plus potential links between adjacent buildings	Provides alternative connections for MST optimization
Optimized MST network	(T)	29	28	Selected minimum-weight edges from (G_B)	Produces the minimum total cable length while maintaining connectivity

The reconstructed graph introduces higher flexibility in determining efficient paths. Several shorter inter-building routes that did not previously exist were added into the optimization model (Table 2).

3.3. Expected return estimation

Kruskal's algorithm was applied to the reconstructed weighted graph GB to obtain the Minimum Spanning Tree (MST). The algorithm works by selecting edges with the smallest weights while avoiding cycles until all vertices are connected. The optimization process required $n - 1 = 29 - 1 = 28$ edges to form a spanning tree. The algorithm selected edges sequentially from the smallest weights, beginning with: e23 =26 meters, e40 = 73 meters, e20 = 74 meters, and continuing until all buildings were connected. The resulting MST produced a total cable length of $W(T) = 5632$ meters.

Table 3
Optimization result using Kruskal's algorithm

Parameter	Result
Number of vertices	29
Number of selected edges	28
Total MST weight	5,632 m
Number of iterations	28
Final topology	Tree topology

The obtained MST significantly reduced unnecessary cable usage while maintaining complete connectivity between all buildings.

3.4. Optimization using prim's algorithm

Prim's algorithm was also implemented on the reconstructed graph G_B. Unlike Kruskal's algorithm, Prim's algorithm begins from a selected starting vertex and continuously expands the spanning tree by choosing the minimum adjacent edge. The optimization process started from the ICT Center vertex v_1, which serves as the central network server. The resulting MST generated by Prim's algorithm was identical to the result obtained from Kruskal's algorithm, producing $W(T) = 5632$ meters with 28 selected edges. The identical results indicate that both algorithms successfully generated the same optimal spanning tree for the network.

3.5. Comparative analysis of network efficiency

The comparison between the original network and the optimized MST network demonstrates substantial efficiency improvements in cable utilization (Table 4). The total cable reduction can be calculated as equation (7).

$$\Delta L = \boldsymbol{L_{existing}} - \boldsymbol{L_{MST}} \qquad (7)$$

Substituting the measured values:

$$\Delta L = 11175 - 5632$$

$$\Delta L = 5543 \text{ meters}$$

The percentage efficiency improvement is use equation (3):

$$\boldsymbol{E} = \frac{11175 - 5632}{11175} \times \mathbf{100\%}$$

$$\boldsymbol{E} = 49.6\%$$

Table 4
Efficiency comparison between existing and MST networks

Parameter	Existing Network	MST Network
Number of buildings	29	29
Number of cable connections	29	28
Total cable length	11,175 m	5,632 m
Cable reduction	–	5,543 m
Efficiency improvement	–	49.6%

The optimization results reveal that the existing USK fiber optic backbone network has not yet achieved optimal cable efficiency. The MST topology successfully reduced nearly half of the total cable requirement while maintaining full connectivity among all network nodes. Furthermore, the resulting tree topology provides a more economical network structure suitable for future expansion of campus infrastructure. The optimized design can reduce installation costs, maintenance complexity, and network deployment time. Overall, the implementation of Minimum Spanning Tree methods using Kruskal's and Prim's algorithms proved effective for fiber optic backbone network optimization in a large-scale campus environment.

4. Conclusion

This study successfully demonstrated the application of the Minimum Spanning Tree (MST) concept for optimizing the fiber optic backbone network at Universitas Syiah Kuala (USK). The existing network infrastructure was modeled into a weighted graph representing buildings as vertices and fiber optic cable routes as weighted edges. The optimization process was conducted by reconstructing the network topology based on adjacent building connectivity and applying Kruskal's and Prim's algorithms. The results showed that both algorithms produced the same optimal solution, generating an MST consisting of 29 vertices and 28 edges with a total cable length of 5,632 meters. Compared with the existing installed network length of 11,175 meters, the optimized MST topology reduced cable usage by 5,543 meters, corresponding to an efficiency improvement of approximately 49.6%.

The findings indicate that the existing USK fiber optic network has not yet achieved optimal cable efficiency due to the dominant implementation of star topology, which requires large amounts of cable. In contrast, the MST-based topology provides a more economical and efficient network structure while maintaining full connectivity among all buildings. Therefore, the implementation of Kruskal's and Prim's algorithms proved effective for minimizing fiber optic cable utilization in campus-scale backbone network design. The proposed MST approach can serve as a practical reference for future network expansion and infrastructure planning at Universitas Syiah Kuala and other large institutional environments.

CRediT authorship contribution statement

Siti Nurhaliza: Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nurmaulidar:** Writing – review & editing, Investigation. **Bonno Andri Wibowo:** Formal analysis, Writing – review & editing, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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References

1. Bai, C., Zhu, Q., and Sarkis, J. (2024). Do Blockchain Capabilities Help Overcome Supply and Operational Risks: Insights from Firm Market Returns during COVID-19, Omega, Vol. 126, 103049. Doi: 10.1016/j.omega.2024.103049
2. Yang, C., and Wu, H. (2021). Investor Sentiment with Information Shock in the Stock Market, Emerging Markets Finance and Trade, Vol. 57, 510–524. Doi: 10.1080/1540496X.2019.1593136
3. Kalaycı, B., Purutçuoğlu, V., and Weber, G. W. (2022). Operation Research in Neuroscience: A Recent Perspective of Operation Research Application in Finance, Operations Research, 170–190.
4. Zhou, Z., Gao, M., Xiao, H., Wang, R., and Liu, W. (2021). Big Data and Portfolio Optimization: A Novel Approach Integrating DEA with Multiple Data Sources, Omega, Vol. 104, 102479. Doi: 10.1016/j.omega.2021.102479
5. Chu, L., He, X. Z., Li, K., and Tu, J. (2022). Investor Sentiment and Paradigm Shifts in Equity Return Forecasting, Management Science, Vol. 68, No. 6, 4301–4325. Doi : 10.1287/mnsc.2020.3834
6. He, Y., Qu, L., Wei, R., and Zhao, X. (2022). Media-Based Investor Sentiment and Stock Returns: A Textual Analysis Based on Newspapers, Applied Economics, Vol. 54, 774–792. Doi: 10.1080/00036846.2021.1966369
7. Liu, Y. J., Yang, G. S., and Zhang, W. G. (2024). A Novel Regret-Rejoice Cross-Efficiency Approach for Energy Stock Portfolio Optimization, Omega, Vol. 126, 103051. Doi: 10.1016/j.omega.2024.103051
8. Cerqueti, R., Cesarone, F., and Ficcadenti, V. (2024). Portfolio Decision Analysis for Pandemic Sentiment Assessment Based on Finance and Web Queries, Annals of Operations Research, 1–31.
9. Baker, M., and Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns, Journal of Finance, Vol. 61, 1645–1680. Doi : 10.1111/j.1540-6261.2006.00885.x
10. Zhou, Y., Fan, J. Q., and Xue, L. R. (2024). How Much Can Machines Learn Finance from Chinese Text Data?, Management Science.
11. Li, H., and Wu, D. (2024). Online Investor Attention and Firm Restructuring Performance: Insights from an Event-Based DEA-Tobit Model, Omega, Vol. 122, 102967. Doi: 10.1016/j.omega.2023.102967
12. Dechow, P., Lawrence, A., Luo, M., and Stamenov, V. (2024). Media Attention and Event-Based Grouping of Stocks: An Examination of Stocks Hyped by Media Outlets as Benefiting from the Olympics, Management Science.
13. Kehinde, T. O., Chan, F. T. S., and Chung, S. H. (2023). Scientometric Review and Analysis of Recent Approaches to Stock Market Forecasting: Two Decades Survey, Expert Systems with Applications, Vol. 213, 119299. Doi: 10.1016/j.eswa.2022.119299
14. Pai, P. F., and Lin, C. S. (2005). A Hybrid ARIMA and Support Vector Machines Model in Stock Price Forecasting, Omega, Vol. 33, 497–505. Doi: 10.1016/j.omega.2004.07.024
15. Wang, J. J., Wang, J. Z., Zhang, Z. G., and Guo, S. P. (2012). Stock Index Forecasting Based on a Hybrid Model, Omega, Vol. 40, 758–766. Doi: 10.1016/j.omega.2011.07.008
16. Gao, J., Mao, Y. S., Xu, Z. S., and Luo, Q. L. (2024). Quantitative Investment Decisions Based on Machine Learning and Investor Attention Analysis, Technological and Economic Development of Economy, Vol. 30, No. 3, 527–561.
17. Li, Y., Shen, D., Wang, P., and Zhang, W. (2020). Does Intraday Time-Series Momentum Exist in Chinese Stock Index Futures Market?, Finance Research Letters, Vol. 35, 101292. Doi : 10.1016/j.frl.2019.09.007
18. Olgun, O., and Yetkiner, I. H. (2011). Determination of Optimal Hedging Strategy for Index Futures: Evidence from Turkey, Emerging Markets Finance and Trade, Vol. 47, 68–79. Doi : 10.2753/REE1540-496X470604
19. Makarov, I., and Schoar, A. (2020). Trading and Arbitrage in Cryptocurrency Markets, Journal of Financial Economics, Vol. 135, 293–319. Doi : 10.1016/j.jfineco.2019.07.001
20 Goldstein, M., Kwan, A., and Philip, R. (2022). High-Frequency Trading Strategies, Management Science, Vol. 69, No. 8, 4413–4434.
21. Aggarwal, P., and K. K. (2023). Analysis of the Impact of COVID-19 on the Stock Market and Capability of Investing Strategies, AIP Conference Proceedings, Vol. 2782, 020112. Doi : 10.1063/5.0154174
22. Marshall, B. R., Nguyen, N. H., and Visaltanachoti, N. (2017). Time Series Momentum and Moving Average Trading Rules, Quantitative Finance, Vol. 17, 405–421. Doi : 10.1080/14697688.2016.1205209
23. Niţoi, M., and Pochea, M. M. (2020). Time-Varying Dependence in European Equity Markets: A Contagion and Investor Sentiment Driven Analysis, Economic Modelling, Vol. 86, 133–147. Doi : 10.1016/j.econmod.2019.06.007
24. Baker, M., Wurgler, J., and Yuan, Y. (2009). Global, Local, and Contagious Investor Sentiment, Journal of Financial Economics, Vol. 104, 272–287.
25. Jing, N., Wu, Z., and Wang, H. (2021). A Hybrid Model Integrating Deep Learning with Investor Sentiment Analysis for Stock Price Prediction, Expert Systems with Applications, Vol. 178, 115019. Doi : 10.1016/j.eswa.2021.115019
26. Li, H., and Wu, D. (2024). Online Investor Attention and Firm Restructuring Performance: Insights from an Event-Based DEA-Tobit Model, Omega, Vol. 122, 102967. Doi: 10.1016/j.omega.2023.102967
27. Schmeling, M. (2009). Investor Sentiment and Stock Returns: Some International Evidence, Journal of Empirical Finance, Vol. 16, 394–408. Doi: 10.1016/j.jempfin.2009.01.002
28. Tetlock, P. C. (2007). Giving Content to Investor Sentiment: The Role of Media in the Stock Market, Journal of Finance, Vol. 62, 1139–1168. Doi: 10.1111/j.1540-6261.2007.01232.x
29. Chen, R., Wang, S., Jin, C., Yu, J., Zhang, X., and Zhang, S. (2023). Comovements between Multidimensional Investor Sentiment and Returns on Internet Financial Products, International Review of Financial Analysis, Vol. 85, 102433. Doi: 10.1016/j.irfa.2022.102433