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RESEARCH ARTICLE OPEN ACCESS

ENHANCING OPTICAL DISTRIBUTION POINT PLACEMENT: A DECISION SUPPORT SYSTEM INTEGRATING WEIGHTED PRODUCT METHOD, CONTENT-BASED FILTERING, AND LOCATION-BASED SERVICES

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ABSTRACT

The Optical Distribution Point (ODP) is a crucial element in fiber-optic internet networks, playing a key role in ensuring efficient service delivery. This study presents an integrated Decision Support System (DSS) that combines the Weighted Product Method (WPM), Content-Based Filtering (CBF), and Location-Based Services (LBS) to optimize ODP placement in urban areas. By considering multiple criteria such as ODP categories, customer preferences, and business types, the DSS provides a data-driven approach to strategic decision-making. The system's ability to recommend ODPs based on customer needs, while visualizing key data through LBS, enhances the effectiveness of network expansion strategies. This comprehensive framework improves decision-making in urban internet services and offers a scalable solution for optimizing network infrastructure. The study demonstrates the potential of combining analytical models with user-focused technology to streamline service deployment and improve customer satisfaction.

I. INTRODUCTION

In the world of fiber-optic communication, the Optical Distribution Point (ODP) is like the heart of the network, playing a crucial role in delivering fast and reliable internet services. Think of it as the essential hub where connections are made, ensuring that data travels efficiently from one place to another. However, to truly maximize its effectiveness, we need to strategically place these ODPs in urban areas, taking into account factors such as their proximity to users, capacity, and operational conditions [1], [2]. Monitoring the capacity of ODPs is vital not just for installation, but also for ensuring that customers receive the high-quality service they expect [3–6].

This research introduces a novel Decision Support System (DSS) that aims to optimize the placement of ODPs using the Weighted Product method. By analyzing various factors—like customer preferences, ODP recommendations, and data from local business surveys—this system helps identify the best locations for ODPs[7], [8]. The ultimate goal is to enhance decision-making and support effective business strategies in our increasingly connected urban environments [9].

To make these recommendations even more precise, we've incorporated a Content-Based Filtering approach. This means that the system takes into account what customers want, focusing on their specific needs such as proximity and service types [10]. By aligning the recommendations with user preferences, we can identify the most promising areas for promoting ODP services [11].

Moreover, integrating Location-Based Service (LBS) technology adds another layer of depth to our DSS. It allows us to visualize ODP data in real-time, providing interactive maps that display essential information such as capacity and distances from potential customers [12], [13]. Despite advancements in DSS, the integration of multiple decision-making techniques remains limited, and existing literature often addresses these methodologies in isolation, missing out on their combined strengths. This study aims to fill this gap by proposing a comprehensive DSS that seamlessly integrates the Weighted Product method, Content-Based Filtering, and LBS technology. This robust framework not only enhances ODP placement but also strengthens the overall decision-making process in urban internet service provision [14], [15].

In this study, we seek to answer a fundamental question: **How can we effectively optimize ODP placement to improve**

service delivery for urban customers? Our objectives include developing a comprehensive DSS framework that merges the Weighted Product method, Content-Based Filtering, and LBS while also acknowledging the challenges of data accuracy and scalability. By tackling these issues, we aim to contribute valuable insights to the field of telecommunications and network optimization, ultimately enhancing customer experiences in urban settings.

II. RELATED WORKS

The development of Decision Support Systems (DSS) for recommending the placement of Optical Distribution Points (ODPs) in internet networks has gained attention in recent years, focusing on the application of advanced technologies and analytical methods to enhance service efficiency and effectiveness. Several studies have explored various approaches related to DSS, the Weighted Product method, Content-Based Filtering, and data visualization using Location-Based Services (LBS).

A DSS is defined as an interactive information system designed to provide data analysis, modeling, and manipulation to support decision-making processes [16]. Weighted Product (WP) is a well-established method utilized within Multi-Attribute Decision Making (MADM), where the attributes of each alternative are multiplied by their respective weights, allowing for efficient decision-making [16]. For instance, a study that applied the WP method to determine optimal village funding solutions, demonstrating its efficacy in integrating multiple criteria for effective decision support [17]. The WP method is versatile and effective in educational settings, particularly in selecting exemplary students and teachers. It ensures objective and systematic decision-making by evaluating multiple criteria, similar to other methods like Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Analytical Hierarchy Process (AHP), which are also used for student selection [16], [18], [19]. This versatility underscores the method's broad applicability across different domains within education.

Content-Based Filtering (CBF) in recommendation systems focuses on providing personalized item suggestions based solely on user preferences, independent of other users' inputs. CBF systems rely on data attributes and user profiles to generate recommendations, addressing cold start issues by analyzing item content and user feedback to measure item similarity [20]. This approach builds a user profile based on explicit or implicit data provided by the user, such as past interactions with items, and uses this profile to recommend new items that match the user's preferences [20–22].

This approach has proven effective in various applications, from media recommendations to restaurant selections. For example, implementing a CBF system for restaurant recommendations can significantly enhance the selection process and improve user satisfaction by providing tailored suggestions based on individual preferences and behaviors [23–26]. Additionally, Content-based filtering is commonly used to suggest items based on user likes and past actions, leveraging attributes like movie genre, director, and user ratings and cosine similarity is a key evaluation metric used to measure the similarity between items, regardless of their dimensions, and is commonly employed in content-based recommendation systems [27], [28].

Location-Based Services (LBS) enhance decision-making by providing real-time, location-specific information through the integration of GIS, positioning technologies, and communication networks. Their applications span various fields, including tourism, emergency services, and navigation, making them indispensable tools in modern geographic data visualization and interaction [28–30].

The key features of Location-Based Services (LBS) that contribute to enhancing user experience in mapping services include personalized information retrieval, real-time traffic information, and the ability to provide location-specific and customized services [31–33]. The integration of LBS technology in decision support systems facilitates informed choices based on accurate spatial data by enabling the collection of GPS data logs, location chronicles, and the deployment of multi-criteria decision analysis (MCDA) tools for personalized decision outcomes [33], [34]. The enumerations of citations in the body of the article must be sequenced in the order in which they appear, according to the example shown below.

III. PROPOSED METHOD

The framework for the proposed method in this study integrates Decision Support Systems (DSS) with Content-Based Filtering (CBF) and Location-Based Services (LBS) to optimize Optical Distribution Point (ODP) selection for fiber-optic network expansion. The method is structured into several stages, each of which contributes to a comprehensive and data-driven decision-making process. Figure 1 below explains the method proposed in this study.

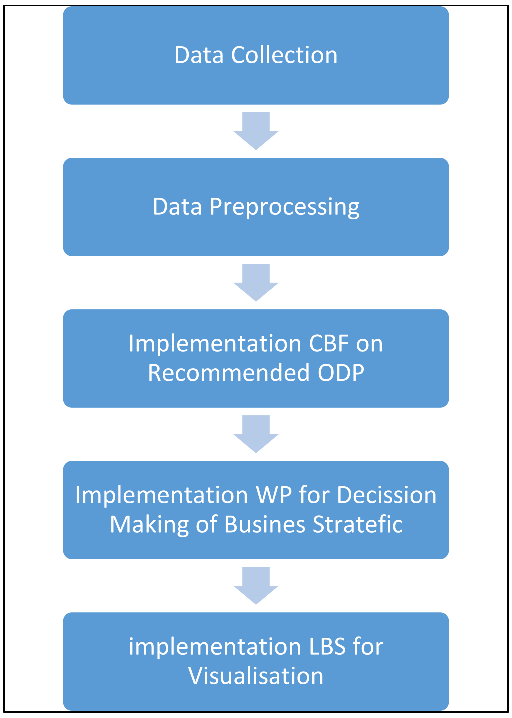

Figure 1: The Architecture of Proposed Method.
Source: Authors, (2024).

III.1 DATA COLLECTION

Relevant data are gathered, ODP data included information such as the ODP name, geographic coordinates, total capacity, the number of empty, filled, and reserved charging ports, and the ODP category. In addition, customer data, consisted of the customer's business name, location coordinates, the chosen service package, and the current status of their order, are collected. Finally, business survey data captured the business name, address, coordinates, and the type of business participating in the survey. This information forms the dataset used for the subsequent analysis.

III.2 DATA PREPROCESSING

Data preprocessing involves cleaning and transforming the raw data to ensure consistency, completeness, and accuracy [35], [36]. This step includes removing duplicates, handling missing values, and standardizing the data format. The preprocessed dataset is then divided into relevant criteria for further analysis. For instance, ODP capacity, distance from the customer, and business categories are considered critical factors in the decision-making process.

III.3 CONTENT BASED FILTERING

The next step involves applying Content-Based Filtering (CBF) to recommend ODPs based on customer preferences and service needs [37]. The CBF algorithm leverages data related to ODP attributes (e.g., proximity to customers, type of business, and customer demand in a specific area) to filter and recommend the most suitable ODPs for promotional targeting. By tailoring recommendations according to customer-specific preferences, the system increases the likelihood of successful service installations, enhancing customer satisfaction [38].

The process begins with data collection, where the data used comes from data collected within 250 m of the user point. The data used is ODP data such as distance, ODP category, and check highway. Next, the criteria values are weighted according to the data used. Next, the cosine similarity calculation is performed for points within a 250 m radius of the user point. After the cosine similarity results are obtained, a list of recommendation results based on these two calculations is displayed. The criteria weighting process uses the criteria rules as in Data Table 1.

Table 1: Recommendation ODP Criteria.

No.	Recommendation Criteria
1)	Distance from ODP to Potential Customer Location < 250m
2)	Does Not Cross Protocol Road
3)	ODP Category

Source: Authors, (2024).

To facilitate calculations between data, the data needs to be converted into a numerical scale. In Tables 2, 3, and 4 are the assessments of each criterion.

Table 2: ODP Category Criteria.

Criteria	Value	Description
Black	0	Not Good
Red	1	Less Good
Yellow	2	Fairly Good
Green	3	Good

Source: Authors, (2024).

Table 3: Check Highway Criteria.

Criteria	Value	Description
Passed	0	Not Good
Not Passed	1	Good

Source: Authors, (2024).

Table 4: Distance Criteria.

Criteria	Value	Description
> 250 m	0	Very Poor
<= 250 m	1	Not Good
<= 200 m	2	Less Good
<= 150 m	3	Fairly Good
<= 100 m	4	Good
<= 50 m	5	Very Good

Source: Authors, (2024).

After data collection and weighting based on criteria have been carried out, the development of a recommendation system with Content Based Filtering is continued by calculating Cosine Similarity between the value of the user and the detected ODP in order to get recommendation results. The calculation process will be carried out in Experiments and Results.

III.4 WEIGHTED PRODUCT

The filtered ODP recommendations are further analyzed using the Weighted Product (WP) method, a widely used Multi-Criteria Decision Making (MCDM) technique. The WP method is applied to rank the potential ODP locations based on multiple factors, including proximity, capacity, and demand. Each factor is assigned a weight that reflects its importance to the decision-making process. By multiplying the ratings of each alternative by its corresponding attribute values and raising them to their assigned weights, the WP method provides a clear ranking of ODPs, identifying areas with the highest potential for business growth.

III.4.1 alternatives

To apply the Decision Support System with the Weighted Product Method, it is necessary to determine the alternative as the output under consideration. Alternatives are a set of different objects, each of which has the same opportunity to be selected by the decision maker [7], [16], [39]. Alternatives are the different options being evaluated. For instance, in selecting teachers for a school, each teacher represents an alternative with unique qualifications and performance metrics [16]. The alternatives used in this study are listed in Table 5

Table 5: Alternatives.

No.	Alternatives
A1	250 m to the north
A2	250 m to the south

Source: Authors, (2024).

III.4.2 criteria

Criteria are standards used to evaluate and compare alternatives in decision making42. Criteria help assess the advantages and suitability of each option, making it easier to choose the most appropriate one to achieve the goal. The following in Table 6 are the criteria that will be used for the decision-making process.

Table 6: Criteria.

No.	Criteria
C1	ODP Categories
C2	Non-Subscriber Business Count
C3	Business Type
C4	ODP Count

Source: Authors, (2024).

III.4.3 weight of each criteria

The following is the weighting of each ODP category criterion, namely the most recommended ODP category, the number of unsubscribed businesses, the most business types, the number of recommended ODP.

Table 7: Weight of ODP Category Criteria.

Criteria	Value	Description
Black	1	Not Good
Red	2	Less Good
Yellow	3	Good
Green	4	Very Good

Source: Authors, (2024).

Table 7 above is the weighting of the ODP Category Criteria. This ODP consists of two types of ODP, namely 8 port ODP and 16 port ODP. The Green category is an ODP with 8 - 6 available ports for 8 ports and 16 - 11 for 16 ports, which is the category with the most available ports. The Yellow category is an ODP with 5 - 3 available ports for 8 ports and 10 - 5 for 16 ports, which is a category with quite a lot of available ports. The Red category is an ODP with 2 -1 available ports for 8 ports and 4 - 1 for 16 ports, which is the category with the least available ports. The Black category is an ODP with 0 available ports, which is a category with no available ports and cannot be used.

Table 8: Weight of Non-Subscriber Business Count Criteria.

Criteria	Value	Description
Few Non-Subscribers	1	Less Good
Many Non-Subscribers	2	Good
Most Non-Subscribers	3	Very Good

Source: Authors, (2024).

In Table 8 above is the weighting of the Number of Unsubscribed Business Criteria, which is done by comparing the number of customers from order data and the amount of survey data from businesses that have not subscribed. The highest number of unsubscribed is obtained from the number of business surveys that are more than the number of customers. The number of subscriptions is a condition where the number of business surveys is equal to the number of customers. The number of unsubscribed is not much obtained from the comparison of the number of business surveys that are smaller than the number of customers.

Table 9: Weight of Business Type Criteria.

Criteria	Value	Description
Small Business	1	Less Good
Medium Business	2	Good
Large Business	3	Very Good

Source: Authors, (2024).

Table 9 above shows the weighting of the business type criteria, which is divided into 3 types of businesses classified according to the scope and amount of Internet network usage, namely small businesses, medium businesses, and large businesses. Small Businesses consist of Other, Public Facilities, Real Estate (Housing Complex), Business Service. Medium businesses consist of Gov Office, Enterprise, Retail & Distribution, and Manufacturing. Large Businesses consist of Media & Communication, Education, Health, Finance, and Hospitality & Tourism.

Table 10: Weight of ODP Count Criteria.

Criteria	Value	Description
Few ODPs	1	Less Good
Moderate ODPs	2	Good
Many ODPs	3	Very Good

Source: Authors, (2024).

The weighting of the criteria for the number of ODPs available is shown in Table 10 above. For classification, less than 8 is worth 1, less than 16 is worth 2, and greater than or equal to 24 is worth 3.

III.4.4 weighted normalized values

The following is a weight normalization where the weight value used has been determined on the basis of the evaluation priorities of the agency in question. Please refer to Table 11 for more details.

Table 11: Weighted Normalized Value.

No.	Criteria	Value	Normalized Value
C1	ODP Categories	4	0.26
C2	Non-Subscriber Business Count	5	0.33
C3	Business Type	3	0.2
C4	ODP Count	3	0.2

Source: Authors, (2024).

After weighting based on criteria and normalizing the weight of the criteria has been obtained, the development of a decision support system with the Weighted Product algorithm is continued with the calculation of alternatives per criterion from the user point used, calculation of the decision matrix, calculation of the vector (S) and ends with the calculation of preferences (Vi) in order to get results. The calculation process will be carried out in Experiments and Results.

IV. EXPERIMENTS AND RESULTS

IV.1 CONTENT BASED FILTERING FOR RECOMMENDATION ODP

At this stage will continue the process of developing the Content Based Filtering Recommendation System, namely the calculation of Cosine Similarity. Where previously the data collection process had been carried out to weight the criteria. For this calculation process, one user point will be used which is located at **latitude -2.188012** and **longitude 113.895569**. To calculate cosine similarity on ODP data is to use the following formula in Eq. (1).

Cosine Similarity

$$\mathrm{sim}(a,b) = \frac{\mathrm{n}(\mathrm{A} \cap \mathrm{B})}{\sqrt{(\mathrm{n}(\mathrm{A} \cap \mathrm{B}))}} \quad (1)$$

Where:

- sim(a,b) = Similarity score between user item and ODP item
- n(A) = Number of features of the user item
- n(B) = Number of features of the ODP item
- n(A ∩ B) = Number of features common to both the user item and the ODP item

To determine n(A), values are assigned based on the criteria of distance, category, and road status from the user, yielding the following.

User = [distance <= 50, category = green, check highway = not passed]

n(A) = [5,3,1]

Next, the values of n(B) are gathered from ODP data within a 250 m radius of the user point, as shown below on Table 12.

Table 12: Detected ODP Data.

ODP Name	Distance (m)	Category	Check Highway
ODP-PLK-FQ/006	59.95	Yellow	Not Passed
ODP-PLK-FQ/048	161.60	Green	Not Passed
ODP-PLK-FBD/007	225.88	Red	Passed
ODP-PLK-FQ/051	163.77	Red	Not Passed
ODP-PLK-FBD/035	135.16	Yellow	Passed

Source: Authors, (2024).

The detected data is converted using a scale for each of the criteria, resulting in the following in Table 13.

Table 13: ODP Data Conversion Based on Criteria.

ODP Name	Distance (m)	Category	Check Highway
ODP-PLK-FQ/006	4	2	1
ODP-PLK-FQ/048	2	3	1
ODP-PLK-FBD/007	1	1	0
ODP-PLK-FQ/051	2	1	1
ODP-PLK-FBD/035	3	2	0

Source: Authors, (2024).

The following calculations determine the cosine similarity for the nearest ODP recommendation system. The following table summarizes the similarity calculations between the user and the detected ODPs, ordered from highest to lowest similarity score. See Table 14 for details.

Table 14: ODP Data Conversion Based on Criteria.

2	Cosine Similarity	Order
ODP-PLK-FQ/006	0.98778	1
ODP-PLK-FQ/048	0.98450	2
ODP-PLK-FBD/007	0.90453	3
ODP-PLK-FQ/051	0.90619	4
ODP-PLK-FBD/035	0.67612	5

Source: Authors, (2024).

Thus, the recommended ODP for the user is as per the results in Table 14, with the top recommendation being ODP-PLK-FQ/006, followed by ODP-PLK-FBD/035 for last.

IV.2 WEIGHTED PRODUCT FOR DECISION MAKING OF BUSINESS STRATEGIC

This phase involves the development of the Decision Support System using the Weighted Product Algorithm, which includes alternative weighting per criterion based on the user point, decision matrix calculations, vector (S) calculations, and preference (Vi) value calculations. The user point coordinates are **latitude -2.188012** and **longitude 113.895569**.

After weighting each criterion, the ratings for each alternative based on the user's location were determined. Below is an example rating for each alternative according to the criteria. See Table 15.

Table 15: Alternatives per Criterion.

Alternatives	Criteria			
	C1 (ODP Category)	C2 (Non-Subscriber Business Count)	C3 (Business Type)	C4 (ODP Count)
A1	Yellow	The most	Intermediate	3
A2	Red	The most	Large	2

Source: Authors, (2024).

In Table 16, this matrix is then used in the next step to calculate the weighted score for each alternative, which allows comparison between A1 and A2 based on the importance weight of each criterion.

Table 16: Decision Matrix Value.

Alternatives	Criteria			
	C1	C2	C3	C4
A1	3	3	2	1
A2	2	3	3	1

Source: Authors, (2024).

The vector value determination utilizes the converted data from the alternative criteria as shown in the table. The vector (S) is calculated using the following Eq. (2).

Vector Values (S)

$$S_i = \prod_{j-1}^{n} X_{ij} W_j \tag{2}$$

Once all vector values are identified, preference values are calculated using the Eq. (3).

Preference Values (Vi)

$$V_i = \frac{\prod_{j-1}^{n} X_{ij} W_j}{\prod_{j-1}^{n} (X_j^{w}) W_j} \tag{3}$$

Based on the calculations through vector (S) and Preference (Vi), the highest value is found in alternative A1. Thus, the Decision-Making System for the Priority Promotion Area is set for A1, or 250 m north of the User Point. See Table 17 for more details.

Table 17: Weighted Product Values.

Alternatives	Si	Vi	Order
A1	2.1964	0.506	1
A2	2.1435	0.494	2

Source: Authors, (2024).

IV.3 LOCATION BASED SERVICE FOR VISUALITATION RESULT OF DECISION MAKING

The outcomes of the calculations using cosine similarity and the weighted product provide a strategic business decision that can be viewed in the application interface as illustrated in Figure. 2.

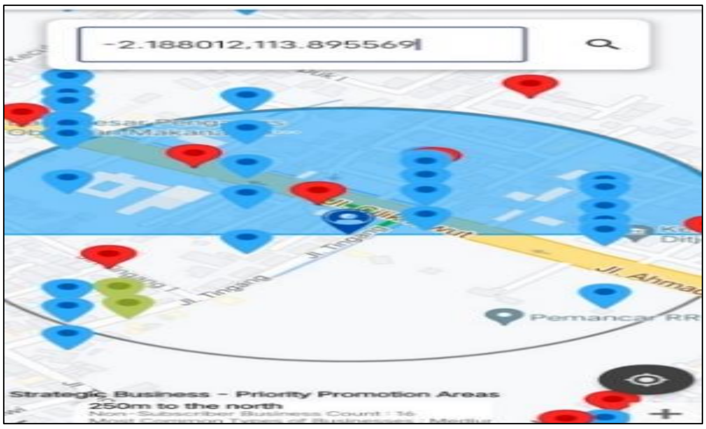

Figure 2: Location Based Service of Strategic Business.
Source: Authors, (2024).

In the application, four markers are visible: the user marker, red marker (ODP), blue marker (non-subscribing businesses), and green marker (customers). From the user point, a 250 m radius is delineated by a straight line dividing the northern and southern sections. The display at the bottom shows a list of DSS results for the business strategy, indicating priority promotion areas. Based on the top result in the list, the corresponding area on the map is colored, clearly indicating the priority region.

V. DISCUSSION

The integration of the Weighted Product Method (WPM), Content-Based Filtering (CBF), and Location-Based Services (LBS) into a Decision Support System (DSS) has yielded significant insights into optimizing Optical Distribution Point (ODP) placement in urban fiber-optic networks. Our results demonstrate not only the efficacy of this integrated approach but also its practical applications in enhancing service delivery.

The recommendation of ODP-PLK-FQ/006, which achieved a high **Cosine Similarity score of 0.98778**, reflects a strong alignment between the ODP's characteristics and user needs. This finding underscores the importance of incorporating user-specific preferences into the decision-making process, as emphasized in the Introduction. By tailoring ODP selections based on proximity and service categories, we enhance customer satisfaction and ensure that services are readily accessible.

The application of the WPM facilitated a structured ranking of alternatives based on multiple criteria, confirming that a multi-criteria approach is essential for making informed decisions. The preference scores for **Alternative A1 (250 m north)** and **Alternative A2 (250 m south)** highlight how nuanced factors like ODP category and business type can influence optimal placements. These insights contribute to a deeper understanding of the criteria that matter most in the context of urban internet services.

While our study achieves significant milestones, such as demonstrating the practicality of integrating WPM, CBF, and LBS, several limitations must be acknowledged. The accuracy of the recommendations is contingent on the quality and completeness of the input data. Missing or outdated information from customer surveys could lead to suboptimal ODP placements, which could impact overall service quality. Furthermore, while our DSS performed effectively within the scope of this study, its scalability in larger urban environments with complex network demands has yet to be tested.

One of the most innovative aspects of this study is the seamless integration of diverse methodologies into a single DSS framework. By leveraging LBS technology for real-time visualizations, we can provide stakeholders with interactive maps that enhance understanding of spatial relationships. This capability not only aids in decision-making but also serves as a valuable tool for communicating strategies to network engineers and business managers. The practical application of this system has the potential to revolutionize how ODP placements are approached in urban settings.

In conclusion, this study demonstrates that a comprehensive DSS integrating WPM, CBF, and LBS can significantly improve the optimization of ODP placements in urban environments. However, unresolved issues remain, particularly regarding data accuracy and system scalability. Future research should focus on testing the DSS in larger, more dynamic urban contexts to evaluate its robustness and adaptability.

To further enhance the effectiveness of the Decision Support System (DSS), we recommend incorporating machine learning algorithms to enable the system to adaptively learn from incoming data, improving its responsiveness to changes in customer demand and market conditions. Additionally, collaborating with telecommunication companies and urban planners to access more comprehensive datasets will enhance the accuracy and reliability of the recommendations. Lastly, continuously engaging with end-users to gather feedback can help refine the system, ensuring it remains aligned with customer needs and expectations. By addressing these recommendations, future iterations of the DSS can become even more effective in optimizing Optical Distribution Point (ODP) placements, ultimately leading to enhanced service delivery in urban networks.

VI. CONCLUSIONS

In conclusion, this research underscores the critical role of Optical Distribution Points (ODPs) in enhancing fiber-optic internet services. By integrating a Decision Support System (DSS) that employs the Weighted Product Method, Content-Based Filtering, and Location-Based Services, we have developed an innovative framework that effectively addresses the challenge of optimizing ODP placement in urban areas.

Our findings reveal that this multi-faceted approach not only improves decision-making by aligning ODP placement with customer needs and preferences but also enhances overall service delivery. Specifically, we have shown that considering various criteria—such as the number of ODPs, non-subscribing businesses, and business types—leads to more informed decisions and better strategic planning.

This study answers the research objective by demonstrating how the proposed DSS can streamline the decision-making process, ultimately facilitating the efficient deployment of ODPs where they are needed most. Looking ahead, we believe that further refining this system will empower stakeholders to adapt to the dynamic landscape of urban internet infrastructure, ensuring that service delivery remains responsive to customer demands.

By embracing this comprehensive approach, we contribute valuable insights to the telecommunications field and set the stage for future innovations that will enhance urban connectivity.

VII. AUTHOR'S CONTRIBUTION

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Approval of the final text: Viktor Handrianus Pranatawijaya, Widiatry Widiatry and Dea Jeany Lestari.

VIII. REFERENCES

[1] Y. A. Auliya et al., "Optimizing the routing of optical distribution points on a fiber network using modified genetic algorithm (GA's) with a travelling salesman problem approach," in The 7th International Conference Of Combinatorics, Graph Theory, And Network Topology 2023, AIP Publishing, 2024, p. 030049. doi: 10.1063/5.0222824.

[2] R. Sidik and Y. Ray, "Interactive Map-Based Optical Distribution Point (ODP) Mapping," Journal of Engineering Science and Technology, vol. 16, no. 3, pp. 2128–2138, 2021.

[3] S. Ashraf and A. K. Bardhan, "A location and capacity-allocation game model for two competing online delivery platforms seeking new customers," Electronic Commerce Research, Aug. 2024, doi: 10.1007/s10660-024-09891-w.

[4] X. Zhou, Y. Ding, C. Wu, J. Huang, and C. Hu, "Measuring the Spatial Allocation Rationality of Service Facilities of Residential Areas Based on Internet Map and Location-Based Service Data," Sustainability, vol. 11, no. 5, p. 1337, Mar. 2019, doi: 10.3390/su11051337.

[5] G. Smaragdakis, N. Laoutaris, K. Oikonomou, I. Stavrakakis, and A. Bestavros, "Distributed Server Migration for Scalable Internet Service Deployment," IEEE/ACM Transactions on Networking, vol. 22, no. 3, pp. 917–930, Jun. 2014, doi: 10.1109/TNET.2013.2270440.

[6] G. Kontsevik, V. Tikhevich, and S. Mityagin, "Enhancing Urban Planning Through Improved Connectivity: A Genetic Algorithm Approach for Optimal Service Placement," in Computational Science and Its Applications – ICCSA 2024, 2024, pp. 395–407. doi: 10.1007/978-3-031-64605-8_27.

[7] D. Wira Trise Putra and A. Agustian Punggara, "Comparison Analysis of Simple Additive Weighting (SAW) and Weigthed Product (WP) In Decision Support Systems," MATEC Web of Conferences, vol. 215, p. 01003, Oct. 2018, doi: 10.1051/matecconf/201821501003.

[8] D. G. H. Divayana, "Simulation of the weighted product method integrated with the CSE-UCLA evaluation model," in THE 8TH INTERNATIONAL CONFERENCE ON TECHNOLOGY AND VOCATIONAL TEACHERS 2022, 2024, p. 030004. doi: 10.1063/5.0214095.

[9] R. Hou, X. Ye, H. B. O. Zaki, and N. A. B. Omar, "Marketing Decision Support System Based on Data Mining Technology," Applied Sciences, vol. 13, no. 7, p. 4315, Mar. 2023, doi: 10.3390/app13074315.

[10] A. Nair and R. Mathews, "Challenges and Solutions in Recommender Systems," in Proceeding of the International Conference on Computer Networks, Big Data and IoT (ICCBI - 2019), 2020, pp. 188–194. doi: 10.1007/978-3-030-43192-1_21.

[11] K. Pasrija and K. Mittal, "A Survey of Recent Advances in Recommendation Systems," in IOT with Smart Systems, 2022, pp. 589–597. doi: 10.1007/978-981-16-3945-6_58.

[12] G. Kaur and R. Gupta, "A Study on Location Based Services and TTP based Privacy Preserving Techniques," in 2021 International Conference on Advances in Computing and Communications (ICACC), IEEE, Oct. 2021, pp. 1–5. doi: 10.1109/ICACC-202152719.2021.9708364.

[13] A. Rathod and V. Jariwala, "Scalable Collaborative Approach For Privacy Preservation In Location Based Services," Indian Journal of Computer Science and Engineering, vol. 13, no. 1, pp. 1–10, Feb. 2022, doi: 10.21817/indjcse/2022/v13i1/221301301.

[14] J. Samuel et al., "UD-SV: Urban data services and visualization framework for sharing multidisciplinary research," Transactions in GIS, vol. 27, no. 3, pp. 841–858, May 2023, doi: 10.1111/tgis.13049.

[15] M. T. Cepero Garcia and L. G. Montane-Jimenez, "Visualization to support decision-making in cities: advances, technology, challenges, and opportunities," in 2020 8th International Conference in Software Engineering Research and Innovation (CONISOFT), IEEE, Nov. 2020, pp. 198–207. doi: 10.1109/CONISOFT50191.2020.00037.

[16] A. Tohir et al., "Decision Support System using WP Algorithm for Teacher Selection," J Phys Conf Ser, vol. 1845, no. 1, p. 012028, Mar. 2021, doi: 10.1088/1742-6596/1845/1/012028.

[17] T. Hastono and F. Syah, "Alternative Solutions for Determining Village Funds Using Weight Product Method," IOP Conf Ser Mater Sci Eng, vol. 835, no. 1, p. 012029, Apr. 2020, doi: 10.1088/1757-899X/835/1/012029.

[18] Setiawansyah, A. A. Aldino, P. Palupiningsih, G. F. Laxmi, E. Delisa Mega, and I. Septiana, "Determining Best Graduates Using TOPSIS with Surrogate Weighting Procedures Approach," in 2023 International Conference on Networking, Electrical Engineering, Computer Science, and Technology (IConNECT), IEEE, Aug. 2023, pp. 60–64. doi: 10.1109/IConNECT56593.2023.10327119.

[19] Y. S. Bagi, S. Suyono, and M. F. Tomatala, "Decision Support System for High Achieving Students Selection Using AHP and TOPSIS," in 2020 2nd International Conference on Cybernetics and Intelligent System (ICORIS), IEEE, Oct. 2020, pp. 1–5. doi: 10.1109/ICORIS50180.2020.9320823.

[20] Y. Ariyanto and T. Widiyaningtyas, "A Systematic Review Of Movie Recommender Systems," Journal of Engineering and Technology for Industrial Applications, vol. 10, no. 47, pp. 34–41, Jul. 2024, doi: 10.5935/jetia.v10i47.1052.

[21] S. Sridhar, D. Dhanasekaran, and G. Charlyn Pushpa Latha, "Content-Based Movie Recommendation System Using MBO with DBN," Intelligent Automation & Soft Computing, vol. 35, no. 3, pp. 3241–3257, 2023, doi: 10.32604/iasc.2023.030361.

[22] N. R. Kota, V. Padmanabhan, and W. N. Bhukya, "Content Based Network Representational Learning for Movie Recommendation (CNMovieRec)," in Multi-disciplinary Trends in Artificial Intelligence (MIWAI 2023), 2023, pp. 112–123. doi: 10.1007/978-3-031-36402-0_10.

[23] Q. Nguyen, V. Nguyen, D. Tran, T. Mai, and T. Quan, "Star2vec: From Subspace Embedding to Whole-Space Embedding for Intelligent Recommendation System (Extended Abstract)," in Computational Data and Social Networks (CSoNet 2019), 2019, pp. 70–71. doi: 10.1007/978-3-030-34980-6_7.

[24] Y. Afoudi, M. Lazaar, and M. Al Achhab, "Impact of Feature selection on content-based recommendation system," in 2019 International Conference on Wireless Technologies, Embedded and Intelligent Systems (WITS), IEEE, Apr. 2019, pp. 1–6. doi: 10.1109/WITS.2019.8723706.

[25] M. Arulprakash, M. Joshikha, and C. Khemka, "Food recommender system using content based filtering," 4TH INTERNATIONAL CONFERENCE ON INTERNET OF THINGS 2023: ICIoT2023, vol. 3075, no. 1, 2024, doi: 10.1063/5.0217594.

[26] M. T. Mishan, A. L. Amir, M. H. Bin Mohd Supir, A. L. Kushan, N. Zulkifli, and M. H. Rahmat, "Integrating Business Intelligence and Recommendation Marketplace System for Hawker Using Content Based Filtering," in 2023 4th International Conference on Artificial Intelligence and Data Sciences (AiDAS), IEEE, Sep. 2023, pp. 200–205. doi: 10.1109/AiDAS60501.2023.10284691.

[27] S. S, Madhumitha. S, Sushma. R, S. M, Subitsha. M, and Swetha. S, "Certain Investigations on Cognitive based Movie Recommendation system using Pairwise Cosine Similarity," in 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS), IEEE, Mar. 2023, pp. 2139–2143. doi: 10.1109/ICACCS57279.2023.10112790.

[28] M. K. Delimayanti et al., "Web-Based Movie Recommendation System using Content-Based Filtering and KNN Algorithm," in 2022 9th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE), IEEE, Aug. 2022, pp. 314–318. doi: 10.1109/ICITACEE55701.2022.9923974.

[29] M. E. Elalami, I. A. Elshafei, and H. E. Abdelkader, "Location-Based Services Using Web-Gis By An Android Platform To Improve Students' Navigation During Covid-19," J Theor Appl Inf Technol, vol. 100, no. 10, 2022, [Online]. Available: www.jatit.org

[30] M. Deidda, A. Pala, and G. Vacca, "An example of a tourist location-based service (LBS) with open-source software," Applied Geomatics, vol. 5, no. 1, pp. 73–86, Mar. 2013, doi: 10.1007/s12518-012-0097-x.

[31] V. Paliulionis, "Issues of integrating GIS and mobile technologies in location-based services," Geodesy and cartography, vol. 30, no. 4, pp. 117–122, Aug. 2012, doi: 10.3846/13921541.2004.9636654.

[32] V. Poornima and R. Ganesan, "Implementation of health information system using Location Based Services," in 2014 IEEE International Conference on

Advanced Communications, Control and Computing Technologies, IEEE, May 2014, pp. 1692–1696. doi: 10.1109/ICACCCT.2014.7019397.

[33] D. Parmar and U. P. Rao, "Dummy Generation-Based Privacy Preservation for Location-Based Services," in Proceedings of the 21st International Conference on Distributed Computing and Networking, New York, NY, USA: ACM, Jan. 2020, pp. 1–1. doi: 10.1145/3369740.3373805.

[34] S. Ganapati, "Mobile Location-Based Service (LBS) Apps for the Public Sector," in Routledge Handbook on Information Technology in Government, Routledge, 2017, pp. 108–123. doi: 10.4324/9781315683645-7.

[35] F. Xiao et al., "A Data Processing Method for Load Data of Electric Boiler with Heat Reservoir," in Intelligent Computing Theories and Application (ICIC 2021), 2021, pp. 395–405. doi: 10.1007/978-3-030-84529-2_33.

[36] S. M. Mostafa, "Towards improving machine learning algorithms accuracy by benefiting from similarities between cases," Journal of Intelligent & Fuzzy Systems, vol. 40, no. 1, pp. 947–972, Jan. 2021, doi: 10.3233/JIFS-201077.

[37] H. Zitouni, S. Meshoul, and K. Taouche, "Enhancing Content Based Filtering Using Web of Data," in Computational Intelligence and Its Applications (CIIA 2018), 2018, pp. 609–621. doi: 10.1007/978-3-319-89743-1_52.

[38] N. Belacel, G. Wei, and Y. Bouslimani, "The K closest resemblance classifier for amazon products recommender system," in ICAART 2020 - Proceedings of the 12th International Conference on Agents and Artificial Intelligence, SciTePress, 2020, pp. 873–880. doi: 10.5220/0009155108730880.

[39] Nurmahaludin, G. R. Cahyono, J. Riadi, and I. Wardiah, "Decision support system for the selection of rice varieties using weighted product method," J Phys Conf Ser, vol. 1450, no. 1, p. 012059, Feb. 2020, doi: 10.1088/1742-6596/1450/1/012059.